CONTEXT REASONING UNDER UNCERTAINTY BASED ON EVIDENTIAL

FUSION NETWORKS IN HOME-BASED CARE

by

HYUN LEE

Presented to the Faculty of the Graduate School of

The University of Texas at Arlington in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

THE UNIVERSITY OF TEXAS AT ARLINGTON

August 2010

To my family, for always supporting me in life an being always there for me.

You have made all of this possible. Thank You.

ACKNOWLEDGEMENTS

ABSTRACT

CONTEXT REASONING UNDER UNCERTAINTY BASED ON EVIDENTIAL

FUSION NETWORKS IN HOME-BASED CARE

HYUN LEE, Ph.D.

The University of Texas at Arlington, 2010

Supervising Professor: Ramez Elmasri

Pervasive computing technologies use embedded intelligent systems to enable various real-time applications. Some of these applications are: continuous healthcare monitoring, autonomous diagnosis and treatment, and remote disease management without spatial-temporal limitations. Additional healthcare applications include home-based care, disaster relief management, medical facility management, and sports health management. Issues related to the pervasive healthcare are generally classified into five categories: Hardware, Software, Regulations, Standardization and Organization. Our focus in this dissertation is on software issues. We propose new methods to generate a reliable context in a pervasive information system that has high rates of new measurements over time using data aggregation and data fusion. Different aggregation and fusion techniques can be applied depending on the types of sensed data and autonomous processing within the fusion step.

The goal of this research is to produce a high confidence level in the generated context for remote monitoring of patients. Reliable contextual information of remotely monitored patients can prevent hazardous situations by recognizing emergency

situations in home-based care. However, it is difficult to achieve a high confidence level of contextual information for several reasons. First, the pieces of information obtained from multi-sensors have different degrees of uncertainty. Second, generated contexts can be conflicting even though they are acquired by simultaneous operations. And last, context reasoning over time is difficult because of unpredictable temporal changes in sensory information. In particular, some types of contextual information are more important than others in home-based care. The weight of this information may change, due to the aggregation of the various sensors (evidence) and the variation of the values of the various sensors (evidence) over time. This causes difficulty in defining the absolute weight of the evidence in order to obtain the correct decision making.

In this dissertation, we propose an evidential fusion process as a context reasoning method based on the defined context classification and state-space based context modeling. First, the context reasoning method processes sensed data with an evidential form based on Dezert-Smarandache Theory (DSmT). The DSmT approach reduces ambiguous or conflicting contextual information in multi-sensor networks. Second, we deal with dynamic metrics such as preference, temporal consistency, and relation-dependency of the context using Autonomous Learning Process (ALP) and Temporal Belief Filtering (TBF) in order to improve the confidence level of contextual information that makes a correct decision about the situation of the patient. And last, we deal with both relative and individual importance of the evidence to obtain an optimal weight of the evidence. We then apply dynamic weights of the evidence into Dynamic Evidential Network (DEN) in order to improve the confidence level of the context and to understand the emergency progress of the patient in home-based care.

Finally, we compare the Evidential Fusion Process on DSmT with traditional fusion processes such as Bayesian Networks (BNs), Dempster-Shafer Theory (DST), and Dynamic Bayesian Networks (DBNs). This comparison makes us understand the uncertainty analysis in decision-making by distinguishing sensor reading errors (i.e., false alarm) from new sensor activations or deactivations, and shows the improvement of our proposed method compared to the others.

The main contributions of the proposed context reasoning method under uncertainty based on evidential fusion networks are: 1) Reducing the conflicting mass in uncertainty level and improving the confidence level by adapting the DSmT, 2) Distinguishing the sensor reading error from new sensor activations or deactivations by considering the ALP and the TBF algorithm, and 3) Representing optimal weights of the evidence by applying the normalized weighting technique into related context attributes. These advantages help to make correct decisions about the situation of the patient in home-based care.

TABLE OF CONTENTS

LIST OF FIGURES

xiv

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Introduction

In recent years, healthcare applications such as home-based care, disaster re-
lief management, medical facility management and sports health management have
gained considerable interest [22, 79, 98, 126] as a pervasive computing area. A wide
range of pervasive computing technologies use embedded intelligent systems in order
to provide autonomous and pro-active services to the users. A Pervasive Healthcare
Monitoring System (PHMS) enables independent living, general wellness and remote
disease management in real time without spatial-temporal restrictions using these
technologies for everyday healthcare management. This PHMS approach gives advan-
tages: comprehensive health monitoring services, intelligent emergency management
services and self-adaptable automation services [41, 112, 128] to the elderly person or
patient using advanced pervasive technologies: Body Sensor Network (BSN), Wireless
Sensor Network (WSN), Mobile devices such as PDA, Handheld, and Cell-phone and
IT-based network such as Bluetooth, WiFi, Zigbee, and internet [136, 129, 11, 64].

A PHMS is composed of the combination of four components: Elderly person
or patient, Medical Sensor Networks, Information System, and Doctor as shown in
Figure 1.1. Sensor devices installed in medical sensor networks collect sensed data
continuously from an elderly person or a patient and the environment. Information
system aggregates sensed data based on data fusion techniques in order to generate
the context for a particular situation of an elderly person or a patient. Finally, a
doctor analyzes the situation using analysis tools and provides feedback to an elderly
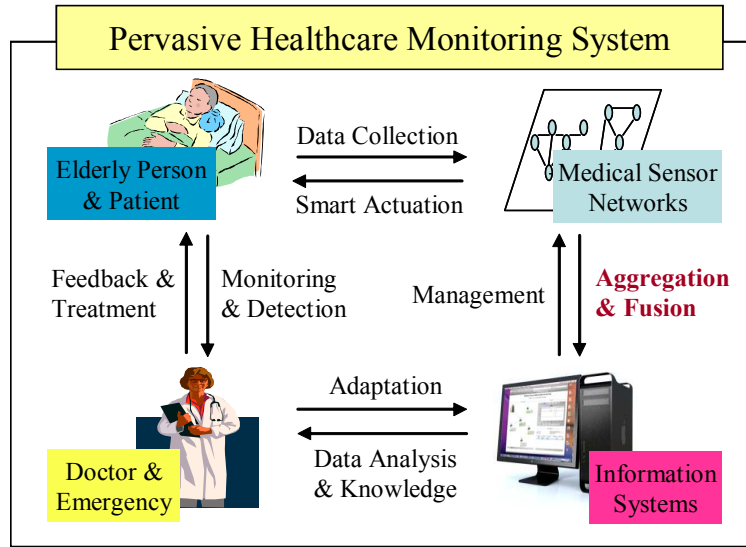
Figure 1.1. A Pervasive Healthcare Monitoring System (PHMS).

person or a patient. If an emergency situation occurs, medical emergency aid can be requested by a doctor or an emergency alarm system.

Issues related to everyday healthcare management still exist in pervasive healthcare area. These healthcare management issues can be classified into five categories: Hardware, Software, Regulation, Standardization and Organization [6, 122]. The hardware issue deals with low power, energy scavenging, material constraints and long-term operation. The software issue deals with reliability, energy-efficiency, security, fault-tolerance, context-awareness and actuation. The regulation issue deals with authority and legislation. The standard issue deals with hardware-software interfaces, software-software interfaces, data communication and data storage. The organization issue deals with methods so as to define who will deploy and control such systems and who will cover the costs of installation, management and repair. Our research focus in this dissertation is on the software issues. In particular, our research challenge is how to generate reliable context in a pervasive information system that has high rates of new measurements over time using data aggregation and data fusion tech-

niques. Different aggregation and fusion techniques can be applied depending on the types of sensed data and autonomous processing within the fusion step. In addition, our research goal is to produce a high confidence level of contextual information for remote monitoring of an elderly person or a patient. Reliable contextual information of remotely monitored patients can prevent hazardous situations by recognizing emergency situations of the patient in home-based care.

However, it is difficult in achieving a high confidence level of contextual information for several reasons. First, the pieces of information obtained from multi-sensors have different degrees of uncertainty. Second, generated contexts can be conflicting even though they are acquired by simultaneous operations. And last, context reasoning over time is difficult because of unpredictable temporal changes in sensory information. In particular, some types of contextual information are more important than others in home-based care. The weight of this information may change, due to the aggregation of the various sensors and the variation of the values of the various sensors over time. This causes the difficulty in defining the absolute weight of the evidence in order to obtain the correct decision making.

Therefore, in this dissertation, we make the scenario that reliable contextual information of remotely monitored patients should be generated to prevent hazardous situations by recognizing emergency situations correctly in home-based care. Based on the scenario, we propose an evidential fusion process under uncertainty as a context reasoning method. The proposed context reasoning methods deal with different aspects of the imperfection of information such as reliable, partial reliable, or completely unreliable. The proposed context reasoning methods also deal with dynamic weights of sensed data by considering dynamic metrics such as preference, temporal consistency and relation-dependency of contextual information. In this dissertation, we show that the proposed context reasoning methods reduce uncertainty of con-

textual information so as to improve the confidence level of contextual information compared to the others such as fusion processes based on Bayesian Networks (BNs) [105, 108], Dempster-Shafer Theory (DST) [56, 134] and Dynamic Bayesian Networks (DBNs) [29, 90, 141].

1.2 Challenges and Problem Statement

An instance of such an intelligent indoor healthcare environment perceives the surroundings through multi-sensors and acts on it with the help of related actuators.[25]. In this environment, the activities of the elderly person or patient create uncertainty of the context depending on his/her location and time. Context is defined as any information that can be used to characterize the situation of an entity, where an entity is a person, place or object [34]. A relevant to the interaction between a user and an application, including the user and the application themselves, is considered as context. In order to be cognizant of his/her contexts correctly, we need to minimize this uncertainty and improve the confidence level that is generally used as a decision criterion for the situation of the elderly person or patient. In particular, we consider data fusion techniques depending on the types of context. The types of context involves his/her location, activities and vital signs that can provide health related and wellness management services in an intelligent way so as to promote independent living and medical automated diagnosis and treatment.

Contextual information should be presented by some generalized forms of context classification and modeling to deal with all aspects of the contexts correctly. The quality of a given piece of contextual information should be considered based on the applied context classification and modeling [106]. However, a generalized context classification is difficult to produce. Context classification defines the way in order to implicate contextual information itself. For instance, the number of ways to describe

an event or an object is unlimited and there are no standards or guidelines regarding granularity of context information. Contextual information of interest is not confined to traditional parameter measurements that manage uncertainty by using error propagation rules and statistical weighting of redundant measurements. In addition, reliable contextual information should be generated by applying a context reasoning method [98]. This is helpful to recognize the activities of the elderly person or patient correctly so as to identify hazardous situation using data fusion techniques. However, multi-sensors may provide fault information due to inaccurate sensor readings and conflicted reading errors. Some sensor readings give information about context only at an abstract level that can include uncertainty to some extent. It is difficult to generate a context reasoning method under uncertainty for inferring the correct situation of the elderly person or patient directly. Moreover, context reasoning over time is important in order to find wrong contextual information and emergency progress of the patient by considering unpredictable temporal changes in sensory information [108]. Dynamic and active information fusion method is used in [141] to deal with temporal changes in sensory information based on Dynamic Bayesian Networks (DBNs) by considering the sensor selection. However, the [141] did not consider temporal consistency and relation-dependency of consecutive time-indexed states. The association or correlation between consecutive time-indexed states should be considered in order to reduce the affection of wrong sensor operations that may happen at one of time-indexed states. Finally, the weights of the information are applied to the pervasive healthcare system in order to strongly indicate the specific situation of the patient [97]. However, it is difficult in defining the absolute weight of selected sensors. The weight of the selected sensor is different depending on the aggregation of selected sensors and the variation of the value of the selected sensors over time. The [97] only did consider the pre-defined weight of selected sensors.

Therefore, in this dissertation, we define the problem statement as follow: what the necessary concepts and methods are for generalized context classification, modeling and reasoning based on an evidential fusion network in a home-based care application so as to improve the confidence level of contextual information of the elderly person or patient.

1.3 Scope and Methodology

A contextual analysis for situation assessment (SA) and metrics have been important topics in the Information Fusion (IF) literature for many years [17, 47, 109]. A 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. A PHMS is one of pervasive healthcare systems for situation assessment (SA).

In order to deal with the problem statement of this dissertation, we define a relation-dependency based context classification as a generalized context classification. We define a state-space based context modeling as a generalized context modeling. In a smart space such as home-based care, an information description vocabulary set is carefully pre-specified in context classification. The qualitative contextual information is transferred to the quantitative representation in the given location and time. All possible values and their ambiguous combinations are considered as evidential forms within the proposed context modeling. In addition, we process sensed data with an evidential form based on Dezert-Smarandache Theory (DSmT) [36, 37, 38] that reduces the uncertainty level using a proportional conflict redistribution no. 5 (PCR5) combination rule [117] and obtains a rational decision of contextual information using a generalized pignistic transformation (GPT) [39]. In particular, we compare the (pignistic) probability level and uncertainty level of Bayesian Networks

(BNs), Dempster-Shafer Theory (DST) and DSmT based on Shafer's model [114]. In this case, we apply different weighting factors and discounting factors into evidential fusion networks. Moreover, we consider the association or correlation of contextual information between two consecutive time-indexed states by considering dynamic metrics: preference, temporal consistency and the relation-dependency of information. We utilize Autonomous Learning Process (ALP) and Temporal Belief Filtering (TBF) so as to find a false alarm from new sensor activations or deactivations. In order to show the improvement of our suggested method, we compare the uncertainty level and confidence (i.e., GPT) level of our approach with those of Static Evidential Fusion Process (SEFP) and Dynamic Bayesian Networks (DBNs) by considering four cases: 1) temporal dependency, 2) relation-dependency, 3) different weighting factors, and 4) different discounting factors. In this case, we use pre-defined thresholds and time window sizes so as to find an optimal context reasoning method based on Dynamic Evidential Network (DEN). Finally, we apply dynamic weights into the various sensors (evidence) in order to represent the variations of the weights depending on the aggregation of the selected sensors over time. In particular, we calculate relative and individual importance of the evidence using the proposed normalized weighting technique so as to update the weights of the evidence. We compare the confidence level of contextual information based on Dynamic Weighting based Evidential Fusion Process (DWEFP) with the previous works [69, 68, 56].

1.4   Key Contributions

As we mentioned, contextual analysis and metrics for Smart Applications have been important topics in the Information Fusion literature for twenty years. There are three areas of key contribution in this dissertation: 1) Static Evidential Fusion Process (SEFP) Approach, 2) Dynamic Evidential Fusion Process (DEFP) Approach,

and 3) Dynamic Weighting based Evidential Fusion Process (DWEFP) Approach. We discuss each of these below.

1.4.1 Static Evidential Fusion Process

With a static evidential fusion process (SEFP) based on DSmT, PCR5 combination rule and GPT, we covered difficult issues in uncertainty analysis in decision-making as to the ability to measure confidence, belief, or uncertainty in a multi-sensor network. Using this approach, we compared our approach to existing methods using home-based care application in our comparison. No previous works with the DSmT in a home-based care application as a context reasoning method under uncertainty. According to this approach, we improved the confidence level of contextual information compared to that of Bayesian Networks (BNs) and we reduced the conflicting mass in uncertainty level of contextual information compared to that of Dempster-Shafer Theory (DST).

1.4.2 Dynamic Evidential Fusion Process

With a dynamic evidential fusion process (DEFP) based on the ALP and TBF algorithm, we made two key contributions. First, we suggested a method in order to distinguish a sensor reading error from new sensor activations or deactivations using the mean of differentiation of consecutive time-indexed states. Second, we established a higher confidence level of contextual information of the elderly person or patient by considering the TBF with an optimal time window sizes compared to that of Dynamic Bayesian Networks (DBNs). This approach is helpful to reduce unnecessary operations of the caregiver or the expert system by checking an emergency progress of the elderly person or patient. No previous works have combined DSmT with Markov Chain (MC) so as to make a temporal belief filtering (TBF) algorithm.

1.4.3   Dynamic Weighting based Evidential Fusion Process

With a dynamic weighting based evidential fusion process (DWEFP) based on the pre-defined rules of a context attribute and the normalized weighting technique, we improved the confidence level of contextual information compared to those of SEFP, DEFP, and DBNs. This approach improved the quality of contextual information by considering a dynamic weight of a context attribute at each time-indexed state.

The main contributions of this dissertation are: 1) Reducing the conflicting mass in uncertainty level and improving the confidence level of contextual information by adapting the DSmT, PCR5 combination rule, and GPT, 2) Distinguishing a sensor reading error from new sensor activations or deactivations and improving the confidence level of contextual information by considering the ALP and TBF algorithm, 3) Representing optimal weights of the evidence by applying the normalized weighting technique. These advantages help to make correct decisions about the situation of the patient compared to the others such as context reasoning methods based on BNs, DST, and DBNs.

1.5   Organization

The remainder of this dissertation is organized as follows. In Chapter 2, the basics of context reasoning are introduced. Types of sensors, characteristics of the evidence, relation-dependency based context classification, and state-space based context modeling are introduced. In Chapter 3, we propose the Static Evidential Fusion Process (SEFP) as a context reasoning method. The proposed method is compared to the others based on Static Evidential Network (SEN) so as to reduce the conflicting mass in uncertainty level of contextual information. In Chapter 4, we propose the

Dynamic Evidential Fusion Process (DEFP) as a context reasoning method. This proposed method improves the confidence level of contextual information over time and estimates a sensor reading error from new sensor activations or deactivations by adapting the Autonomous Learning Process (ALP) and Temporal Belief Filtering (TBF) algorithm. In Chapter 5, we propose the Dynamic Weighting based Fusion Process (DWEFP) as a context reasoning method. The proposed method represents optimal weights of the evidence in order to improve the quality of contextual information by adapting a normalized weighting technique. In Chapter 6, related work is summarized and this dissertation is positioned among and against other publications with regard to novelties in our approach and differences to previous work. Finally, the dissertation is summarized by pointing out the main arguments and the scientific contribution and giving an outlook on possible future research in Chapter 7.

CHAPTER 2

BASICS OF CONTEXT REASONING

2.1 Introduction

A wide range of pervasive computing technologies aim to provide pervasive services to the occupants using intelligent embedded systems in smart spaces (e.g., smart home, smart office, smart home-based care, smart environment, etc.) [25, 98, 28]. In smart spaces, reliable contextual information should be obtained by a context reasoning method that recognizes the correct status of the occupants in order to provide adaptive pervasive services to them. A pervasive computing system shows different degrees of reliability depending on the types of sensors and the applied application. In addition, the quality of a given piece of information should be considered based on the applied context classification and context modeling [106]. In this chapter, we introduce some concepts and the basics of context reasoning such as types of sensors, characteristics of the evidence, context classification and context modeling. In particular, we assume that the PHMS is used as a pervasive healthcare system in home-based care environment so as to deal with the basics of context reasoning with a selected smart space.

2.2 Types of Sensors

In general, several types of sensors such as medical body sensors, environmental sensors and actuators, location sensors, and time stamps are utilized in PHMS. We show the relationship among these types of sensors in terms of distance between their locations and the position of a patient as shown in Figure 2.1.
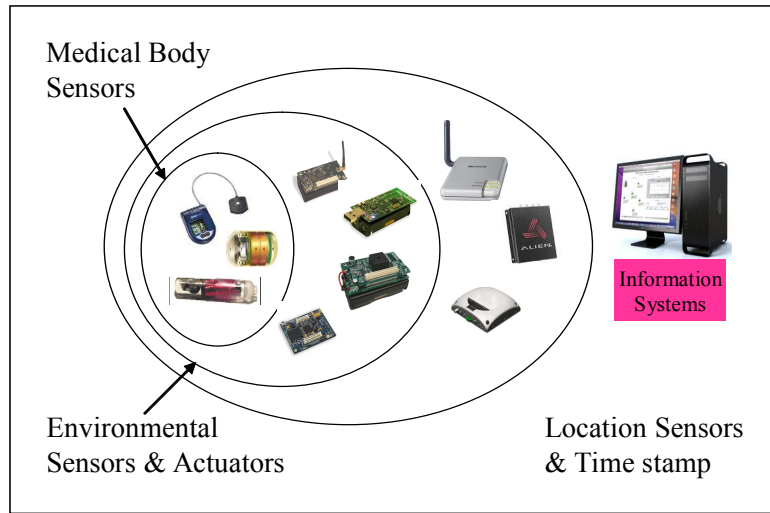
Figure 2.1. An example of types of sensors.

2.2.1 Medical Body Sensors

In pervasive healthcare applications, body sensor devices play an important role in order to obtain information of a patient's body condition. Broadly, we divide body sensor devices into two classes: 1) internal sensor devices and 2) external sensor devices.

2.2.1.1 Internal Sensor Devices

Internal types of body sensor devices include ingestible capsule and implanted sensors. A core temperature sensor embedded in an ingestible capsule that is easy to swallow can measure a core body temperature (CBT) [1, 5]. the [1, 5] introduces new products for checking the core body temperature. Some implanted sensor can check medical information using an implanted chip. These chips diagnose conditions of the patient such as Parkinson's disease and Paralysis [4, 2]. The VeriChip [4] is a small Radio Frequency Identification (RFID) chip sized grain of rice that is implanted under the skin. The Neurotech has Neural Signals to check the progress of the Parkinson's

disease [2]. The Endoscope sensor implemented by RF system lab measures internal body conditions using two products Noriak3 (2001) and Sayaka (2005) [3].

2.2.1.2 External Sensor Devices

External types of body sensor devices include wearable and detachable electrical signaling sensors. A pulse oximeter sensor measures a heart rate (HR) and a blood oxygen saturation. For blood oxygen saturation, the sensor detects colors of beams based on hemoglobin molecules. The sensor utilizes two beams on finger or earlobe then calculates the amount of beam reflected by hemoglobin. A HR is measured by contracting and expanding of blood vessels [116]. An electrocardiograph sensor checks the cardiac information. Sensors detect a cardiac rhythm then electrocardiograph obtains the information signal from the contraction and extension of the cardiac muscle. Products of these types of sensors are discussed in [42]. A skin temperatures is detected by dermal body temperature sensor patched as introduced in [44].

2.2.2 Environmental Sensors and Actuators

Environmental variables are important factors in a PHMS. Environmental sensing data is combined with sensed body/location/time data so as to assist the analysis of personal situations of the elder person or patient. Decision making is enhanced by operating smart actuators or providing feedback requests of a doctor. In this case, parameters such as temperature, humidity, air quality, illumination and noise are calculated and applied to the current PHMS. For instance, we assume that an elderly person enters a bathroom. We check the physiological condition using body sensors and find the location using location sensors. However, we can not easily distinguish a cardiac episode from a period of staying in a hot tub unless the location information is provided correctly because both situations can cause rapid heartbeat and degener-

ated ECG signal. In this situation, temperature and humidity sensors help to analyze the current situation and an acoustic sensor traces the activity of the elderly person so as to make a context. A pre-installed actuator reduces the CO_2 level and controls the lighting level based on the air quality and illumination sensor readings in order to support better conditions of the elderly person or patient. Thus, environmental types of sensors are important so as to determine a reliable context generation and a better quality of service. A dimmable lighting, fire alarm, flood alarm, heater, ventilate and air-conditioning are examples of systems that can be controlled by various types of actuators.

2.2.3   Location

Spatial information of a single or multiple persons is one of the important factors in order to check the targeted person's condition in a PHMS. In pervasive healthcare area, the system has to keep tracking the person's location because a body condition of a body sensor worn person might be changed depending on the location. For example, the person's heart rate and body temperature can increase. These changes of a body condition are normal when the person exercises in a fitness room. If a PHMS is not location-aware, the system might falsely warn to a medical institution. Thus, the accurate location information is a momentous factor in order to make a correct decision of the need for emergency aid. The most uncomplicated solution is that each healthcare needing person uses a Global Positioning System (GPS) receiver. A home gateway system intercommunicates with the GPS receiver to track the person. However, the GPS is not a practical solution because the GPS is limited in indoor circumstances. Accuracy of this system is not stable due to the several sources of error such as ionospheric effects, ephemeris errors, and satellite clock errors. Relative localization in the indoor healthcare area is required among sensor

nodes in a pre-specified space (e.g., home arrangement and furniture places). In order to obtain a high accuracy, the home gateway device has to pre-acquire localized sensors' precise location. It maps the targeted person's spatial information based on the sensed data into the pre-specified space [91]. Types of on-board sensing equipment include acoustic, Infra-Red, pressure and camera. With the use of the sensed data, the location of a person can be processed by triangulation, trilateration, or multilateration approaches [121]. Multilateration, also known as hyperbolic positioning, is the process of locating an object by accurately computing the time difference of arrival (TDOA) of a signal emitted from that object to three or more receivers. It refers to the case of locating a receiver by measuring the TDOA of a signal transmitted from three or more synchronized transmitters. An active RFID based localization schemes can be employed in the indoor health care system such as LANDMARC [92] and its variation [61].

2.2.4   Time

Time can give medical doctors or caregivers valuable temporal information to deal with patients appropriately. In order to generate correct context from the given sensors that we mentioned so far, each type of sensor has to have a function to record the time stamp on each data packet of sensed data. Time stamps along with sensed data from different types of sensors play an important role in analyzing a situation. Dey [33] specify time as one of the primary context types for characterizing a particular situation with other context types, including location, identity and activity. For instance, if location sensors detect a patient in a living room staying for several hours, the system can generate different context based on whether it was at 2:00 am or 2:00 pm. A function for time stamp generation exists in all the types of sensors: body, environmental and location. A function for time stamp generation creates an

additional issue of clock synchronization among the various sensors, however, we do not discuss this issue in this dissertation.

2.3   Characteristics of the Evidence

Multi-sensors such as medical body sensors, Radio Frequency Identification (RFID) devices, environmental sensors and actuators, location sensors, and time stamps are utilized in a PHMS [74]. These sensors are operated by pre-defined 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 over the pre-defined 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 types of a sensor may have various discounting factors (D) $(0 \leq D \leq 1)$. 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):

$$R = 1 - D \tag{2.1}$$

For inferring the activity of the patient based on evidential theory, reliability discounting methods that transform beliefs of each source are used so as to reflect the

sensor's credibility, in terms of discount factor (D) $(0 \leq D \leq 1)$. The discount mass function is defined as:

$$m^D(X) = \begin{cases} (1-D)m(X) & X \subset \Theta \\ D + (1-D)m(\Theta) & X = \Theta \end{cases} \tag{2.2}$$

where the source is absolutely reliable $(D = 0)$, the source is reliable with a discounting factor (D) $(0 < D < 1)$, and the source is completely unreliable $(D = 1)$.

2.4   Pragmatic Context Classification

Contextual information of a patient should be presented by some generalized forms of context classification in order to determine reliable contextual information. The quality of a given piece of contextual information should be considered by the applied context classification [106]. Context classification defined as the taxonomy of contextual information needs to be developed in order to provide a reference for better managing the context elements. It is valuable for providing the improved quality of contextual information. It can manipulate unfounded certainty from ignoring inherent or generated errors. However, it is an impossible task to build a general context classification so as to capture all aspects of the patient's contextual information in smart spaces. Context classification is not how to define some orthogonal dimensions that can categorize the context contents but rather its origin is in the nature of the far-reaching implications of context information itself [133]. For example, the numbers of ways to describe an event or an object are unlimited and there are no standards or guidelines regarding granularity of contextual information. In addition, the quality of a given piece of contextual information is not guaranteed by uncertainty. Contextual information of interest is not confined to traditional pa-

rameter measurements that manage uncertainty by using error propagation rules and statistical weighting of redundant measurements.

In this dissertation, we propose a pragmatic context classification [67] so as to provide reliable contextual information in smart spaces. An information description vocabulary set for given applications is carefully pre-specified in context classification in order to make a practical solution by adopting "*occupant-centered pragmatic*" approach and "*relation-dependency*" approach. The occupant-centered approach has three categories: 1) physical environments; 2) the activities of the occupant; and 3) occupant's physiological states. The relation-dependency approach based on spatial-temporal limitations has three categories: 1) discrete environmental facts; 2) continuous environmental facts; and 3) occupant-interaction events.

2.4.1 An Occupant-Centered Pragmatic Approach

An occupant-centered pragmatic approach includes the following aspects of contextual information, defined as the relations among three subcategories of the proposed approach, for making a context classification as shown in Figure 2.2.

2.4.1.1 Physical environments around the occupant

In Figure 2.2, an environmental context description is composed of four aspects of information: location, time, people, and facilities and devices. "*Location*" related information includes where the occupant is at the current time-indexed state. "*Time*" related information can be either in the sense of time stamp (discrete) or in the sense of time period/intervals (continuous). It will affect the methodology for fusion modeling. "*People*" around the occupant decide what interactions the occupant might engage in. For instance, different actuator's operation policies are determined by the number of people within the same location. If multiple people stay within
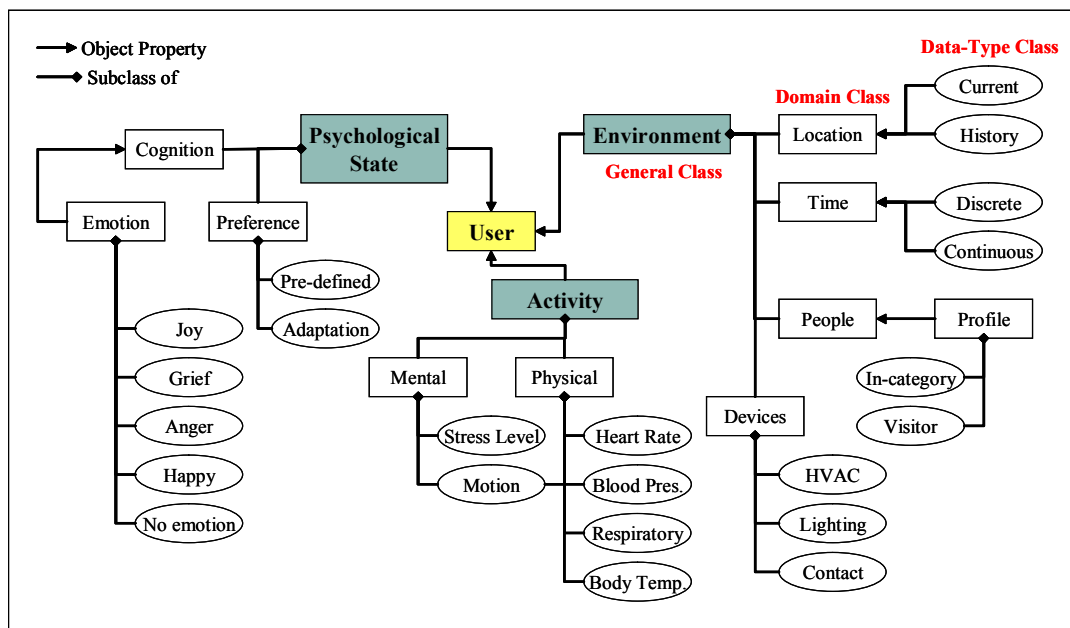
Figure 2.2. An Occupant-Centered Pragmatic Approach.

the same location, conflict resolution methods such as [66] can be applied to embedded intelligent systems. "*Facilities* and *devices*" information (i.e., activation or deactivation) include what facilities and devices he/she can reach and possibly use. In particular, environmental sensors and actuators such as the heating, ventilating, and air conditioning (HVAC) and the lighting system are members of this category.

2.4.1.2 The activities of the occupant

A context description for the activities of the occupant is composed of two aspects of information: mental activity and physical activity. "*Mental Activity*" includes conceptual activities (e.g., working, resting, thinking, etc.) without any changing of the physical conditions of the body. "*Physical activity*" includes measurable activities (e.g., writing, shaking, walking, etc.) with any changing of the physical conditions of the body. In particular, multi-sensors or RFID tags attached on the

body of the occupant can be used in order to fuse sensed data that represent the physical activity of the occupant.

2.4.1.3 The Physiological states of the occupant

A context description for physiological states of the occupant is composed of two aspects of information: preference and feeling. The "*preference*" of the occupant includes the current likeness and the historical likenesses of the occupant. It will be helpful to predict next patterns autonomously using a learning algorithm as shown in [72]. It can analyze and apply occupant's preferences into intelligent embedded systems. The occupant's "feeling" or emotional status would be too difficult to describe correctly. Even if we set up the pattern of occupant's feeling by adapting occupant's preferences, occupant's feeling may be changed unpredictable. Hence occupant's manual interactions are needed in this category.

2.4.2 A Relation-Dependency Approach

The dependency is a special type of relationship that exists not between entities and attributes but between associations themselves [54]. Without knowledge of such dependencies, inappropriate decisions may be made by context-aware applications that can lead to wrong operations to the elderly person or patient. We consider the relation-dependency approach based on spatial-temporal criteria as shown in Figure 2.3. In this approach, contexts are represented by three relation-dependencies: "*Discrete facts*", "*Continuous facts*", and "*Occupant's interaction events*". These relation-dependency components consist of "Context state $(S(t))$", defined as the collection and aggregation of activated or deactivated context attributes [67], "Sensor's static threshold $(T(t))$", "Location of the patient $(R(t))$", "Primary context (P)", "Secondary context (S)" and "Preference $(Pref)$".
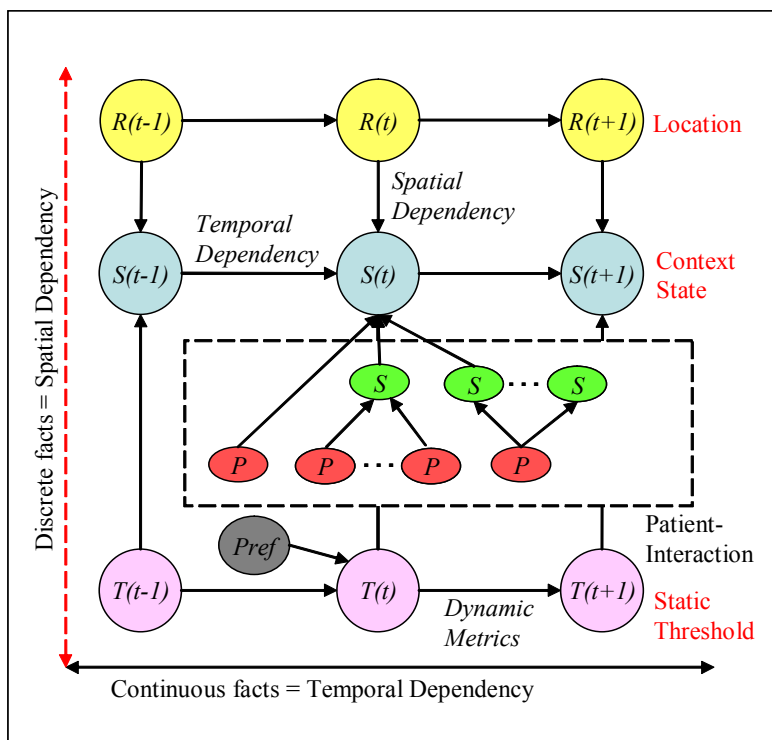
Figure 2.3. A Relation-dependency approach.

2.4.2.1   Discrete Facts

Context can be represented by three types of discrete facts: "*Discrete value*", "*Enumerative set*" and "*State context*". Discrete value of a context has no dependency so it can lead to contextual information in some cases directly. In general, the values of a 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 even though the total size of the set may be infinite theoretically. The state context that 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 composed of the enumerative set can recognize a particular contextual information of the patient: *Emergency or No-Emergency*.

2.4.2.2 Continuous Facts

Context can be represented by two types of continuous facts: "*Static threshold*" and "*Dynamic metrics*". A static threshold of a context is defined by pre-defined rules even though the value of a context changes continuously. Upper bounds, lower bounds, and comparative criteria are involved in this category. Dynamic metrics that combine preference values into the static threshold are used so as to estimate or infer the future contextual information autonomously. An occupant's location and activity often change from one time-indexed state to the next. The preference or the past location's information is helpful to estimate the next location of an occupant within the given time and location.

2.4.2.3 Occupant-Interaction Events

Two types of a context, "*Primary context* (P)" and "*Secondary context* (S)", are derived from multi-sensors or information sources. "P" maintains directly one-to-one interaction event that has a discrete value. Discounting factors (D) of sensors should be reduced in order to improve the quality of generated contextual information. In smart space, we can not recognize the correct situation or activity of the occupant using only direct contextual information. We need to derive context using derived or secondary context so as to get more reliable contextual information. "S" maintains two different interactions: "many-to-one" interactions and "one-to-many" interactions. More than one "P" (e.g., humidity, temperature, lighting level, etc.) 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.
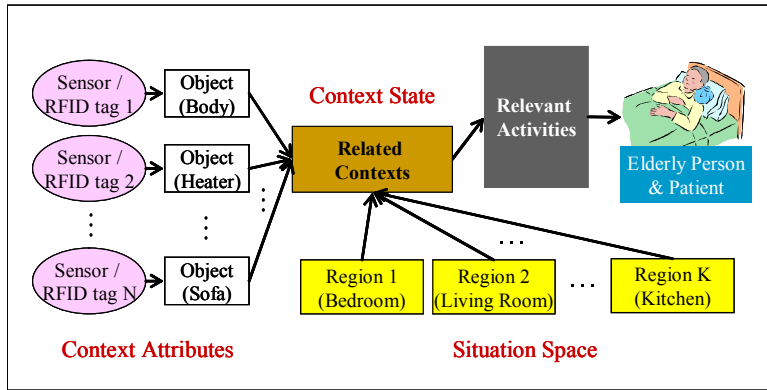
Figure 2.4. An inter-relationship based on state-space context modeling.

The weighting factors [108] of each sensor should be considered in order to improve the quality of generated contextual information.

2.5   State-Space based Context Modeling

In [67], we defined a state-space based context modeling with an evidential form as a generalized context modeling so as to represent the situation of the patient using context concepts that are similarly used in [97] and in order to improve the quality of a given piece of contextual information by reducing uncertainty. Within the proposed modeling, all possible values and their ambiguous combinations are considered in order to improve the quality of data in the given time and location. We assign a probability value to each related set so as to achieve an efficient uncertainty representation. This can transfer a qualitative context information to a quantitative representation. Static weighting factors of the selected data are applied in order to represent the quality of data initially within the given time t and location R. This context modeling consists of a hierarchical interrelationship among multi-sensors, related contexts, and relevant activities within a selected region as shown in Figure 2.4. Each context concept is defined as follow.

2.5.1 Context Attribute

A *context attribute*, denoted by α_i, is defined as any type of data that is utilized in the process of 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 instance, the pressure sensor attached on the sofa or the temperature sensor attached on the body of the patient are examples of a context attribute in home-based care application. These sensors are unable to directly identify situations on their own, but they can estimate the situation by combining their values as context attributes.

2.5.2 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 N context attribute values so as to represent a specific state of the system at the given time t. A context state is denoted as $S_i^t = (\alpha_1^t, \alpha_2^t, \ldots, \alpha_N^t)$, 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 that can be used in order to make context attributes, 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 these sensors in home-based care application.

2.5.3 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 some pre-defined situations. It 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., $\alpha_i^R = V \setminus P(V)$). A particular contextual information can be performed or associated with a certain selected region. For instance, a sleeping activity of the patient, which is pre-defined in the expert system, can be associated with a selected region such as bedroom, living room, and so on in home-based care application.

2.5.4 Quality of Data

Given a context attribute i, a *quality of data* ψ_i associates weights $\omega_1, \omega_2, \ldots, \omega_M$ with combined attributes of values $\alpha_1^t + \alpha_1^R, \alpha_2^t + \alpha_2^R, \ldots, \alpha_N^t + \alpha_K^R$ of i, respectively, where $\sum_{j=1}^M \omega_j = 1$. 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 while other context attributes such as the blood pressure and the body temperature may not be so important in order to estimate that specific situation of the patient. In addition, a context attribute (α_i^t) within a context state $(S_i^t = (\alpha_1^t, \alpha_2^t, \ldots, \alpha_N^t))$ 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 $(50Hz)$ at the current time-indexed state is a strong indication of the fainting situation of the patient compared to a respiratory rate $(21Hz)$ at previous time-indexed state. The same context attribute can have different degrees of importance in different contexts. In this dissertation, we only consider the quality of data with the pre-defined context attributes, a selected region, and relevant activities (e.g., sleeping or fainting situation of the patient) initially. We then apply dynamic weights into both relative and individual importance of the evidence in order to obtain an optimal weight of the evidence.

2.6 Summary

We introduced concepts: types of sensors, characteristics of the evidence, context classification and context modeling as the basics of context reasoning in this chapter. In particular, we defined a pragmatic context classification and a generalized context modeling so as to improve the quality of the given contextual information in smart spaces such as in home-based care. In order to make a context classification, we introduced two approaches: 1) Occupant-centered pragmatic approach and 2) Relation-dependency approach. In addition, we defined a state-space based context modeling that consists of selected sensors, related context, and relevant activities with an evidential form as a generalized context modeling based on the proposed context classification. The defined context modeling supports an evidential fusion network that considers uncertainty of contextual information in order to improve the quality of contextual information in ambiguous situation of the patient.

In the next chapter, we will make a context reasoning method based on the static evidential network (SEN) so as to reduce the conflict mass in uncertainty level of contextual information in home-based care.

CHAPTER 3

STATIC EVIDENTIAL NETWORK

3.1   Introduction

For many years, a contextual analysis for situation assessment (SA) and metrics have been important topics in the Information Fusion (IF) literature. A SA synthesizes different kinds of information using fusion processes, provides interfaces between the user and the automation, and focuses on data collection and management. While a SA has been recognized in the IF and human factors literature, there exists issues related to context reasoning methods in some applications [17]. For instance, a pervasive healthcare monitoring system (PHMS) [74], which supports pervasive services to the patient using pervasive computing technologies such as Radio Frequency Identification (RFID) devices and multi-sensors can analyze contextual information of the patient correctly [19, 99, 103]. A PHMS enables continuous healthcare monitoring with the help of these embedded components so as to provide methods for remote disease management in real time and independent safe living as shown in Figure 1.1. Reliable contextual information should be generated to recognize the activities correctly in order to identify hazardous situations of the patient by applying a context reasoning method [98]. However, a high confidence level in the generated contexts is difficult to produce because multi-sensors may not provide reliable information due to faults, operational tolerance levels or corrupted data. Inaccurate sensor readings can produce misunderstandings that lead to incorrect services to the patient. Some sensor readings give information about context only at an abstract level that can include uncertainty to some extent. Contextual information of the patient is more ambiguous

if sensed data obtained from multi-sensors are corrupted or conflicted. It is difficult to make a context reasoning for inferring the correct situation of the patient directly.

In order to deal with these problems within a new application in smart spaces such as a home-based care, we defined the relation-dependency approach as a context classification. We then constructed a state-space context modeling based on the defined context classification in the previous chapter. In this chapter, we propose a static evidential fusion process (SEFP) as a context reasoning method so as to obtain a high confidence level of contextual information. In particular, we process sensed data with an evidential form based on Dezert-Smarandache Theory (DSmT) [36, 37, 38]. The DSmT reduces the conflicting mass in uncertainty level using a proportional conflict redistribution no. 5 (PCR5) combination rule [117]. The PCR5 combination rule redistributes the partial conflicting mass to the elements involved in the partial conflict by considering the canonical form of the partial conflict. The PCR5 combination rule is mathematically exact redistribution of conflicting mass to non-empty sets following the logic of the conjunctive rule [37]. Thus, we use the PCR5 combination rule as a combination rule in this dissertation. In addition, the DSmT obtains a rational decision of contextual information using a generalized pignistic transformation (GPT) [39]. In order to take a rational decision, the GPT generalizes the classical pignistic transformation (CPT) that has two level processes: "*credal*" for combination of the evidence and "*pignistic*" for decision-making within the DSmT framework [118, 119]. The beliefs are represented by belief functions at the credal level then the beliefs induce a probability function at the pignistic level in order to make decisions. The decision is taken by the maximum of the pignistic probability function. Finally, we compare the SEFP approach based on DSmT with existing and contemporary methods such as Bayesian networks (BNs) [105, 108] and Dempster-Shafer theory (DST) [56, 134] for performing an uncertainty analysis in

decision-making as to the ability to measure the probability, belief, or uncertainty in multi-sensor based networks.

The rest of this chapter is organized as follows. The basics of sensor data fusion methods such as Bayesian and Probability Theory (i.e., BNs), Dempster-Shafer Theory (DST), Dezert-Smarandache Theory (DSmT), Combination rule (i.e., Dempster and PCR5), and Pignistic transformations (i.e., CPT and GPT) are introduced in section 3.2. We introduce the SEFP based on the static evidential network (SEN) as a context reasoning method in section 3.3. Finally, we perform a case study in order to infer the situation of the patient using the SEFP approach based on DSmT. We compare and analyze the results of our approach with those of BNs and DST so as to show the improvement of our approach in section 3.4.

3.2   Sensor Data Fusion Methods

In pervasive and ubiquitous computing area such as smart homes, offices, hospitals, and spaces [40, 47, 78, 83, 115, 135], fusion techniques have been proposed in order to reduce uncertainty and achieve reliable data processing and analysis in a fusion system as shown in Figure 3.1. However, it is still open problem to obtain the reliable contextual information in specific applications using the proposed fusion techniques. No commonly accepted approaches that can estimate uncertainty in a fusion system exist. Raw-level data or input-output characteristics of each device may cause total uncertainty of estimation or inference. A high inference can not correct possible errors that may occur in a lower level of data processing. Identification tasks and decision makings based on multiple classifications may suffer from wrongly selected data set [81, 108]. Therefore, in this dissertation, we introduce two commonly used sensor data fusion techniques such as BNs and DST among sensor data fusion techniques [70] as comparative criteria. In addition, we introduce the
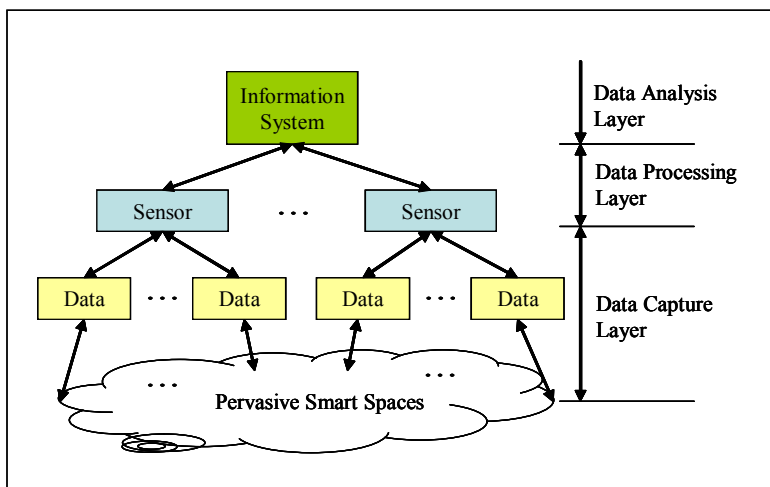
Figure 3.1. A fusion system consists of three layers.

DSmT, the PCR5 combination rule and the GPT as the selected fusion and decision techniques. In particular, we compare the PCR5 combination rule and the GPT with the Dempster's combination rule and the classical pignistic transformation (CPT), respectively.

3.2.1 Bayesian and Probability Theory

Bayesian Networks (BNs) apply Bayes' theorem and satisfy Markov's condition [31] in order to model probabilistic relationships among distinct interests in uncertain reasoning. The BNs are directed acyclic graphs, where the nodes are random variables representing various events and the arcs between nodes represent causal relationships. The possibility of the particular configuration of BNs refers to an instantiation of random variables with values from two dimensional value vectors. It 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 in the presence of either fully or partially observed variables. In any case, the objective of the learning is to find a single model which best explains

the observed evidence. BNs does not necessarily require a transition from one state to another for computing the global or local state of the network. BNs compute a single high level context as an abstraction of numerous primitive contexts. However, BNs can not represent the ignorance [84], which manages the degree of uncertainty, caused by the lack of information.

3.2.2 Dempster-Shafer Theory (DST)

Dempster Shafer Theory (DST) (i.e., evidential theory) offers an alternative to probabilistic theory by providing schemes in order to encode the epistemic uncertainty into the model of a system [114]. DST is a generalization of traditional probability. It allows us to better quantify uncertainty. Shafer's model, denoted here by $M^0(\Theta)$, considers $\Theta = \{\theta_1, \cdots, \theta_n\}$ as a finite set of n exhaustive and exclusive elements representing 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 "the value of a sensor is over the pre-defined threshold" and zero(0) represents that "the value is not over the pre-defined threshold." The power set of Θ, denoted 2^Θ, is defined by the rules 1, 2 and 3 based on Θ and $M^0(\Theta)$.

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

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

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

Without loss of a generality, the general set, denoted by G^Θ, on which will be defined the general basic belief assignments (GBBA) is equal to 2^Θ if Shafer's model $M^0(\Theta)$ is adopted. In general, many factors surrounding 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] in order to represent the degree of a belief in the observation. The

distribution of the unit of a belief over the frame (Θ) is called "*evidence*". A mass function $m(.) : G^\Theta \to [0, 1]$ associated with a given source, say s, of the evidence is defined so as to represent the distribution of a belief. This satisfies the following two conditions:

$$m_s(\emptyset) = 0 \qquad \text{and} \qquad \sum_{X \in G^\Theta} m_s(X) = 1 \tag{3.1}$$

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

$$Bel(X) \triangleq \sum_{\substack{Y \subseteq X \\ Y \in G^\Theta}} m(Y) \quad \text{and} \quad Pl(X) \triangleq \sum_{\substack{Y \cap X = \emptyset \\ Y \in G^\Theta}} m(Y) \tag{3.2}$$

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 based on eq. (3.2). DST is often employed to combine the evidence gathered from two or more independent sources in order to minimize the effect of imprecision. As a generalized probabilistic approach, DST, which considers the upper and lower bounds on probability, has some distinct features compared to Bayesian methods. DST represents the ignorance caused by the lack of information and aggregates the belief when new pieces of evidence are accumulated [56]. This feature is useful for managing the degree of uncertainty.

3.2.3   Dezert-Smarandache Theory (DSmT)

The basic idea of DSmT is to consider all elements of Θ as not precisely defined and separated. No refinement of Θ into a new finer set Θ^{ref} of disjoint hypotheses

is possible in general, unless some integrity constraints are known, and in such case they will be included in the DSm model of the frame. Shafer's model [114] assumes Θ to be truly exclusive and appears only as a special case of the DSm hybrid model in DSmT. The hyper-power set, denoted by D^Θ, is defined by the rules 1, 2 and 3 without additional assumption on Θ but the exhaustivity of its elements in DSmT.

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

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 rules 1) or 2)

When Shafer's model $M^0(\Theta)$ 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.

3.2.4 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:

$$m_{12}(X) = \sum_{\substack{X_1, X_2 \in G^\Theta \\ X_1 \cap X_2 = X}} m_1(X_1) m_2(X_2) \tag{3.3}$$

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

$$k_{12} = \sum_{\substack{X_1, X_2 \in G^\Theta \\ X_1 \cap X_2 = \emptyset}} m_1(X_1) m_2(X_2) = \sum_{\substack{X_1, X_2 \in G^\Theta \\ X_1 \cap X_2 = \emptyset}} m(X_1 \cap X_2) \tag{3.4}$$

The total conflicting mass is the sum of partial conflicting masses based on eqs. (3.3) and (3.4). If the total conflicting mass k_{12} is close to 1, the two sources are almost in total conflict. Whereas if the total conflicting mass 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 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:

$$m_{DS}(X) = \frac{1}{1 - k_{12}} m_{12}(X), \quad (k_{12} \neq 1) \tag{3.5}$$

where $m_{12}(X)$ and k_{12} are defined by eqs. (3.3) and (3.4). Dempster's combination 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 Dempster's combination have a low confidence when a conflict becomes important between sources [38, 36, 89]. For instance, consider $\Theta = \{X_1, X_2\}$ and the basic belief masses that are represented by the following mass matrix:

$$\mathbf{M} = \begin{pmatrix} m_1(X_1) = 1 & m_1(X_2) = 0 & m_1(X_1 \cup X_2) = 0 \\ m_2(X_1) = 0 & m_2(X_2) = 1 & m_2(X_1 \cup X_2) = 0 \end{pmatrix}$$

In this case, we can not apply Dempster's combination rule. The conflicting mass of two pieces of independent evidence is equal to 1 ($k_{12} = 1$). One formally gets $m_{12}(X_1) = 0/0$ and $m_{12}(X_2) = 0/0$ as well. However, if one adopts Shafer's model $M^0(\Theta)$ then applies the PCR5 combination rule, one formally gets $m_{12}(X_1) = 0.5$ and $m_{12}(X_2) = 0.5$. Hence, we can overcome drawbacks of Dempster's combination rule by using the PCR5 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 combination rule calculates the conjunctive rule of the belief masses of sources. Second, it calculates the total or partial conflicting masses. And last, it 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 [38]: $m_{PCR5}(\emptyset) = 0$ and $\forall(X \neq \emptyset) \in G^\Theta$,

$$m_{PCR5}(X) = m_{12}(X)+$$
$$\sum_{\substack{Y \in G^\Theta \setminus \{X\} \\ X \cap Y = \emptyset}} [\frac{m_1(X)^2 m_2(Y)}{m_1(X) + m_2(Y)} + \frac{m_2(X)^2 m_1(Y)}{m_2(X) + m_1(Y)}] \tag{3.6}$$

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 $A \cap B$.

3.2.5   Pignistic Transformations (CPT and GPT)

When a decision must be taken, the expected utility theory, which requires a classical pignistic transformation (CPT) from a basic belief assignment $m(.)$ to a probability function $P\{.\}$, is defined in [39] as follows:

$$P\{A\} = \sum_{X \in 2^\Theta} \frac{|X \cap A|}{|X|} m(X) \tag{3.7}$$

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 [118]. Decisions are achieved by computing the expected utilities. In particular, 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 generalized pignistic transformation (GPT) is defined by [39]: $\forall(A) \in D^\Theta$,

$$P\{A\} = \sum_{X \in D^\Theta} \frac{C_M(X \cap A)}{C_M(X)} m(X) \tag{3.8}$$

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 Shafer's model $M^0(\Theta)$,

eq. (3.8) reduces to eq. (3.7) when D^Θ reduces to 2^Θ. For instance, we gets a basic belief assignment with non null masses only on X_1, X_2 and $X_1 \cup X_2$. After applying GPT, we get:

$$P\{\emptyset\} = 0, \qquad P\{X_1 \cap X_2\} = 0$$
$$P\{X_1\} = m(X_1) + \tfrac{1}{2}m(X_1 \cup X_2)$$
$$P\{X_2\} = m(X_2) + \tfrac{1}{2}m(X_1 \cup X_2)$$
$$P\{X_1 \cup X_2\} = m(X_1) + m(X_2) + m(X_1 \cup X_2) = 1$$

3.3   Static Evidential Fusion Process (SEFP)

We perform context reasoning based on the proposed static evidential network (SEN) that is constructed depending on the defined state-space context modeling in order to reduce the conflicting mass in uncertainty level of contextual information of a patient's situation. In particular, we propose the Static Evidential Fusion Process (SEFP) as a context reasoning method by using the concepts of evidential fusion processes such as a frame of discernment, a multi-valued mapping, a combination rule and a decision rule. The SEFP approach helps decision makings in smart spaces such as a home-based care.

3.3.1   Evidential Operations with Static Evidential Network

Based on the proposed state-space context modeling, the Static Evidential Network (SEN) is constructed as shown in Figure 3.2. Within a SEN, context reasoning is performed in order to make a high confidence level of the situation of the patient. In this case, a context attribute consists of binary values of multi-sensors. The binary values are determined by the pre-defined threshold values controlled by the expert system. In order to infer the activity of the patient along the SEN, first, the binary values are represented as an evidential form which is either active (1) or inactive (0).
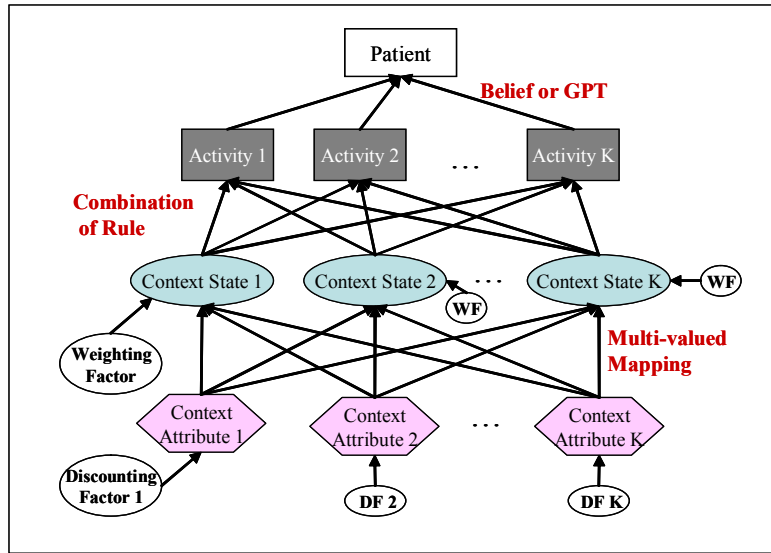
Figure 3.2. A Static Evidential Network (SEN).

Table 3.1. An example 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	$\{State_{-On}, State_{-Off}\}$

The evidential form can represent all possible values and their combination values of the sensors. Table 3.1 shows an example of evidential forms such as *the frames of discernment* (Θ) for selected sensors (i.e., threshold over or not), context attributes (i.e., active or inactive), and context states (i.e., on or off). These evidential forms are components of the SEN.

Second, reliability discounting mass functions defined as eq. (2.2) transform the beliefs of individual sources so as to reflect the *credibility* of the sensor. Within a SEN, a discounting factor (D) that depends on the technical limitations of the sensors or environmental noise is applied to each context attribute. For instance, if a sensor has a 10% discounting factor, $m^D(S) = 0.90$ and $m^D(S, \neg S) = 0.10$.

Third, a *multi-valued mapping* is applied in order 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 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, a translation can be utilized so as to determine the impact of the evidence that originally appears on the frame of discernment on elements of the 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:

$$m'(B_j) = \sum_{\Gamma(e_i)=B_j} m(e_i) \tag{3.9}$$

where $e_i \in \Theta_A, B_j \subseteq \Theta_B$, and $\Gamma : \Theta_A \rightarrow 2^{\Theta_B}$ 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. Hence, an evidential mapping assigns probabilities to elements e_i of Θ_A instead of a set of subsets to represent such uncertain relationships. A piece of the evidence on Θ_A is also propagated to Θ_B through an evidential mapping when the relationship is uncertain. A translation is a special case of propagation, in which relationships between the evidence space Θ_A and the hypothesis space Θ_B are certain. However, we do not consider the evidential mapping, since we use a translation which assumes that the relationships are certain in home-based care applications.

Within a SEN, a multi-valued mapping is applied to the context attributes so as to represent the relationships between sensors and associated objects by translating mass functions. In addition, this mapping is applied to the related context state, which consists of context attributes having an active (1) value and an inactive (0) value, in order to represent the relationships among context attributes. In this case, each context state has different static weighting factors. These weighting factors help

Table 3.2. An example of a multi-valued mapping

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

to infer an activity using a multi-valued mapping among context states. We assume that the weighting factors of the context state are same (e.g., two context states, (S_1) and (S_2), have same weights, 0.5 and 0.5, respectively). Table 3.2 shows an example of a multi-valued mapping.

Fourth, the belief mass distributions on the same frame can be combined by several independent sources of the evidence in order to achieve the conjunctive consensus with the conflict mass. Within the DST framework, the Dempster's combination rule (eq. (3.5)) is used. However, the PCR5 combination rule (eq. (3.6)) is currently used as a combination rule within the DSmT framework. Regardless of whether the conflicting mass is bigger or smaller, the PCR5 combination rule mathematically does a better redistribution of the conflicting mass than other rules, because the PCR5 combination rule goes backwards on the tracks of the conjunctive rule. In this dissertation, the PCR5 combination rule is applied to context states so as to get a consensus for recognizing the activity of the patient within a SEN.

Finally, a range of probabilities (i.e., the lower and upper bounds on probability) are calculated to represent the degree of belief using eq. (3.2), 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):

$$\text{Uncertainty Levels (I)} = Pl - Bel; \tag{3.10}$$

For making a correct decision based on the inference of the activity of the patient, the expected utility and the maximum of the pignistic probability (eq. (3.8)) are 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, these fusion process steps composed of the aggregation of sensed data based on evidential networks can make the SEFP approach. The procedures of the SEFP approach that is the 1st proposed context reasoning method consist of six steps.

3.3.2 SEFP Approach

1. (**Define the Frame of Discernment**): the evidential form represents all possible values of the sensors and their combination values.

2. (**Sensor's Credibility**): reliability discounting mass functions defined as eqs. (2.1) and (2.2) transform beliefs of individual evidence in order to reflect the credibility of the sensor. A discounting factor (D) is applied to each context attribute within a SEN.

3. (**Multi-valued Mapping**): a multi-valued mapping represents the evidence to the same problem with different views. In particular, it can be applied to the context attributes so as to represent the relationships between sensors and associated objects by translating mass functions. A multi-valued mapping also can be applied to the related context state in order to represent the relationships

among context attributes. Each context state consists of different pre-defined static weight of the evidence (*Relative importance*).

4. (**Consensus**): several independent sources of the evidence combine the belief mass distributions on the same frame so as to achieve the conjunctive consensus with the conflict mass. The PCR5 combination rule [117] is applied to context states in order to obtain a consensus that helps to recognize the activity of the patient.

5. (**Degree of Belief**): Lower (*Belief (Bel)*) and upper bounds (*Plausibility (Pl)*) on probability is calculated so as to represent the degree of belief. Then the uncertainty levels (*Pl - Bel*) of the evidence in evidential framework is measured by using belief functions such as *Belief (Bel)* and *Plausibility (Pl)* after applying the PCR5 combination rule.

6. (**Decision Making**): The expected utility and the maximum of the pignistic probability such as Generalized Pignistic Transformations (GPT) is used as a decision criterion. The situation of the patient is inferred by calculating the belief, uncertainty, and confidence (i.e., GPT) levels of contextual information within a SEN.

3.4   A Case Study

In this section, we assume that a specific situation (i.e., fainting or sleeping) of the patient is happened when the patient sits on the sofa in the living room of the smart home for a long time without any movement. We then describe a static evidential fusion process (SEFP) as a mathematical tool in order to calculate the sensed data and infer the situation of the patient based on the applied scenario as shown in Figure 3.3.
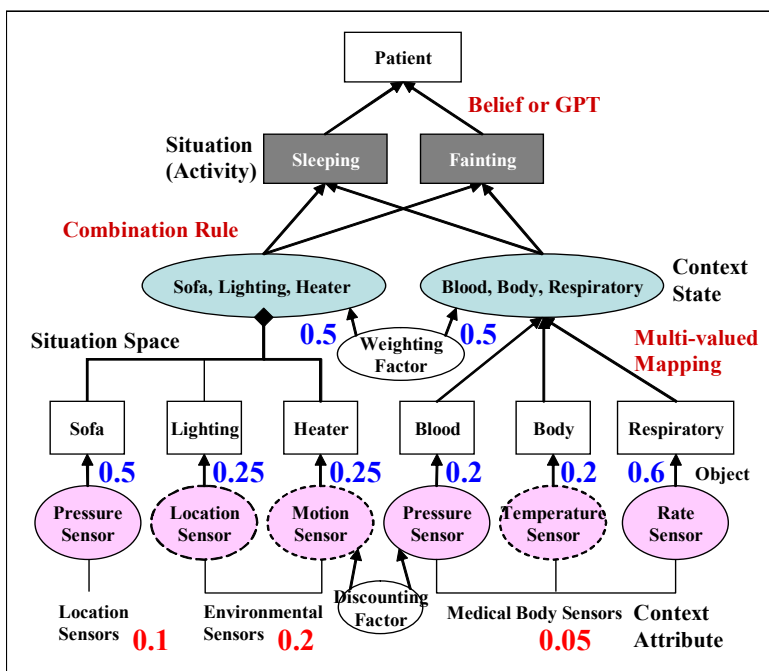
Figure 3.3. An example of a patient's situation based on the SEN.

3.4.1   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 check the status of the patient continuously, medical body sensors (i.e., the blood pressure sensor, the body temperature sensor, and the respiratory rate sensor) are operated by the expert system. Six types of different sensors are used in this scenario. Each sensor has a pre-defined threshold and its operation can be represented by an evidential form. We can derive a static evidential network (SEN) based on these simplified two cases as shown in Figure 3.3. We then find out more closely correct situations through context reasoning by calculating the belief, uncertainty and pignistic probability levels of each related activity. To calcu-

late them, we assume that a discounting factor (D) and a static weighting factor of each sensor are fixed. In particular, 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. In addition, we apply different simulation error rates (r) (i.e., 0%, 20%, and 50%) into each sensor in order to calculate the evidential fusion process based on DSmT with a 95% confidence interval. Three sensors - the location sensor, the motion sensor and the body temperature sensor - are not activated in Figure 3.3.

3.4.2 Situation Inference

We infer the situation of the patient using the proposed evidential fusion method such as the SEFP. 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 measured evidence is then translated into the relevant activity recognition by applying a multi-valued mapping. On an activity recognition step, several belief mass distributions can be combined by two different rules (Dempster's and PCR5) of combination. Then, a decision is made by using the degree of belief, uncertainty, and maximum of pignistic probability (i.e., GPT). Based on the simplified scenario, context reasoning is performed by six steps of evidential operations as described in section 3.3.2.

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 Figure 3.3. We then represent a piece of the evidence on each sensor as a mass function at first step.

$$m_{Ps}(\{Ps\}) = 1; \qquad m_{Ls}(\{\neg Ls\}) = 1; \qquad m_{Ms}(\{\neg Ms\}) = 1;$$
$$m_{Bps}(\{Bps\}) = 1; \qquad m_{Bts}(\{\neg Bts\}) = 1; \qquad m_{Rs}(\{Rs\}) = 1;$$

Second, we apply a discounting factor (D) to each sensor using eqs. (2.1) and (2.2) so as to obtain each sensor credibility. Within the scenario, we assume that the location sensor (Ps) has a 10% discounting factor, the environmental sensors (Ls and Ms) have a 20% discounting factor, and the medical body sensors (Bps, Bts and Rs) have a 5% discounting factor when they are manufactured. It means that we have to apply a discounting factor into each sensor for reliability discounting mass functions. We apply a multi-valued mapping in order to represent the belief level of a context attribute by translating a mass function using eq. (3.9). 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. A mass function on "S", "L", "H", "Bp", "Bt" and "R" are translated onto context state 1 ($CS1$) and context state 2 ($CS2$), respectively. Both "$CS1$" and "$CS2$" are used so as to determine the relevant activities of the patient.

$$m1_{CS1}(\{CS1\}) = m_S(\{S\}) = m_{Ps}^D(\{Ps\}) = 0.90;$$

$$m1_{CS1}(\{CS1, \neg CS1\}) = m_S(\{S, \neg S\}) = m_{Ps}^D(\{Ps, \neg Ps\}) = 0.10;$$

$$m2_{CS1}(\{\neg CS1\}) = m_L(\{\neg L\}) = m_{Ls}^D(\{\neg Ls\}) = 0.80;$$

$$m2_{CS1}(\{CS1, \neg CS1\}) = m_L(\{L, \neg L\}) = m_{Ls}^D(\{Ls, \neg Ls\}) = 0.20;$$

$$m3_{CS1}(\{\neg CS1\}) = m_H(\{\neg H\}) = m_{Ms}^D(\{\neg Ms\}) = 0.80;$$

$$m3_{CS1}(\{CS1, \neg CS1\}) = m_H(\{H, \neg H\}) = m_{Ms}^D(\{Ms, \neg Ms\}) = 0.20;$$

$$m1_{CS2}(\{CS2\}) = m_{Bp}(\{Bp\}) = m_{Bps}^D(\{Bps\}) = 0.95;$$

$$m1_{CS2}(\{CS2, \neg CS2\}) = m_S(\{Bp, \neg Bp\}) = m_{Bps}^D(\{Bps, \neg Bps\}) = 0.05;$$

$$m2_{CS2}(\{\neg CS2\}) = m_{Bt}(\{\neg Bt\}) = m_{Bts}^D(\{\neg Bts\}) = 0.95;$$

$$m2_{CS2}(\{CS2, \neg CS2\}) = m_{Bt}(\{Bt, \neg Bt\}) = m_{Bts}^D(\{Bts, \neg Bts\}) = 0.05;$$

$$m3_{CS2}(\{CS2\}) = m_R(\{R\}) = m_{Rs}^D(\{Rs\}) = 0.95;$$

$$m3_{CS2}(\{CS2, \neg CS2\}) = m_R(\{R, \neg R\}) = m_{Rs}^D(\{Rs, \neg Rs\}) = 0.05;$$

Third, we sum up a context state by adapting a different static weighting factor into 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 that of "$CS2$" consists of "Bp" (20%), "Bt" (20%) and "R" (60%).

$m_{CS1}(\{CS1\}) = (0.5)(m1_{CS1}) = 0.45;$

$m_{CS1}(\{\neg CS1\}) = (0.25)(m2_{CS1} + m3_{CS1}) = 0.40;$

$m_{CS1}(\{CS1, \neg CS1\}) = (0.5)(m1_{CS1}) + (0.25)(m2_{CS1} + m3_{CS1}) = 0.15;$

$m_{CS2}(\{CS2\}) = (0.2)(m1_{CS2}) + (0.6)(m3_{CS2}) = 0.76;$

$m_{CS2}(\{\neg CS2\}) = (0.2)(m2_{CS2}) = 0.19;$

$m_{CS2}(\{CS2, \neg CS2\}) = (0.2)(m1_{CS2} + m2_{CS2}) + (0.6)(m3_{CS2}) = 0.05;$

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

$m1_F(\{F\}) = m_{CS1}(\{CS1\}) = 0.45;$

$m1_F(\{\neg F\}) = m_{CS1}(\{\neg CS1\}) = 0.40;$

$m1_F(\{F, \neg F\}) = m_{CS1}(\{CS1, \neg CS1\}) = 0.15;$

$m2_F(\{F\}) = m_{CS2}(\{CS2\}) = 0.76;$

$m2_F(\{\neg F\}) = m_{CS2}(\{\neg CS2\}) = 0.19;$

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

Fourth, we apply eqs. (3.3), (3.4), and (3.5) into $m1_F$ and $m2_F$ so as to achieve the conjunctive consensus by combining two sources with the conflicting mass (k_{12}). We then redistribute the partial conflicting mass using eq. (3.6) as follows:

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

$$m_{12}(\emptyset) = 0; \quad m_{12}(F) = 0.4785; \quad m_{12}(\neg F) = 0.1245; \quad m_{12}(F \cup \neg F) = 0.0075;$$

$$k_{12} = m_{12}(F \cap \neg F) = m_1(F)m_2(\neg F) + m_1(\neg F)m_2(F) = 0.3895;$$

$$m_{DS}(F) = m_1 \oplus m_2(F) = \frac{1}{1-k_{12}}m_{12}(F) = 0.7838;$$

$$m_{DS}(\neg F) = \frac{1}{1-k_{12}}m_{12}(\neg F) = 0.2039;$$

$$m_{DS}(F \cup \neg F) = \frac{1}{1-k_{12}}m_{12}(F \cup \neg F) = 0.0123;$$

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 be the conflicting mass to be redistributed to "F" and "$\neg F$", respectively, so as 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, $x_1 = 0.0601, \qquad y_1 = 0.0254;$

In addition, 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. We suppose that x_2 and y_2 be the conflicting mass to be redistributed to "F" and "$\neg F$", respectively, so as 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, $x_2 = 0.1992, \qquad y_2 = 0.1048;$

We obtain two results of the redistribution for each corresponding set "F" and "$\neg F$", respectively. We then obtain the result of the PCR5 combination rule based on eq. (3.6) as follows:

$$m_{PCR5}(F) = m_{12}(F) + x_1 + x_2 = 0.7378;$$

$$m_{PCR5}(\neg F) = m_{12}(\neg F) + y_1 + y_2 = 0.2547;$$

$$m_{PCR5}(F \cup \neg F) = m_{12}(F \cup \neg F) + 0 = 0.0075;$$

Finally, we calculate the belief and uncertainty levels of the "fainting (F)" situation with two combination rules using eqs. (3.1), (3.2) and (3.10). We then calculate the maximum of pignistic probability (i.e., GPT) level with a decision rule using eqs. (3.7) and (3.8).

$$Bel(\{F\}) = m_{DS}(\{F\}) = 0.7838;$$

$$Pl(\{F\}) = m_{DS}(\{F\}) + m_{DS}(\{F, \neg F\}) = 0.7961;$$

$$Pl(\{F\}) - Bel(\{F\}) = m_{DS}(\{F, \neg F\}) = 0.0123;$$

$$Bel(\{F\}) = m_{PCR5}(\{F\}) = 0.7378;$$

$$Pl(\{F\}) = m_{PCR5}(\{F\}) + m_{PCR5}(\{F, \neg F\}) = 0.7453;$$

$$Pl(\{F\}) - Bel(\{F\}) = m_{PCR5}(\{F, \neg F\}) = 0.0075;$$

$$P_{DS}(\{F\}) = m_{DS}(\{F\}) + \tfrac{1}{2}m_{DS}(\{F, \neg F\}) = 0.78995;$$

$$P_{PCR5}(\{F\}) = m_{PCR5}(\{F\}) + \tfrac{1}{2}m_{PCR5}(\{F, \neg F\}) = 0.74155;$$

In this example, we simply know that the mass of ignorance committed by the PCR5 combination rule (i.e., $m_{PCR5}(F \cup \neg F) = 0.0075$) is less than that of ignorance committed by the Dempster's combination rule (i.e., $m_{DS}(F \cup \neg F) = 0.0123$), because Dempster's combination rule takes the total conflicting mass then redistributes it to all non-empty 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 combination rule (i.e., $P_{PCR5}(\{F\}) = 0.74155$) is less than that of Dempster's combination rule (i.e., $P_{DS}(\{F\}) = 0.78995$), because the PCR5 combination rule redistributes the partial conflicting mass to both positive and negative result of mass distributions concurrently. Therefore, we need to analyze the reason that the DSmT approach based on PCR5 combination rule is better than the DST approach based on Dempster's combination rule, even though the GPT level of the DST approach is higher than that of the DSmT approach. In the next section, we compare the be-

lief, uncertainty and GPT levels of contextual information with different discounting factors and weighting factors.

3.5   Comparison and Analysis

In this section, we compare the confidence (i.e. GPT) 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 factors into the two fusion processes.

3.5.1   GPT levels of BNs, DST and DSmT

We assume that $\Theta = \{Sl, F\}$ be the frame made of only two hypotheses in order to compare DSmT with BNs and DST. The probability theory (i.e., BNs) and the DST deal 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 under the assumptions on exclusivity and exhaustivity of hypotheses. The DSmT deals with the GBBA $m(.) \in [0,1]$ such that $m(Sl) + m(F) + m(Sl \cup F) + m(Sl \cap F) = 1$ under only assumption on exhaustivity of hypotheses. However, we utilize the same underlying model (i.e., Shafer's model $M^0(\Theta)$) [114], 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. In particular, we calculate the GPT levels of three cases with 95% confidence intervals by considering three different simulation error rates (i.e., 0%, 20% and 50%). Then, we compare the GPT level of our approach with those of BNs and DST, respectively,

Table 3.3. GPT levels based on the increased sensors' activation

$Activated Sensors$	$Probability$(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

using paired observations [59] that construct a confidence interval for the difference. The analysis of paired observation deals with two processes as one process of n pairs. For each pair, the difference in performance can be computed. Then, if the confidence interval includes zero, two fusion processes are not significantly different.

Table 3.3 shows the results of the average of GPT levels based on the increased sensors' activation for 500 simulation iterations. In Table 3.3, the GPT levels for the "F" situation of the 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 because BNs do not consider the uncertainty level of two different pieces of the evidence. When four more sensors are activated, the degrees of pignistic probability level of DST are higher than those of others because DST does not consider the conflicting mass, which increases the uncertainty level in evidential networks, of two different pieces of the evidence.

In addition, Figure 3.4, 3.5 and 3.6 show the GPT levels of the three cases based on the numbers of activated sensors. In this case, we apply the same static weighting factors and same discounting factors within the scenario. According to Figure 3.4, the
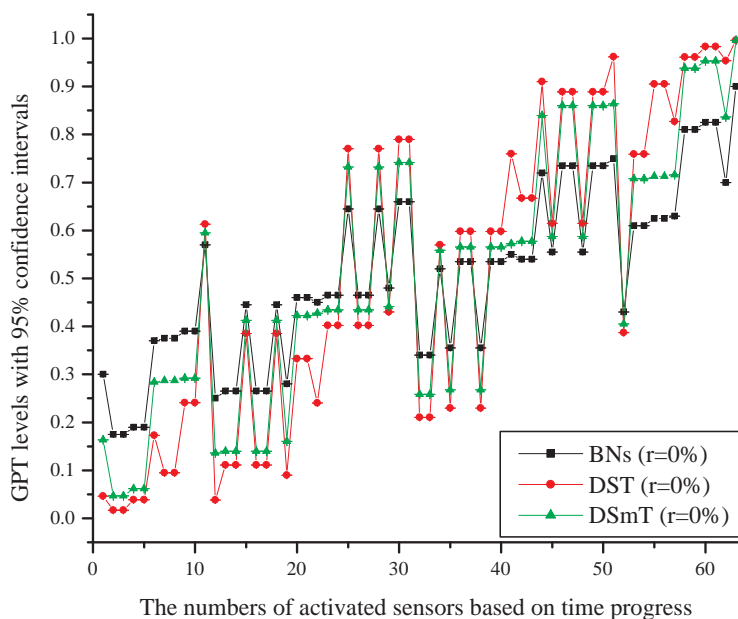
Figure 3.4. GPT levels of BNs, DST and DSmT with r=0%.
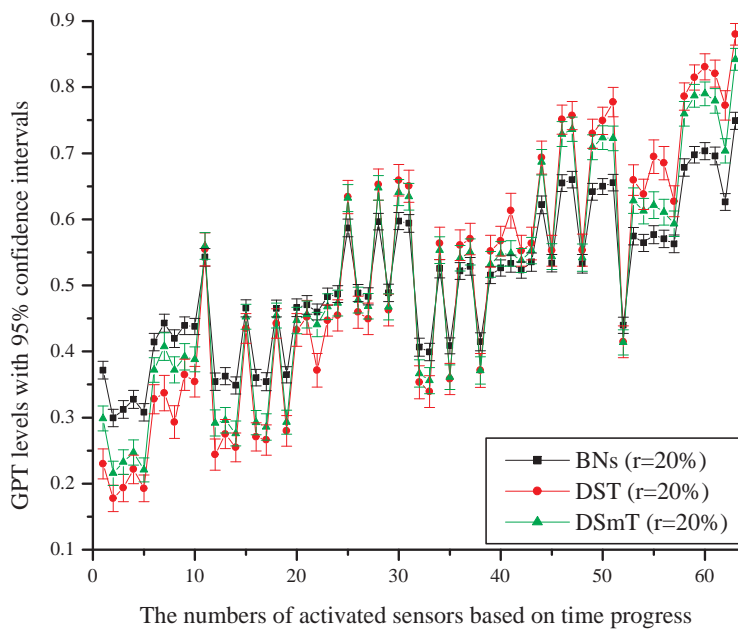
Figure 3.5. GPT levels of BNs, DST and DSmT with r=20%.

GPT level of DST is higher than those of others when the degree of GPT is over 0.5. However, Figure 3.5 and 3.6 show ambiguous results with 95% confidence intervals.
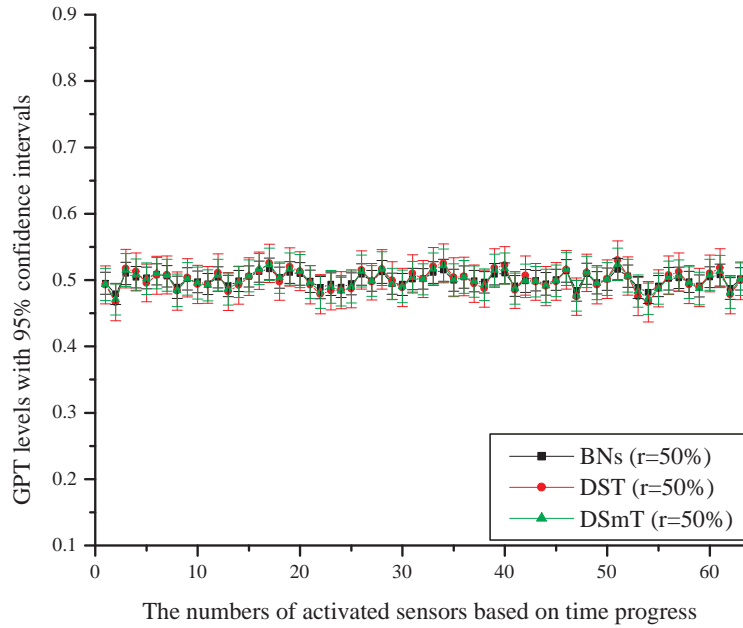
Figure 3.6. GPT levels of BNs, DST and DSmT with r=50%.

In particular, the GPT levels of BNs, DST and DSmT are almost same after we applied a 50% error rate into evidential fusion processes. We can not distinguish the better one among BNs, DST and DSmT. Therefore, we compare the GPT level of DSmT with those of BNs and DST, respectively, using paired observations as shown in Figure 3.7. In this case, we calculate the paired observations by applying different error rates (i.e., 0%, 1%, 5%, 10%, 20% and 50%) into each sensor. We also calculate the GPT level when the degree of GPT is over 0.5. The GPT level of DSmT is higher than that of BNs and the GPT level of DSmT is lower than that of DST except for the error rate is a 50% case. Based on the result of Figure 3.7, we know that the GPT level of DST is higher than those of others with small error rates (r) when the degree of GPT is over 0.5.

Moreover, according to Figure 3.4, the degree of GPT at 11th time stamp (e.g., Ps and Rs) is bigger than that at 52nd time stamp (e.g., Ls, Ms and Bps) even if the numbers of activated sensors at 11th time stamp are smaller than that at 52nd time
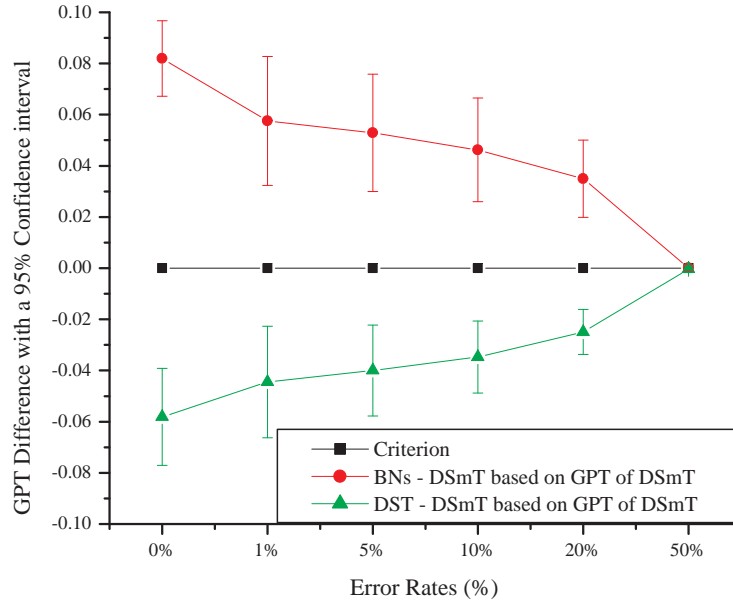
Figure 3.7. Comparison GPT levels of BNs, DST and DSmT.

stamp, because the applied weighting factors at 11th time stamp are bigger than those at 52nd time stamp. This shows the importance of the method in defining a static weighting factor for each context attribute in evidential fusion networks. However, it is difficult in defining the absolute static weight of the evidence. In order to find the optimal weight of the evidence, we deal with the method in Chapter 5.

3.5.2   Uncertainty levels of DST and DSmT

We calculate the uncertainty levels (i.e., ignorance) of two cases: 1) DST and 2) DSmT, which are used for calculating the "fainting (F)" situation of the patient within the applied scenario. We can not calculate the uncertainty level using BNs because BNs, which assume equality between the implication and the conditional belief [107], can not support a certain degree ρ that takes a value from the interval [0,1].
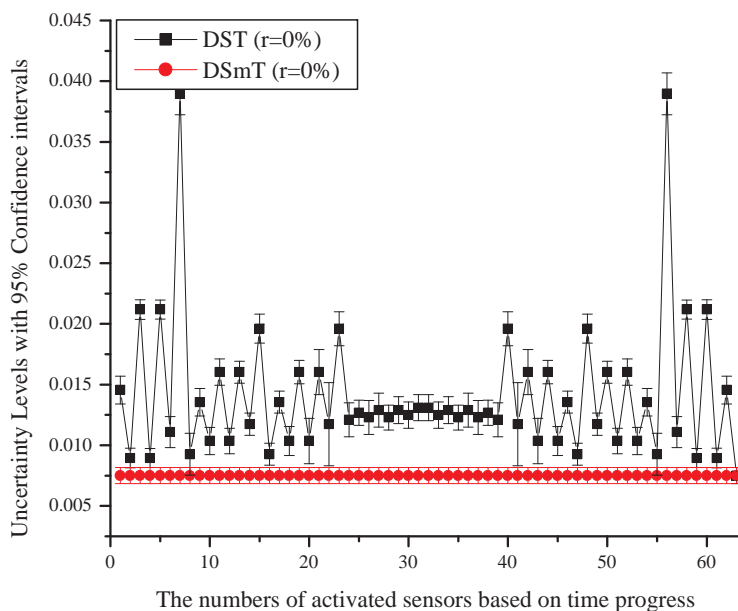
Figure 3.8. Uncertainty levels of DST and DSmT with $r=0\%$.
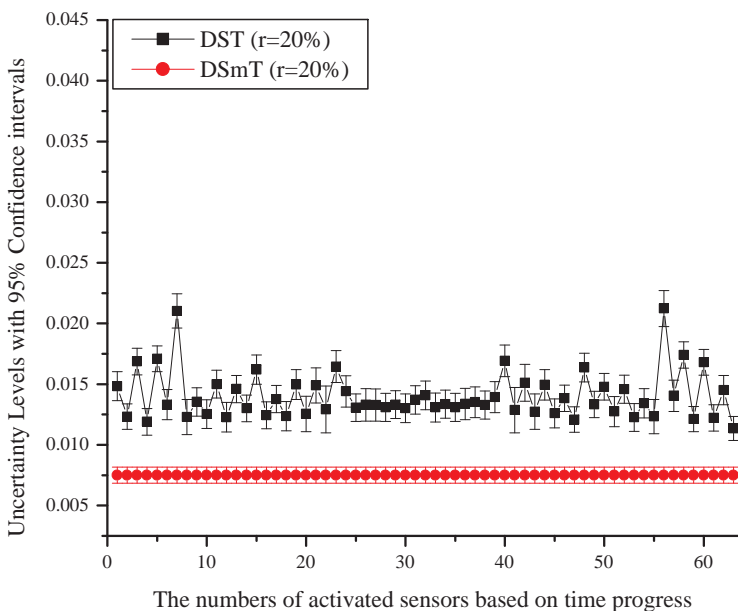
Figure 3.9. Uncertainty levels of DST and DSmT with $r=20\%$.

3.5.2.1 Comparison with static weighting factors

We apply a static weighting factor into each context attribute as shown in Figure 3.3. We also apply error rates (r) (i.e., 0%, 20% and 50%) into the evidential fusion
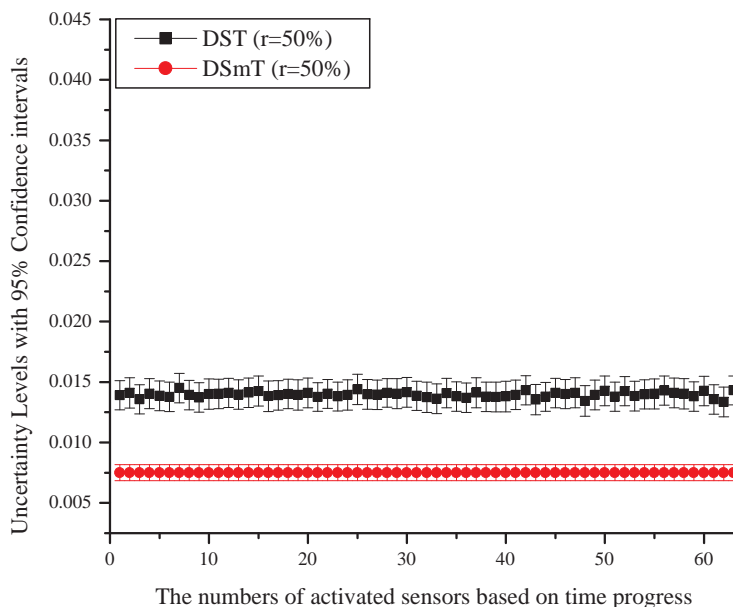
Figure 3.10. Uncertainty levels of DST and DSmT with $r=50\%$.

process that calculates the variations of uncertainty levels. The uncertainty levels of DST and DSmT based on the numbers of activated sensors are shown in Figure 3.8, 3.9 and 3.10. In this case, the evidential fusion process based on DST has more various conflicting mass in the uncertainty level compared to the DSmT approach. In particular, the degrees of uncertainty level of DST show different variations depending on the selected simulation error rates even though the DSmT approach shows constant degrees of uncertainty (i.e., 0.0075). The reason is that the PCR5 combination rule of DSmT redistributes the total conflicting mass as equal to zero within the DSmT framework. However, Dempster's combination rule of DST takes the total conflicting mass and redistributes it to all non-empty sets within the DST framework, even those not involved in the conflict. As shown in Figure 3.8, 3.9 and 3.10, the degrees of uncertainty of DSmT are lower than those of DST. When we compare the uncertainty level of DST with that of DSmT using paired observations with different error rates (r) (i.e., 0%, 1%, 5%, 10%, 20% and 50%), the uncertainty level of DST is higher
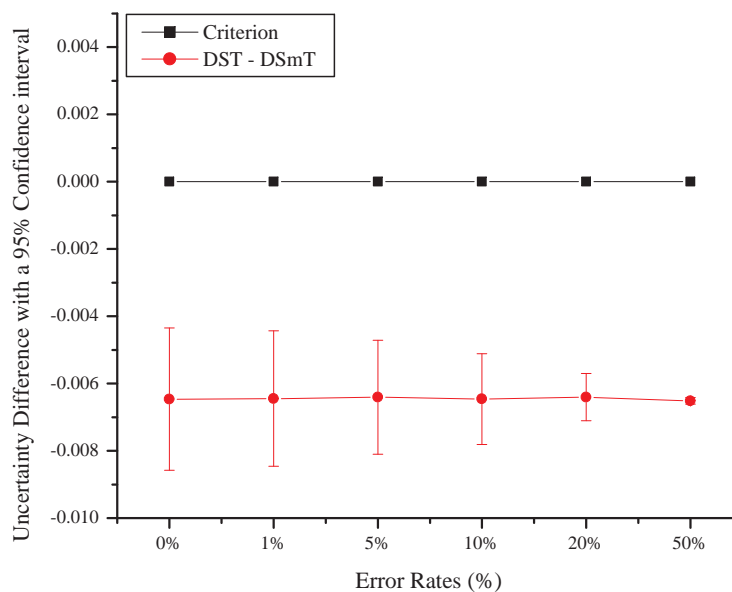
Figure 3.11. Comparison Uncertainty levels of DST and DSmT.

than that of DSmT as shown in Figure 3.11. Therefore, the DSmT approach with static weighting factors reduces the degree of uncertainty (i.e., conflicting mass in uncertainty level) compared to the DST approach.

3.5.2.2 Comparison with different weighting factors

We apply different static weights into each context attribute as shown in Table 3.4 in order to compare the uncertainty levels of two cases: 1) DST and 2) DSmT based on different weighting factors. In this simulation, we calculate four situations: a) "*Bts*", and "*Rs*" are not activated, b) "*Ls*" and "*Bps*" are not activated, c) only "*Bts*" is not activated, and d) all sensors are activated to see the variation of the uncertainty level of contextual information. In addition, we apply 0% and 50% error rates and same discounting factors within the Figure 3.3 into the evidential fusion process with a 95% confidence interval. After we apply different static weights into the evidential fusion process, the uncertainty levels of DST and DSmT based on different

Table 3.4. An example of different static weighting factors

No.	S	L	H	Bp	Bt	R
Case 1	0.9	0.05	0.05	0.05	0.05	0.9
Case 2	0.8	0.1	0.1	0.1	0.1	0.8
Case 3	0.7	0.1	0.2	0.1	0.2	0.7
Case 4	0.6	0.2	0.2	0.2	0.2	0.6
Case 5	0.5	0.2	0.3	0.2	0.3	0.5
Case 6	0.4	0.3	0.3	0.3	0.3	0.4
Case 7	0.3	0.4	0.3	0.3	0.4	0.3
Case 8	0.2	0.4	0.4	0.4	0.4	0.2
Case 9	0.1	0.45	0.45	0.45	0.45	0.1
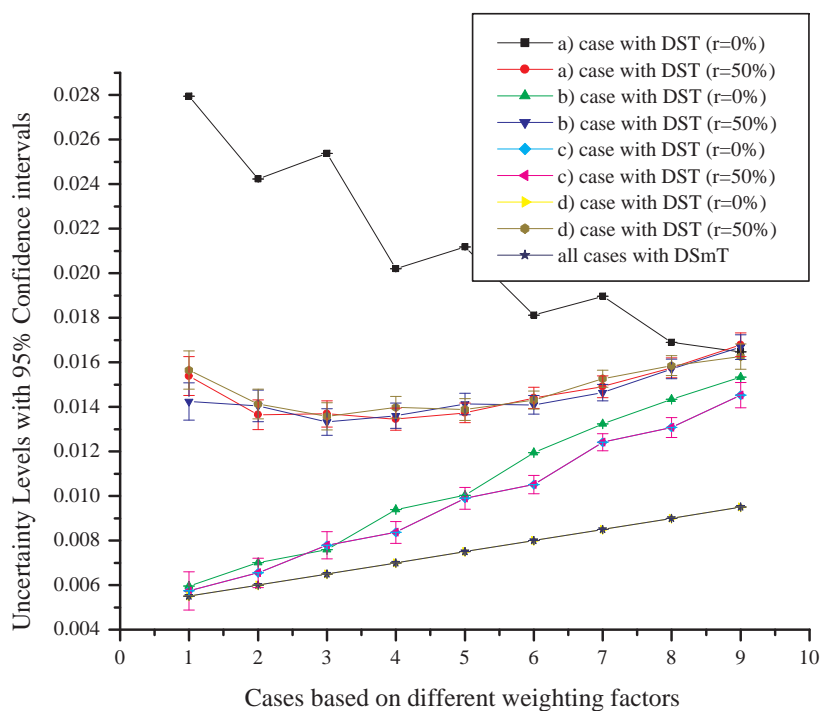
Figure 3.12. Uncertainty levels of DST and DSmT with different weights.

weighting factors are shown in Figure 3.12. The uncertainty levels of DSmT have the same degrees for all cases even though those of DST have different degrees depending on the four situations and the used error rates (r) (i.e., 0% and 50%). In addition, the degrees of uncertainty of DSmT are lower than those of DST. Only when all sensors

Table 3.5. An example of different discounting factors

No.	S	L	H	Bp	Bt	R
Case 1	0%	20%	20%	5%	5%	0%
Case 2	1%	20%	20%	5%	5%	1%
Case 3	2%	20%	20%	5%	5%	2%
Case 4	5%	20%	20%	5%	5%	5%
Case 5	10%	20%	20%	5%	5%	10%
Case 6	20%	20%	20%	5%	5%	20%
Case 7	50%	20%	20%	5%	5%	50%

are activated will the degrees of uncertainty 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. Therefore, the DSmT approach with different weighting factors also shows the better performance than the DST approach in order to reduce the conflicting mass in uncertainty level of contextual information in the progress of "fainting (F)" situation of the patient.

3.5.2.3 Comparison with different discounting factors (D)

We apply different discounting factors (D), which are related to sensor's credibility, into "Ps" and "Rs" in order to calculate the uncertainty levels of DST and DSmT as shown in Table 3.5. Reducing discounting factors (D) on each sensor is an important factor so as to obtain the reliability of contextual information of the patient. We calculate four situations: a) "Bts", and "Bps" are not activated, b) "Ps" and "Bts" are not activated, c) only "Bps" is not activated, and d) all sensors are activated to see the variation of the uncertainty level of contextual information. We apply 0% and 50% error rates and same weighting factors within the Figure 3.3 into
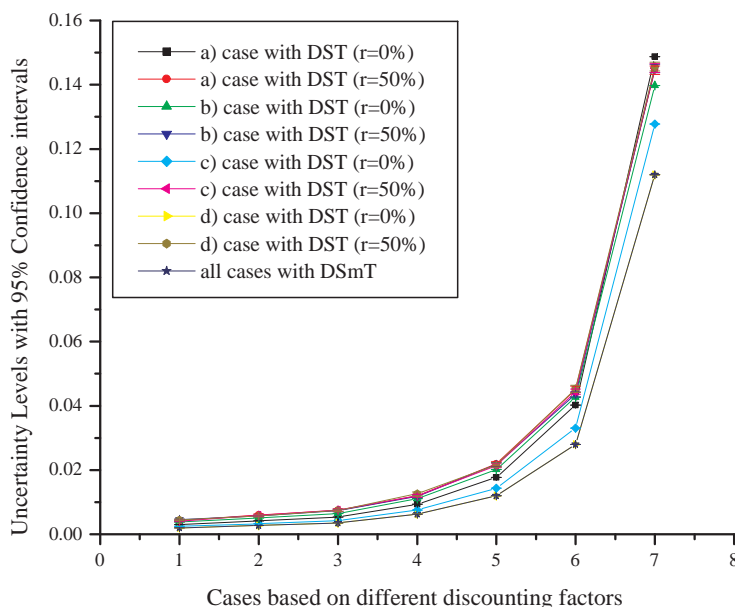
Figure 3.13. Uncertainty levels of DST and DSmT with different D.

the evidential fusion process with a 95% confidence interval. Depending on different D on "Ps" and "Rs", the two cases show different degrees of uncertainty as shown in Figure 3.13. The degrees of uncertainty of DST and DSmT are increased based on the increase of the D as expected. In addition, the uncertainty levels of DSmT have the same degrees for all cases even though those of DST have different degrees for the four situations. In particular, the degrees of uncertainty of DSmT are lower than those of DST. This result also shows that the DSmT approach gets the better performance than the DST approach in order to reduce the conflicting mass in uncertainty level of contextual information in the progress of "F" situation of the patient.

3.6 Summary

In this chapter, we utilized a static evidential fusion process (SEFP) with the PCR5 combination rule as a context reasoning method based on spatial dependency, which is shown in Figure 3.14 in order to reduce the degrees of uncertainty in sensed
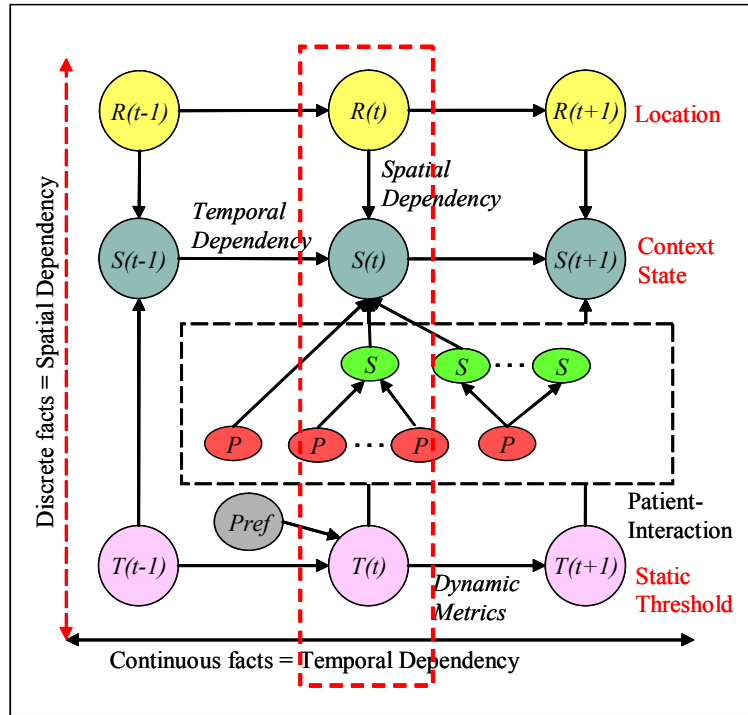
Figure 3.14. Spatial dependency within the applied context classification.

data and in generated contexts. In addition, we applied a generalized pignistic trans-
formation (GPT) so as to understand uncertainty analysis in decision makings. In
particular, we calculated the uncertainty and GPT level of selected contextual in-
formation in order to compare and analyze the SEFP approach with an evidential
fusion process based on BNs or DST. Wwe applied different static weighting factors,
discounting factors and simulation error rates into the SEFP approach. According
to the results of our simulation, the SEFP approach based on DSmT is better than
that based on BNs so as to improve the GPT level of contextual information. The
SEFP approach based on DSmT is better than that based on DST approach so as to
reduce the conflicting mass in uncertainty level of contextual information. However,
this approach does not deal with the variations of the evidence over time that is one
of important factors in order to estimate the correct situation of the patient.

In the next chapter, we will improve the GPT level of selected contextual information based on Dynamic Evidential Network (DEN) by considering dynamic metrics: preference, temporal consistency, and relation-dependency of the evidence using Autonomous Learning Process (ALP) and Temporal Belief Filtering (TBF) [68].

CHAPTER 4

DYNAMIC EVIDENTIAL NETWORK

4.1 Introduction

During emergency situations of the patient in home-based care, a PHMS [74] is significantly overloaded with pieces of contextual information of different known reliability (reliable, partial reliable, or completely unreliable) or unknown reliability. The pieces of the information should be processed, interpreted, and combined in order to recognize the situation of the patient as accurate as possible. In such a context, the information obtained from different sources such as multi-sensors and Radio Frequency Identification (RFID) devices can be imperfect due to the imperfection of contextual information itself or unreliability of the sources. In order to deal with different aspects of the imperfection of contextual information, we proposed a Static Evidential Network (SEN) [69] as a mathematical tool so as to characterize and combine the imperfect information in Chapter 3. As a context reasoning method, SEN utilizes Dezert-Smarandache Theory (DSmT) [38]. SEN reduces the uncertainty level of contextual information compared to Dempster-Shafer Theory (DST) [134]. However, context reasoning over time is a difficult in an emergency context, because unpredictable temporal changes in sensory information may happen [108]. SEN also did not consider dynamic metrics [67] of the context. Dynamic metrics combine upper bounds, lower bounds, or comparative criteria into a static threshold so as to estimate or infer future contextual information autonomously. In this chapter, we propose a Dynamic Evidential Network (DEN) as the 2nd context reasoning method. DEN deals with the relations between two consecutive time-indexed states of the in-
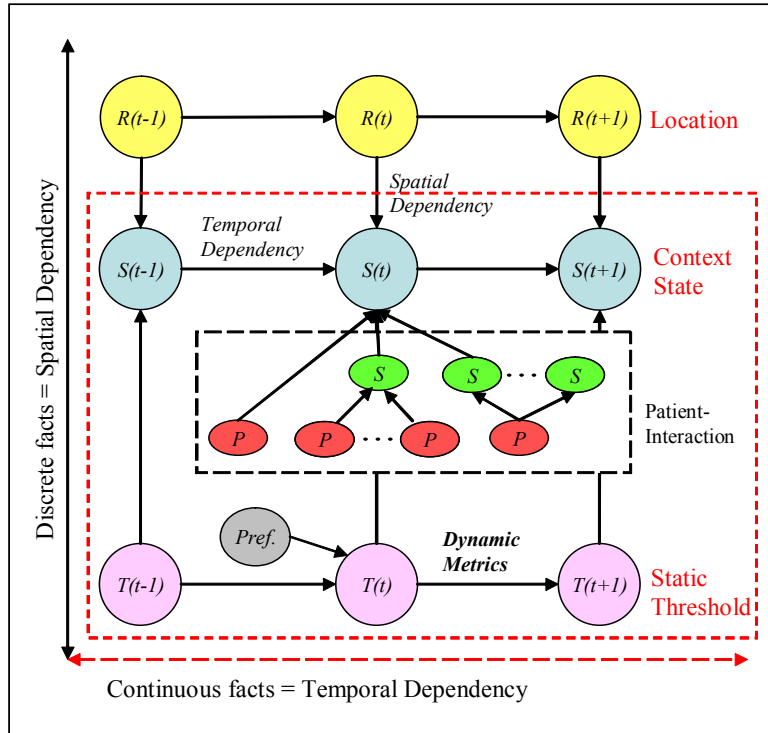
Figure 4.1. Temporal dependency within the applied context classification.

formation by considering dynamic metrics: preference, temporal consistency, and the relation-dependency of the information as shown in Figure 4.1. DEN produces Autonomous Learning Process (ALP) in order to improve the confidence (i.e., GPT) level of contextual information using the Temporal Belief Filtering (TBF) algorithm. Finally, we compare the proposed fusion process with a fusion process based on Dynamic Bayesian Networks (DBNs) [90] that has the same assumption of the environments, so as to show the improvement of our proposed method in an emergency situation of the patient.

The rest of this chapter is organized as follows. The basics of autonomous learning process principles such as Disjunctive rule of combination, State-Markov model for temporal dependency, Autonomous Learning Process (ALP) and Temporal Belief Filtering (TBF) are introduced in section 4.2. We introduce the Dynamic Evidential

Fusion Process (DEFP) based on the Dynamic Evidential Network (DEN) as a context reasoning method in section 4.3. Finally, we perform a case study in order to distinguish a sensor reading error from new sensor activations or deactivations in the emergency situation of the patient using the DEFP approach. We then compare and analyze the results of our approach with those of DBNs so as to show the improvement of our approach in section 4.4.

4.2 Autonomous Learning Process Principles

4.2.1 Disjunctive Rule for Temporal Belief Filtering (TBF)

Temporal Belief Filtering (TBF) [104], which reflects that only one hypothesis concerning activity is true at each time-indexed state, ensures a temporal consistency with an exclusivity. Within a TBF, the disjunctive rule of combination $(m_\cup(.))$ is used so as to compute *prediction* from previous mass distributions and model of evolution. $m_\cup(.)$ is defined for two sources: $m_\cup(\emptyset) = 0$ and $\forall(C) \subset \Theta$,

$$m_\cup(C) = \sum_{\substack{i,j \\ C=X_i \cup Y_j}} m_1(X_i)m_2(Y_j), \qquad \forall(C \neq \emptyset) \in \Theta \tag{4.1}$$

The core of a belief function given by $m_\cup(C)$ equals the union of the cores of $Bel(X)$ and $Bel(Y)$. This rule reflects the disjunctive consensus and is usually preferred when one knows that one of the source X or Y is mistaken but without knowing which one between X and Y.

4.2.2 State-Markov Model for Temporal Dependency

Contextual information of the patient has the association or correlation between two consecutive time-indexed states based on time progress. In order to deal with this context reasoning over time, SEN should include a temporal dimension as shown in Figure 4.2. This new dimension is managed by a time-indexed state that is similar
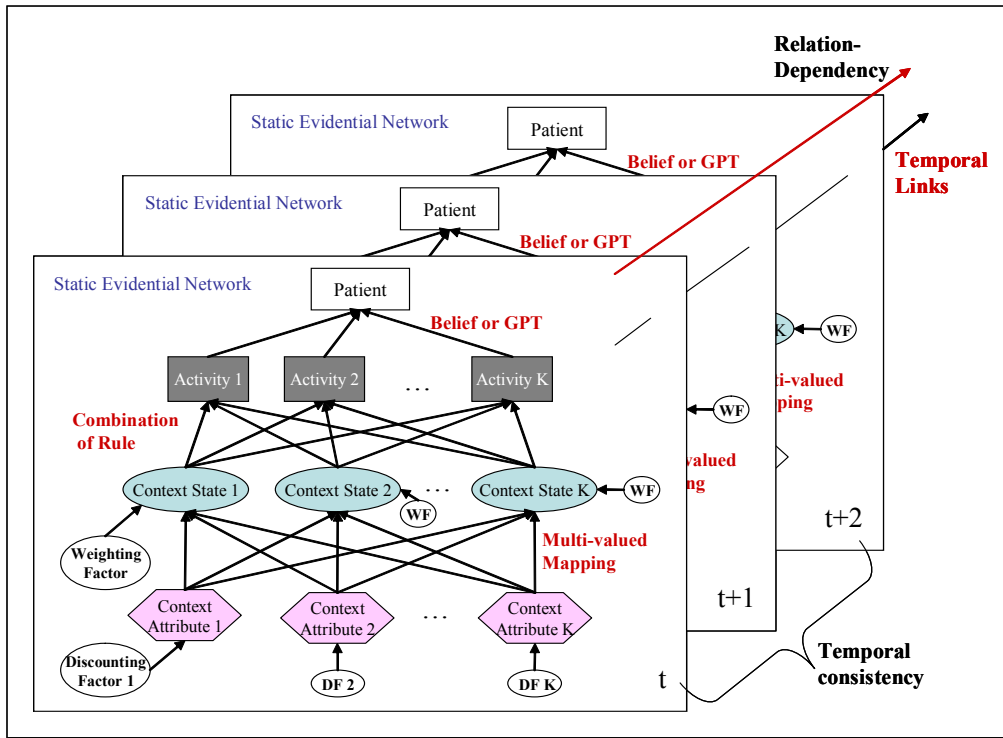
Figure 4.2. SEN with a temporal dimension.
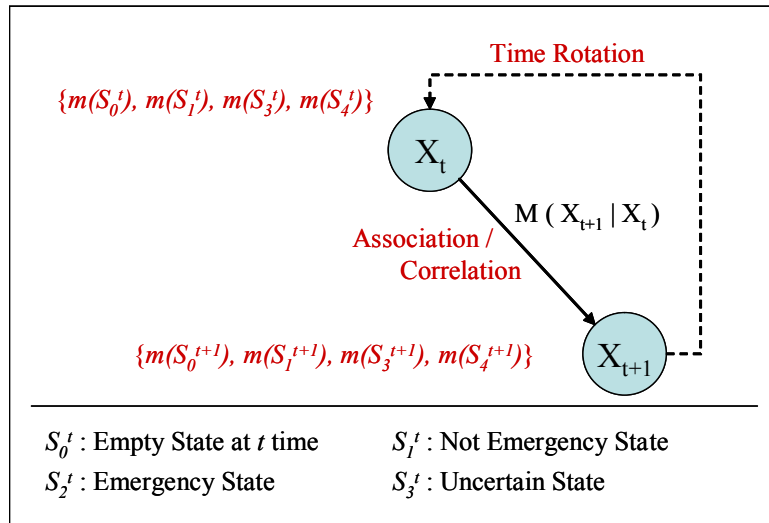
Figure 4.3. Temporal dimension made of two consecutive states.

to that of DBNs as shown in Figure 4.3. The state, denoted by X_t, is represented at time stamp t by a state X with the aggregation of the belief mass assigned to a finite number of focal elements $X_t : \{m(S_0^t), mS(_1^t), m(S_2^t), m(S_3^t)\}$ (e.g., $m(S_0^t)$ denotes the

belief mass assigned to the focal element S_0 at time stamp t). Several time-indexed states are represented by the belief mass distribution of four states relative to the time stamp t. An arc linking the two consecutive states belonging to different time stamps represents a temporal change of the belief mass in order to model the temporal dependence between these states. Defining these impacts as transition-belief masses between focal elements of the state at time stamp t and those at time stamp $t+1$ lead to the definition of the association or correlation of the state relative to inter-time stamps, as it is defined as:

$$M(X_{t+1}|X_t) =$$
$$(\{m(S_0^{t+1}), m(S_1^{t+1}), m(S_2^{t+1}), m(S_3^{t+1})\})|$$
$$(\{m(S_0^t), m(S_1^t), m(S_2^t), m(S_3^t)\}) \tag{4.2}$$

The state of the first time-indexed state does not have any parameters associated conditional probability distribution in Figure 4.3. It is possible to compute the belief mass distribution of any state X_i at time stamp t corresponding to selected (i.e., activated and deactivated) sensors at time stamp t. The belief mass distribution at time stamp $t+1$ is also computed using selected sensors at time stamp $t+1$. The two states are such rotated that the old state is dropped and the new state is used as the time progress. The temporal link between two consecutive time-indexed states reflects the temporal dependency [68], which can distinguish a false alarm from new sensor activations or deactivations by comparing the measured belief mass distribution for three consecutive time-indexed states. We increase the index t by one every time a new observation (i.e., sensory information) arrives, because we only consider discrete-time stochastic processes. In addition, we consider the relation-dependency which has the association or correlation of a sensor's activation or deactivation between two consecutive time-indexed states using the Autonomous Learning Process (ALP).
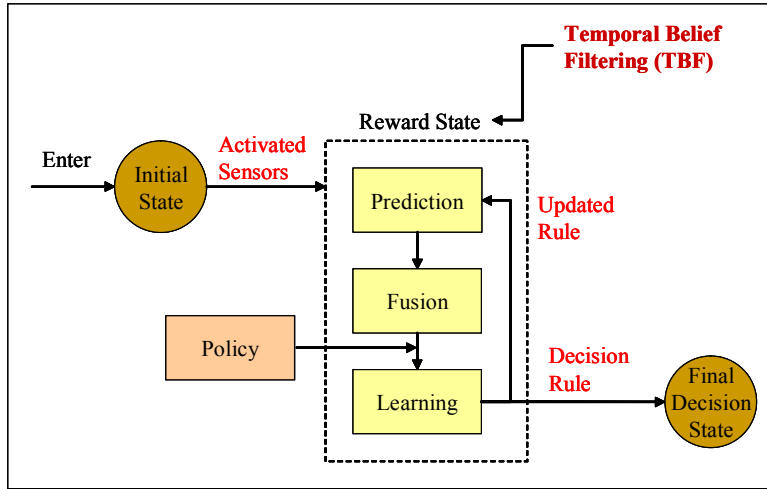
Figure 4.4. Autonomous Learning Process (ALP) Principle.

4.2.3 Autonomous Learning Process (ALP)

Sensors measurements show different values based on temporal changes. We know that the values of the sensor at the current time-indexed state are evolved by the measured values at the previous time-indexed state, because the belief mass distribution can not vary abruptly between two consecutive time-indexed states. In order to deal with this evolution, we utilize an autonomous learning process (ALP) that has three states: 1) Initial State, 2) Reward State, and 3) Final Decision State as shown in Figure 4.4. This ALP is performed based on the Q-learning technology represented by [66, 111]:

$$Q(X_t, m_t(.)) \leftarrow (1 - m_t(.))Q(X_t, m_t(.)) + m_t(.)(Re + D \max m_{t-1}(.)Q(X_{t-1}, m_{t-1}(.)))$$

$$(4.3)$$

In eq. (4.3), X_t is the current state, $m(.)$ is the belief mass distribution, D is the discounting factor, and Re is the reward state to help decision making in final decision state. We are able to support dynamic metrics (e.g., the evolution of the upper bounds or lower bounds of the pre-defined criteria). In particular, Temporal

Belief Filtering (TBF) algorithm is performed in the reward state so as to support the ALP principle.

4.2.4   Temporal Belief Filtering (TBF) for Relation-Dependency

In reward state of the ALP principle, TBF operations: prediction, fusion, learning and update are performed so as to obtain the relation-dependency that represents the association or correlation of two consecutive time-indexed states. TBF ensures temporal consistency with the exclusivity between two consecutive time-indexed states when only one hypothesis concerning activity is true at each time. TBF assumes that the general basic belief assignment (GBBA) at the current time stamp t is close to the GBBA at the previous time stamp $t-1$. Based on this assumption, the evolution process predicts a current GBBA taking the GBBA at $t-1$ into account. The TBF that operates at each time stamp t consists in four steps: 1) Prediction, 2) Fusion, 3) Learning and 4) Updated rule if required. For instance, if the activity of the patient was fainting (F) at $t-1$ then it would be partially fainting (F) at t. This is an implication rule for fainting (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 the frame of discernment (Θ) is used:

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

The evolution process can be interpreted as a GBBA defined as:

$$m_F^\Theta = [\quad 0 \quad 1 - Pl_F \quad Bel_F \quad Pl_F - Bel_F \quad]^T \tag{4.4}$$

4.2.4.1   Prediction

Depending on the current model M with only two focal sets, the disjunctive rule of combination is used in order to compute *prediction* from the previous GBBA

at $t-1$ and model of evolution using eq. (4.1). The disjunctive rule of combination does not allow to assign more belief to a hypothesis than does the previous GBBA. It is well suited for the autonomous evolution process under uncertainty:

$$\hat{m}_{t,M}^{\Theta} = \quad m_{t-1}^{\Theta} \quad (M_{\cup}) \quad m_M^{\Theta} \tag{4.5}$$

where m_{t-1}^{Θ} is the previous GBBA and m_M^{Θ} is model of evolution.

For instance, the prediction for fainting (F) situation of the patient at time stamp t is defined as:

$$\hat{\mathbf{m}}_{t,F}^{\Theta} = \begin{bmatrix} 0 \\ (1 - Pl_F) \times m_{t-1}^{\Theta}(\neg F) \\ Bel_F \times m_{t-1}^{\Theta}(F) \\ 1 - [((1 - Pl_F) \times m_{t-1}^{\Theta}(\neg F)) + Bel_F \times m_{t-1}^{\Theta}(F)] \end{bmatrix} \tag{4.6}$$

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

4.2.4.2 Fusion, Learning and Updated Rule

Prediction $(\hat{m}_{t,M}^{\Theta})$ and *measurement* (m_t^{Θ}) represent two distinct pieces of the information. *Fusion* of the two distinct pieces of the information leads to a new GBBA whose conflict value (C_F) is relevant for belief learning and update requirement. In this case, conflict value (C_F), which is similar to k_{12} of the eq. (3.4), is calculated by the conjunctive rule of combination of $\hat{m}_{t,M}^{\Theta}$ and m_t^{Θ}:

$$C_F = \quad \hat{m}_{t,M}^{\Theta} \quad (M_{\cap}) \quad m_t^{\Theta} \quad (\emptyset) \tag{4.7}$$

In addition, *policy* is required so as to analyze whether the current model M is valid or not. If C_F is not greater than the pre-defined threshold (T), the model at $t-1$ is kept as valid at t. However, if C_F exceeds the T, the model is evolved based

on the result of the conjunctive rule of combination of $\hat{m}_{t,M}^{\Theta}$ and m_t^{Θ}. Depending on the applied policy, the evolution process $(m_{t,M}^{\Theta})$ (i.e., *learning*) is performed as below:

$$m_{t,M}^{\Theta} = \begin{cases} \hat{m}_{t,M}^{\Theta} \quad (M_{\cap}) \quad m_t^{\Theta} \quad , if \quad C_F \geq T \\ m_{t-1,M}^{\Theta} \quad\quad\quad\quad\quad , if \quad C_F < T \end{cases} \tag{4.8}$$

After a learning, a fading memory process (F_a) has been embedded so as to reduce the relation-dependency of the pieces of long past information even though the cumulative sum of conflict value (C_F) between $\hat{m}_{t,M}^{\Theta}$ and m_t^{Θ} is lower than the pre-defined threshold (T) during long time intervals. A fading memory process (F_a) resets the cumulative sum of C_F as a zero (0) and $\hat{m}_{t+w,M}^{\Theta}$ is equal to m_{t+w}^{Θ} based on time window size (W), which is chosen as a constant value (C). Then, *updated rule* is applied to the model of evolution repeatedly after F_a is applied to $m_{t,M}^{\Theta}$.

$$m_{t+w,M}^{\Theta} = \begin{cases} (1) \quad F_a \leftarrow \begin{cases} \sum C_F = 0 \quad\quad , if \quad W = C \\ \hat{m}_{t+w,M}^{\Theta} = m_{t+w}^{\Theta} \end{cases} \\ (2) \quad m_{t,M}^{\Theta} \times (F_a) \end{cases} \tag{4.9}$$

4.2.4.3 Decision Rule

Finally, a decision is taken by the maximum of GPT (i.e., eq. (3.8)) within the DSmT framework after the evolution process is performed. In this dissertation, we adopt Shafer's model [114] in order to compare our approach with DBNs, which can get a BBA with non null masses only on θ_1 and θ_2 (i.e., $P\{\theta_1 \cup \theta_2\} = m(\theta_1) + m(\theta_2) = 1$) where θ_1 and θ_2 are hypotheses of the frame of discernment (Θ) (i.e., focal elements of the state within the frame of the set).

In addition, it is required to assess the recognition performance of a time-indexed state so as to decide whether a temporal sequence of the state has a false alarm or a new sensor activation/deactivation within the defined time window size

(W). It is necessary to find a quality criterion without references to assess this performance. We defined D_F as the differentiation of GPTs of two consecutive time-indexed states. The $\bar{D}_F$ is defined as the mean of D_F (i.e., $\frac{\sum D_F}{W}$) within the defined W as the chosen criterion (i.e., eq. (4.10)) in order to distinguish a sensor reading error from new sensor activations or deactivations (i.e., eq. (4.11)). For instance, as shown in eq. (4.11), if $\bar{D}_F$ is less than δ, there is no error within W. If $\bar{D}_F$ is located between δ and γ, a false alarm happens. And if $\bar{D}_F$ is greater than γ, the emergency situation of the patient progress.

$$\bar{D}_F \triangleq \frac{1}{W} \sum_{i=1,W} D_F^i \tag{4.10}$$

$$Decision(De) = \begin{cases} \text{No errors within the } W & ,if \quad \bar{D}_F < \delta \\ \text{False alarm} & ,if \quad \delta \leq \bar{D}_F < \gamma \\ \text{Emergency Progress} & ,if \quad \gamma \leq \bar{D}_F \end{cases} \tag{4.11}$$

where δ is the defined false alarm threshold and γ is the defined emergency progress threshold for the chosen criterion. In this case, the value of δ is always lower than that of γ, because we assume that the false alarm does not often happen when the new sensor activation or deactivation is detected by the expert system in emergency situation of the patient. Based on the defined threshold (T) for conflict value (C_F) and time window size (W), we can distinguish a sensor reading error from new sensor activations or deactivations. Then, we perform a dynamic evidential fusion process (DEFP) in order to improve the confidence (i.e., GPT) level of contextual information.

4.3 Dynamic Evidential Fusion Process (DEFP)

We perform context reasoning based on DEN that is constructed on SEN with a temporal dimension in order to improve the GPT level of contextual information. The Dynamic Evidential Fusion Process (DEFP) estimates a sensor reading error
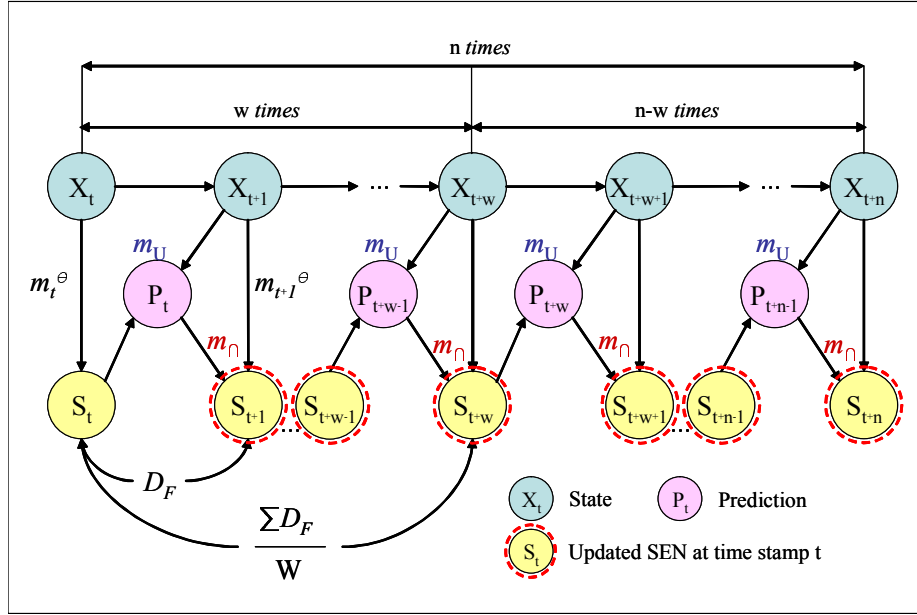
Figure 4.5. The Proposed DEN for n time intervals.

from new sensor activations or deactivations. Then, DEFP helps to make a correct decision about the situation of the patient by comparing the GPT levels of consecutive time-indexed states. In particular, first, we define the threshold (Te) of the GPT level for the emergency situation of the patient. Second, we calculate the GPT level at each time-indexed state using a TBF with defined T and W. And last, if the GPT level is over the defined Te for four continuous time-indexed states, we make a decision about the situation of the patient as an emergency.

4.3.1 Evolution Operations with DEN

The DEN is constructed based on the proposed SEN with a temporal dimension as shown in Figure 4.5. Within a DEN, context reasoning is performed in order to find a false alarm in captured contexts and make a high confidence level of the situation of the patient. We assume that the initial prediction is equal to the 1st measurement at 1st time-indexed state t_1. The consecutive processing of two combination rules

(i.e, disjunctive rule and conjunctive rule) is well adapted to SEN so as to update the belief mass distribution of SEN at time-indexed states. In Figure 4.5, we define n time intervals and time window sizes W so as to reflect a fading memory process (F_a) to the pervasive healthcare system. The F_a can reduce long past contextual information of the patient. Depending on D_F and $\bar{D}_F$, we can trace the emergency progress which can check a false alarm. We then make an optimal time window size (W) that is applied to the evolution process. This consecutive fusion process composed of the combination of two combination rules (i.e., disjunctive rule and conjunctive rule) based on SEN can make the DEFP approach. The procedures of the DEFP approach, which is the 2nd proposed context reasoning method, consist of six steps.

4.3.2   DEFP Approach

1. (**Measure a GBBA of SEN**): Initially, we measure a GBBA of SEN using evidential operations at time stamp t. In TBF algorithm for DEFP, we assume that the first prediction ($\hat{m}_{t_1,M}^{\Theta}$) is equal to measurement ($m_{t_1}^{\Theta}$) at time-indexed state t_1.

2. (**Prediction and Evolution**): We calculate prediction from the previous GBBA and model of evolution using the disjunctive rule of combination (i.e., eq. (4.1)). The disjunctive rule of combination is well suited for the model evolution under uncertainty because it does not allow to assign more belief to an hypothesis than does the previous GBBA. The GBBA of SEN at time stamp $t+1$ will be affected by $\hat{m}_{t+1,M}^{\Theta}$.

3. (**Learning**): We fuse $\hat{m}_{t+1,M}^{\Theta}$ and m_{t+1}^{Θ} using the conjunctive rule of combination so as to make a new GBBA. As a learning, if conflict value is greater than the pre-defined threshold ($C_F > T$), a new GBBA is adapted. Whereas, the previous learned GBBA is adapted as a new GBBA (i.e., eq. (4.8)).

4. (**Fading Memory Process**): We apply a fading memory process (F_a) with the defined time window size (W) so as to reduce the affection of long past information. After the F_a is performed, the GBBA of $\hat{m}_{t+w,M}^{\Theta}$ is equal to the GBBA of m_{t+w}^{Θ}. (i.e., eq. (4.9)). The previous GBBA of $\hat{m}_{t+w-1,M}^{\Theta}$ is ignored at time stamp $t+w$.

5. (**Update and Decision Making**): We calculate the GPT of the frame at each time stamp (i.e., eq. (3.8)) by applying the updated rule, then, we calculate D_F of the two consecutive time-indexed states. Based on $\bar{D}_F$ and the pre-defined value for δ and γ, we can make a decision: No errors, False alarm, or Emergency progress (i.e., eq. (4.11)).

6. (**Comparison the GPT level**): Finally, we compare the GPT level of consecutive time-indexed states. If the GPT level is over the pre-defined threshold (Te), which represents the emergency situation, for four continuous time-indexed states, we make a decision about the situation of the patient as an emergency.

4.4 A Case Study

In this section, we assume that the same specific situation (i.e., fainting or sleeping) of the patient in the living room is occurred so as to describe the DEFP approach as a context reasoning method based on the applied scenario. In addition, we suggest a method to distinguish a sensor reading error from new sensor activations or deactivations.

4.4.1 Applied Scenario

As shown in Figure 3.3, we suppose that the same situation: "sleeping (Sl)" or "fainting (F)" of the patient can happen in smart home applications. We utilize
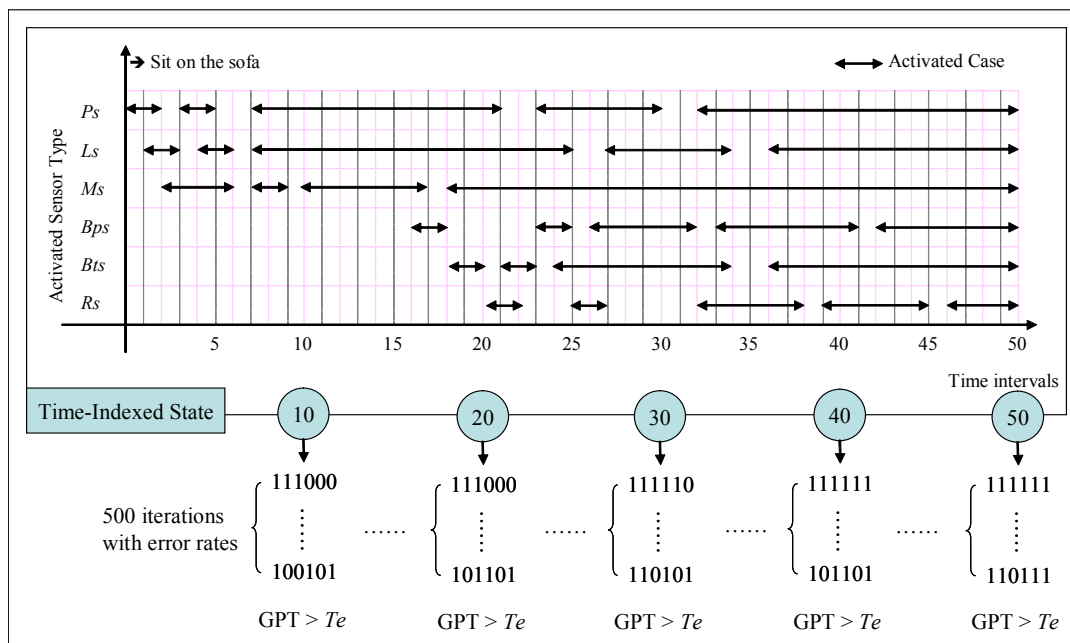
Figure 4.6. An example of sensor activations during 50 time intervals.

six types of different sensors in this scenario. Then, we apply the same % of static weighting factors and discounting factors (D) into each sensor. For instance, we assume that a static weighting factor of *Ps*, *Ls*, *Ms*, *Bps*, *Bts*, and *Rs* are 0.5, 0.25, 0.25, 0.2, 0.2 and 0.6, respectively. Based on the applied scenario, 2^6 cases that depends on activated sensors happen randomly in order to represent temporal changes in sensory information. The GPT level of each case is calculated within a SEN as the default value of the criterion. This default value is used in order to compare the relation-dependency of DEN with that of DBNs [141]. The model evolution (i.e., the association or correlation of two consecutive time-indexed states) of DEN is applied as a transition probability of DBNs so as to compare the GPT of DEN with that of DBNs. In this chapter, we assume that different types of sensors are randomly activated during 50 time intervals in order to simulate evidential operations with two fusion processes such as DEFP and DBNs as shown in Figure 4.6. In this case, we
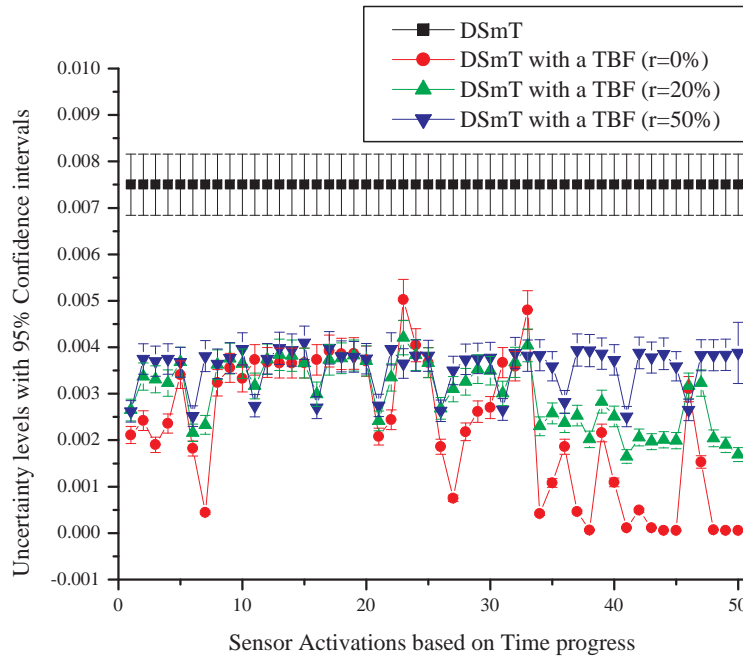
Figure 4.7. Uncertainty levels of SEFP and DEFP.

apply different simulation error rates (e.g., 0%, 20% and 50%) into the evidential fusion process with a 95% confidence interval for 500 iterations.

4.5 Comparison and Analysis

We need the same underlying model (i.e., Shafer model) [114] that reduces D^Θ to 2^Θ without loss of generality by assuming exclusivity between elements of Θ in order to compare the GPT level of DEN with that of DBNs. Based on Shafer model, first, we compare the uncertainty level and the GPT level of two theories: 1) DSmT (i.e., SEFP) and 2) DSmT with a TBF (i.e., DEFP) using paired observations [59]. Second, we compare the GPT level of DEFP with that of DBNs by considering six steps: 1) Checking a temporal dependency of two consecutive time-indexed states, 2) Finding an optimal threshold (T) for a conflict value (C_F) in TBF algorithm, 3) Finding an optimal time window size (W), 4) Calculating the GPT level with the
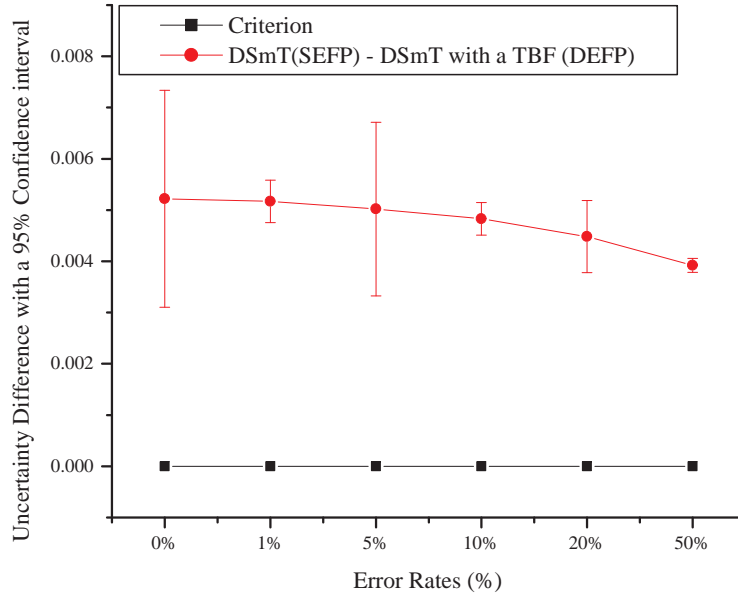
Figure 4.8. Comparison Uncertainty levels of SEFP and DEFP.

pre-defined weights and different error rates (r), 5) Calculating the GPT level with different weights and 6) Calculating the GPT level with different discounting factors (D) with paired observations.

4.5.1 Uncertainty levels of SEFP and DEFP

After performing a SEFP within the evidential network, we apply a TBF using eqs. (4.1), (4.4), (4.5) and (4.6) in order to compare the uncertainty level of DSmT (i.e., SEFP) with that of DSmT with a TBF (i.e., DEFP). We assume that the pre-defined threshold (T) for the conflict value (C_F) is equal to zero. Thus, we always apply the model evolution process (i.e., $C_F > 0$). As shown in Figure 4.7, we can reduce the degrees of uncertainty of DSmT by applying a TBF. In addition, the degrees of uncertainty of the SEFP approach are higher than those of the DEFP approach when we compare the uncertainty levels of SEFP with those of DEFP using paired observations with different error rates (i.e., 0%, 1%, 5%, 10%, 20% and 50%)
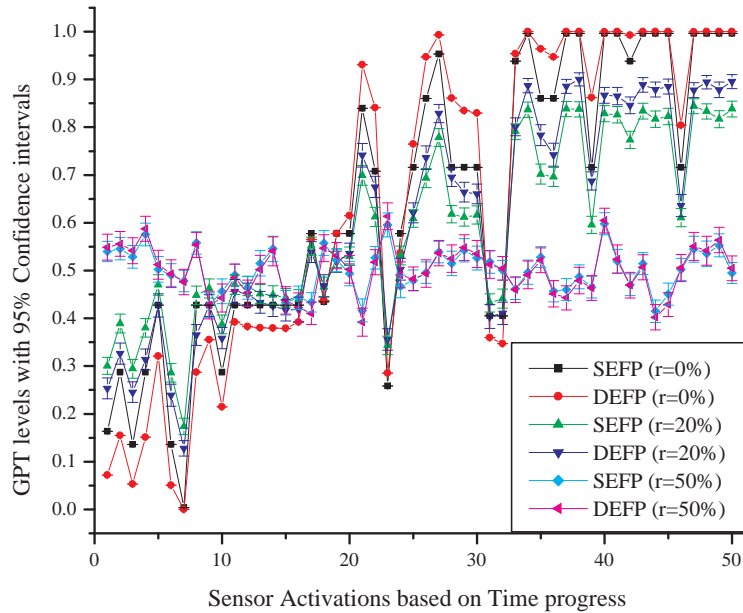
Figure 4.9. GPT levels of SEFP and DEFP.

as shown in Figure 4.8. Therefore, we know that the DEFP approach obtains the better performance than the SEFP approach so as to reduce the conflicting mass in uncertainty level of contextual information of the patient.

4.5.2 GPT levels of SEFP and DEFP

We compare the GPT levels of the DSmT approach by applying a TBF with different error rates (r) (i.e., 0%, 20% and 50%). In a TBF algorithm, a conflict value (C_F) between prediction and measurement requires different model changes depending on the selected thresholds. In particular, we can get a higher GPT level when the conflict value (C_F) between prediction and measurement is greater than zero (i.e., $C_F > 0$), because the model evolution process utilizes the conjunctive rule of combination such as the PCR5 combination rule. It means that we can get higher confidence levels when we adapt more model evolution at each time stamp. As shown in Figure 4.9, the GPT level of DEFP is higher than that of SEFP with a 0% error
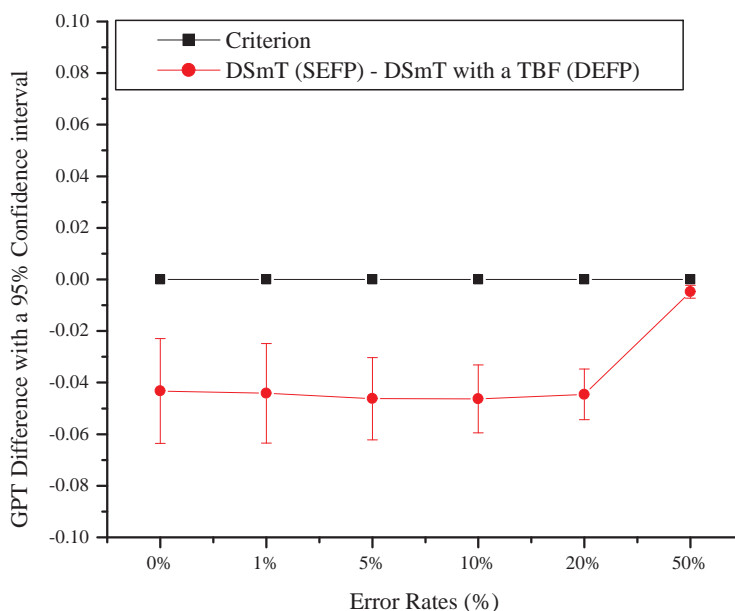
Figure 4.10. Comparison GPT levels of SEFP and DEFP.

rate when the degree of GPT is over 0.5. However, the GPT level of DEFP and that of SEFP are difficult to distinguish with a 20% or a 50% error rate. Thus, we compare the GPT level of DEFP with that of SEFP using paired observations depending on the GPT level of the DEFP approach as shown in Figure 4.10. In this case, we calculate the paired observations by applying different error rates (i.e., 0%, 1%, 5%, 10%, 20% and 50%) into the evidential fusion process for the degree of GPT is over 0.5 case. Based on the results of Figure 4.10, the GPT level of the DEFP approach is higher than that of the SEFP approach when the degree of GPT is over 0.5.

4.5.3   GPT levels of DEFP and DBNs

4.5.3.1   Calculating a temporal dependency

Before we compare the GPT level of DEFP with that of DBNs, we calculate a temporal dependency of DSmT with different error rates (r) (i.e., 0%, 20% and 50%).
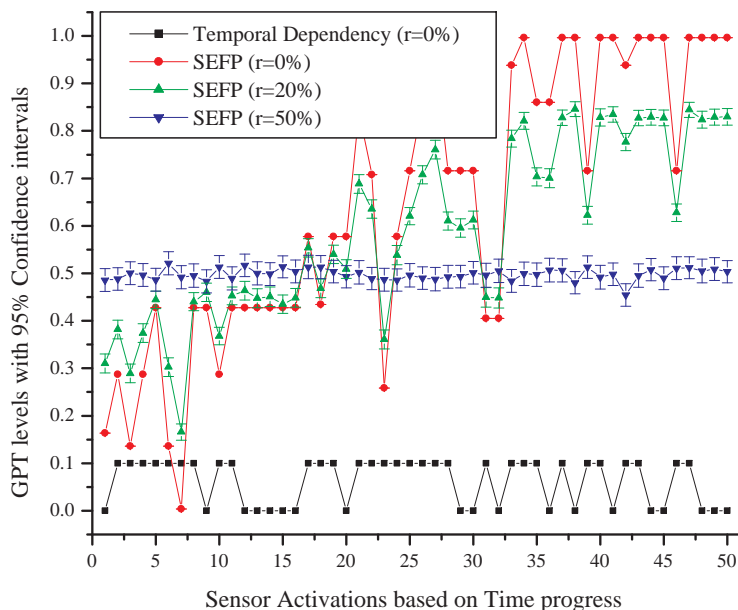
Figure 4.11. A temporal dependency of DSmT.

As shown in Figure 4.11, it is difficult to distinguish a sensor reading error from new sensor activations or deactivations when we check a temporal dependency between two consecutive time-indexed states. A temporal dependency is expressed as 1 or 0 with a 0% error rate if temporal changes happen between two consecutive time-indexed states. For instance, the degree of GPT at $22^{nd} \sim 23^{rd}$ or $32^{nd} \sim 33^{rd}$ time intervals are suddenly decreased in Figure 4.11. It is not easy to estimate a sensor reading error or not, because the values of a temporal dependency show the 1 values between 22nd and 33rd time intervals. In addition, a temporal dependency shows the 1 values constantly if we apply a 20% or a 50% error rate. In this case, we don't know exactly what happens to the patient. Therefore, we need to reduce this ambiguity by calculating the relation-dependency of the consecutive time-indexed states. We consider a temporal consistency that the belief on activity can not vary abruptly between two consecutive time-indexed states using the proposed TBF algorithm. In
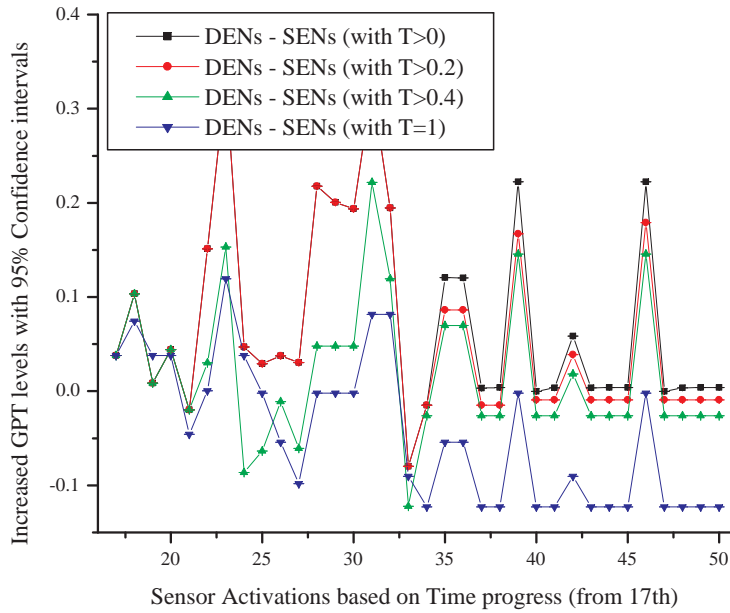
Figure 4.12. Increased GPT levels with different thresholds for a conflict value.

order to apply the TBF algorithm, we will find an optimal threshold (T) for a conflict value (C_F) between prediction and measurement in TBF algorithm.

4.5.3.2 Finding an optimal threshold for a conflict value

In order to calculate the relation-dependency of two consecutive time-indexed states, we have to define the threshold (T) for a conflict value (C_F). In the previous section, the model evolution process is performed based on the conjunctive rule of combination of prediction and measurement. In addition, we can get a higher confidence level when we adapt more model evolution at each time stamp, because the degree of the conjunctive combination rule (i.e., learning) will be increased by depending on small differentiation of prediction and measurement. For example, we compare the GPT levels of DEFP by applying different T ($0 \leq T \leq 1$) (i.e., $T = 0.0, 0.2, 0.4$ and 1.0) with a 0% error rate into the model evolution process. In this case, we only consider time intervals from the 17th, because medical body sensors operate from

that time interval. Depending on the applied threshold (T), different degrees of the learning are adapted to the updated rule. Then, we obtain the increased GPT levels of the DEFP approach based on the GPT levels of the SEFP approach at each time-indexed state as shown in Figure 4.12. The highest GPT level is obtained when we apply $T = 0$ into C_F compared to the others. Whereas the GPT levels of the DEFP approach are lower than those of the SEFP approach. According to the Figure 4.12, we know that we get more GPT level when we adapt a new model evolution process into the TBF algorithm. In the next, we will find an optimal time window size (W) for reducing the affection of long past information in TBF algorithm. In this case, we will define δ (i.e., False alarm threshold) and γ (i.e., Emergency progress threshold) to distinguish a sensor reading error from new sensor activations or deactivations within the same applied scenario.

4.5.3.3   Finding an optimal time window sizes

In order to calculate the relation-dependency of two consecutive time-indexed states, we also have to define the time window size (W) that supports a fading memory process (F_a). We assume that the threshold for a conflict value is equal to zero $(T = 0)$ and the error rate is equal to zero, because some degrees of confidence intervals of the model evolution process are overlapped when we apply a 20% or a 50% error rate. We can not distinguish which one is better than others. As shown in Figure 4.13, we apply different W $(1 \leq W \leq 35)$ (i.e., $W = 2, 3, 5, 15$ and 35) with $T = 0$ into the model evolution process in TBF algorithm. It is difficult to find the highest GPT level between 17th and 27th time intervals, because sensor activations or deactivations among six sensors happen concurrently at those time intervals. However, the higher GPT levels are obtained between 30th and 50th time intervals when we apply the longer time window size. The increased GPT levels of the DEFP approach is reduced
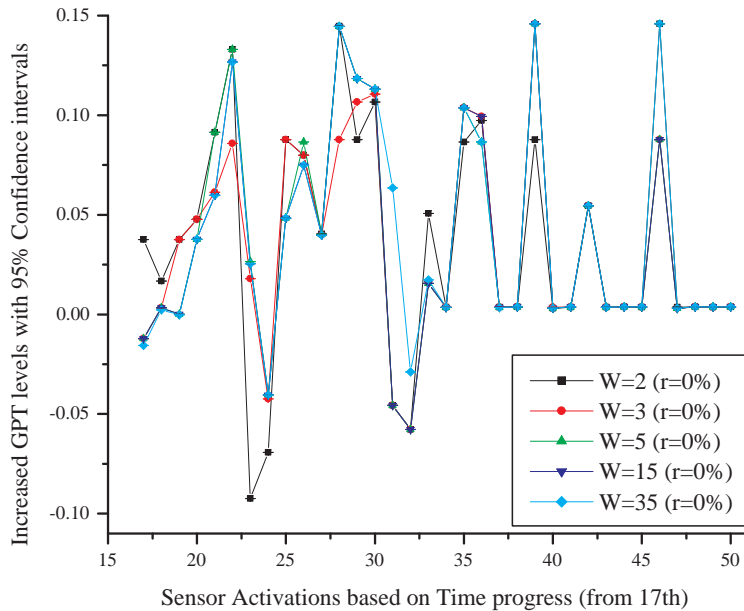
Figure 4.13. Increased GPT levels with different time window sizes.

when we apply a fading memory process (F_a) frequently. The frequent F_a can ignore the relation-dependency of consecutive time-indexed states.

However, the longer time window size can have a difficult to catch a false alarm or an emergency progress. If we apply the longer time window size such as $W = 35$ or $W = 15$, the mean of the differentiation (D_F) between two consecutive time-indexed states (i.e., $\bar{D}_F$) has no variations as shown in Figure 4.14. In Figure 4.14, we assume that $\delta = 0.05$ and $\gamma = 0.08$ in order to make a correct decision (i.e., eq (4.11)) which helps to reduce the ambiguity of the estimation about sensor's activation or deactivation. As shown in Figure 4.14, it is difficult to make a correct decision about sensor's activation or deactivation (e.g., a false alarm or an emergency progress) if we utilize the longer time window sizes. We can distinguish a false alarm from new sensor activations or deactivations if we check the mean of differentiation $(\bar{D}_F)$ frequently. Thus, the shorter time window size can make a decision easily. Based on the results of Figure 4.13 and 4.14, we know that a trade-off exists between the increased GPT
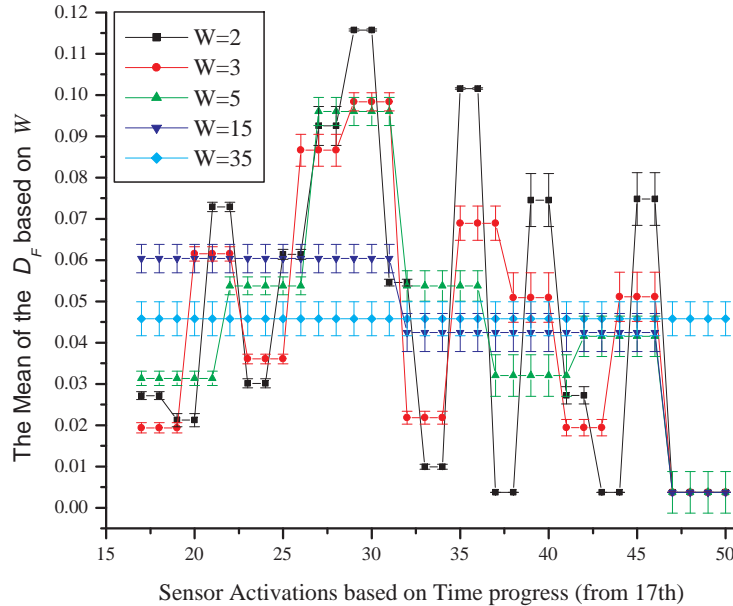
Figure 4.14. Comparison $\bar{D}_F$ with different time window sizes.

level of the DEFP approach and the mean of differentiation $(\bar{D}_F)$. We should consider two factors concurrently in order to compare the GPT level of DEFP with that of DBNs. In the next, we will compare the GPT level of DEFP with that of DBNs by considering different error rates (i.e., 0%, 20% and 50%) and static weighting factors with $T = 0$ and $W = 5$ (e.g., the middle value of the time window sizes: 2, 3, 5, 15 and 35).

4.5.3.4 Comparison GPT levels of DEFP and DBNs

Finally, we compare the GPT level of DEFP with that of DBNs by applying three different error rates (i.e., 0%, 20% and 50%) into the evidential fusion process with a 95% confidence interval. In this case, we calculate the GPT levels based on the same applied scenario. We consider the same static weighting factors with $T = 0$ and $W = 5$. According to Figure 4.15, the GPT level of DEFP is higher than that of DBNs with a 0% and a 20% error rate when the degree of GPT is over 0.5 (e.g., time
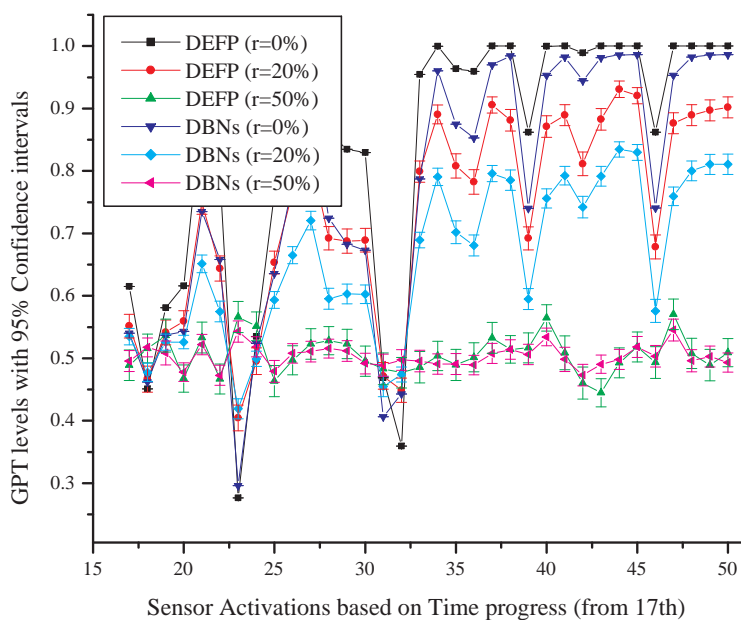
Figure 4.15. GPT levels of DEFP and DBNs.
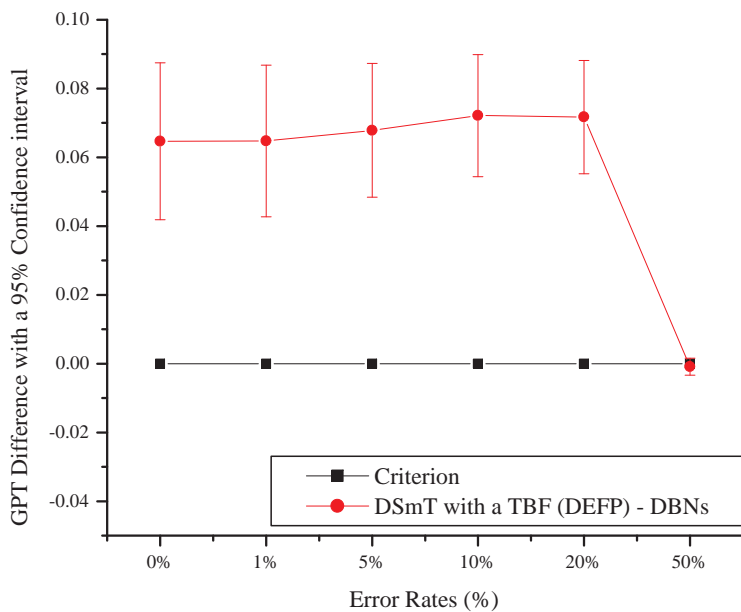
Figure 4.16. Comparison GPT levels of DEFP and DBNs.

intervals from 17th). However, the GPT level of DEFP and that of DBNs is difficult to distinguish with a 50% error rate. Therefore, we compare the GPT level of DEFP

Table 4.1. An example of different weights for DEFP and DBNs

$Case$	Ps	Ls	Ms	Bps	Bts	Rs
1 (DEN)	0.9	0.05	0.05	0.05	0.05	0.9
2 (DEN)	0.5	0.25	0.25	0.2	0.2	0.6
3 (DEN)	0.3	0.4	0.3	0.3	0.3	0.4
4 (DEN)	0.1	0.4	0.5	0.4	0.4	0.2
5 (DBN)	0.9	0.05	0.05	0.05	0.05	0.9
6 (DBN)	0.5	0.25	0.25	0.2	0.2	0.6
7 (DBN)	0.3	0.4	0.3	0.3	0.3	0.4
8 (DBN)	0.1	0.4	0.5	0.4	0.4	0.2

with that of DBNs using paired observations depending on the GPT level of DEFP as shown in Figure 4.16. In this case, we calculate the paired observations by applying different error rates (i.e., 0%, 1%, 5%, 10%, 20% and 50%) into each sensor when the degree of GPT level is over 0.5 case. The GPT level of DEFP is higher than that of DBNs. Based on the results of Figure 4.16, we know that the GPT level of the DEFP approach is higher than that of DBNs when the degree of GPT is over 0.5.

4.5.3.5 Comparison with different weighting factors

We apply different weights to each context attribute based on Ps and Rs as shown in Table 4.1 in order to compare the GPT levels of two cases: 1) DSmT with a TBF (i.e., DEFP) and 2) DBNs based on different weighting factors. We apply 0%, 20% and 50% error rates into the evidential fusion process with a 95% confidence interval in the degree of GPT is over 0.5 (e.g., time intervals from 17th). We apply the same discounting factors within the Figure 3.3.

After we apply different weights into the evidential fusion process, the GPT levels of DEFP and DBNs based on different weighting factors are shown in Figure 4.17. The GPT levels of the eight cases have different degrees of GPT at each time
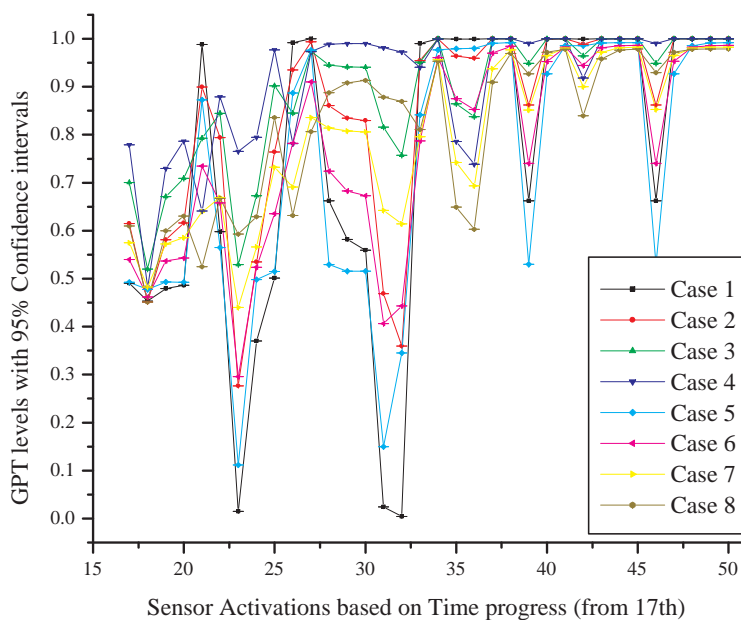
Figure 4.17. GPT levels of DEFP and DBNs with different weights.
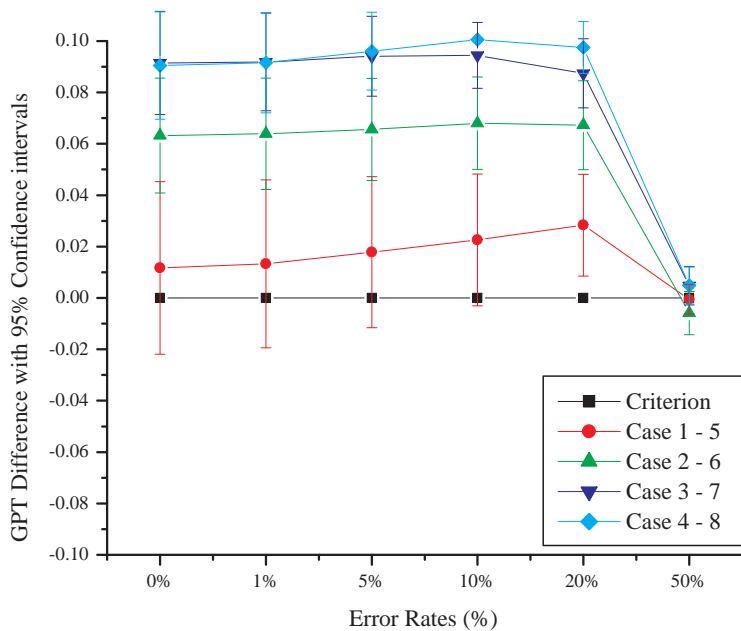
Figure 4.18. Comparison GPT levels of DEFP and DBNs with different weights.

interval. It means that the GPT levels of DEFP and DBNs show different results depending on the applied static weighting factors even though the activated sensors

have the same error rate. Hence, defining the weights is another importance so as to obtain the reliable information in context reasoning. In order to compare the GPT level of DEFP and that of DBNs, we compare the two fusion processes using paired observations. As shown in Figure 4.18, the GPT levels of eight cases have different paired observation results. When we compare the case 1 and case 5, the confidence interval includes zero so we can not distinguish which one is better than the other. The reason is that the degree of GPT is lower than 0.5 sometimes from 17th time intervals. Whereas the confidence intervals of the case 2 and 4, the case 3 and 7, and the case 4 and 8 do not have zero so we can prove that the GPT levels of DEFP are better than those of DBNs (i.e., except for 50% error rate case). Therefore, we know two importance things. One is that defining the weights of each sensor is important in order to improve the confidence level of contextual information and the other is that we should consider the degree of GPT is at least over 0.5 so as to support the reliable contextual information. In the next, we will compare the GPT level of the DEFP approach with that of DBNs with different discounting factors.

4.5.3.6 Comparison with different discounting factors (D)

We apply different discounting factors (D), which are related to sensor's credibility, into "Ps" and "Rs" as shown in Table 3.5 in order to calculate the GPT levels of DEFP and DBNs. Reducing the discounting factor (D) on each sensor is an important factor so as to obtain the reliability of contextual information of the patient. We apply the static weighting factors within the Figure 3.3 into the evidential fusion process. We also calculate the GPT level of the two cases by applying different error rates (i.e., 0%, 20% and 50%). Depending on different D on "Ps" and "Rs", the two cases show different degrees of GPT. Figure 4.19 shows an example of the GPT level of Case 7. In this case, the degrees of GPT of DEFP and DBNs are different
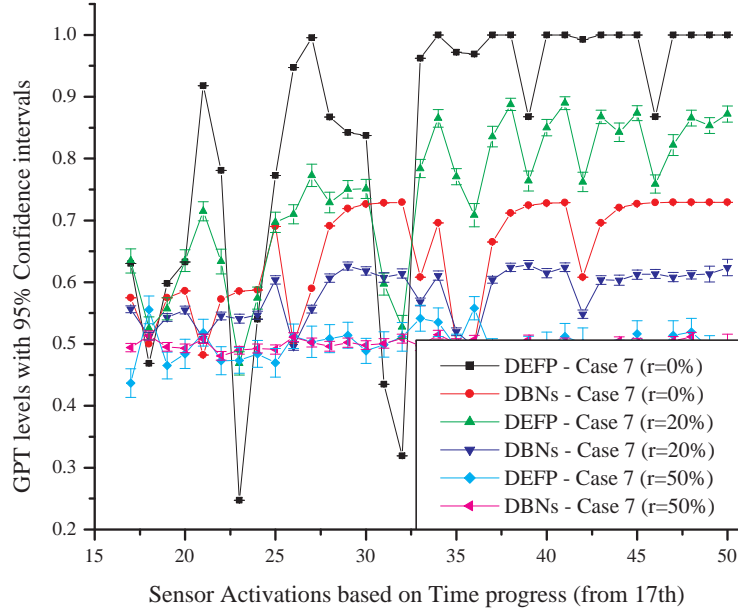
Figure 4.19. An example of the GPT level of Case 7.

depending on the applied error rates (r). Moreover, we can obtain different degrees of GPT based on a selected case. Thus, we compare the GPT of DEFP with that of DBNs using paired observations for all cases in Table 3.5. In order to compare the GPT level of DEFP with that of DBNs with different discounting factors, we apply different error rates (i.e., 0%, 1%, 5%, 10%, 20% and 50%) into the evidential fusion process from 17th time interval as shown in Figure 4.20. According to Figure 4.20, the GPT levels of DBNs are lower than those of the DEFP approach except for the 50% error rate case. This result shows that the DEFP approach gets the better performance than the DBNs for improving the confidence level of contextual information in the progress of fainting (F) situation of the patient.

We know that we get a higher GPT level when we apply a TBF algorithm into evidential fusion process compared to the fusion process based on DBNs. We can improve the GPT level where the degree of GPT is higher than 0.5, because the aggregation of the degree of GPT is over 0.5 and the degree of GPT is not over
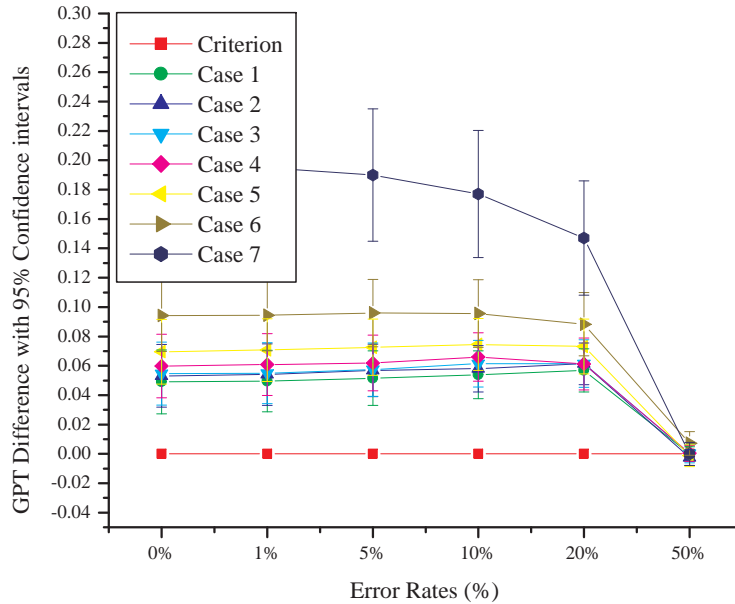
Figure 4.20. Comparison GPT levels of DEFP and DBNs with different D.

0.5 reduces the total GPT level. In addition, an error make the wrong simulation operation then it is nothing if we apply an error is equal to 0.5. We can not believe the sensor activation or deactivation at that time-indexed state. Therefore, we have to consider the degree of GPT is over 0.5 case so as to improve the GPT level of contextual information. We also have to reduce an error rate in order to obtain acceptable decision makings.

Finally, we can infer the situation of the patient by using the mean of the D_F (i.e., $\bar{D}_F$) and pre-defined rule of a decision based on Figure 4.14 and 4.15. For example, we assume that the pre-defined threshold (Te) for an emergency situation is equal to 0.7. If the degree of GPT is over 0.7 for four continuous time-indexed states, we estimate that the patient is an emergency. According to Figure 4.14 and 4.15, we catch a false alarm between 30th and 35th time intervals. Then, we can estimate that the emergency situation of the patient starts from 25th time interval. This is helpful to make a decision about the situation of the patient.

4.6   Summary

In order to achieve a higher confidence level of contextual information and a correct decision making with unpredictable temporal changes in sensory information, we proposed a learning based fusion method (i.e, the DEFP approach) based on DEN as a context reasoning method. The proposed method dealt with a temporal consistency and a relation-dependency of the contexts using the model evolution process such as the TBF algorithm in ALP principle. This method reduced the ambiguity of the consecutive time-indexed states. After comparing the DEFP approach based on DEN with a fusion process based on DBNs with six steps: 1) Checking a temporal dependency of two consecutive time-indexed states, 2) Finding an optimal threshold (T) for a conflict value (C_F) in TBF algorithm, 3) Finding an optimal time window size (W), 4) Calculating the GPT level with static weighting factors and different error rates (r), 5) Calculating the GPT level with different weighting factors and 6) Calculating the GPT level with different discounting factors (D), we knew that our DEFP approach based on DEN is better than a fusion process based on DBNs in order to improve the GPT level of contextual information in the emergency situation of the patient.

In the next chapter, we will improve the quality of a context by considering dynamic weights of the evidence based on the relation-dependency of consecutive time-indexed states. Correct designing the quality of the context is one of important factors for improving the confidence level of contextual information, which helps to make a reliable decision about the situation of the patient.

CHAPTER 5

DYNAMIC WEIGHTING BASED EVIDENTIAL NETWORK

5.1   Introduction

For describing an emergency situation of the patient in home-based care, some types of contextual information are more important than others. A high respiratory rate may be a strong indication of the emergency of the patient others may not be so important to estimate that specific situation [97, 134]. The weight of this information may change, due to the aggregation of the evidence and the variation of the value of the evidence over time. For instance, a respiratory rate (e.g., 50 Hz) at current time-indexed state (S_t) should have more weight compared to a respiratory rate (e.g., 21 Hz) at previous time-indexed state (S_{t-1}), because 50 Hz indicates the emergency situation of the patient strongly [21, 30]. However, the proposed DEN [68], which deals with the relations between two consecutive time-indexed states of the information by using the ALP and TBF algorithm, did not consider dynamic weights of the information over time. In addition, it is difficult in defining the absolute weight of the evidence. In this chapter, we propose the Dynamic Weighting based Evidential Network (DWEN) [70] as the 3rd context reasoning method. DWEN deals with both relative and individual importance of the evidence so as to obtain optimal weights of the evidence. Given a context attribute i, we defined a quality of data ψ_i associates weights $\omega_1, \omega_2, \ldots, \omega_K$, where $\sum_{j=1}^{K} \omega_j = 1$ in Chapter 2. The weight $\omega_j \in (0, 1]$ represents the *relative importance* of a context attribute α_j compared to others in the given time t and region R. A context attribute has individual differences in the same situation space over time [67]. This difference is represented by the *individual*

importance of a context attribute α_j. We only consider the quality of data with the pre-defined context attributes, selected region, and relevant activities as shown in Figure 2.4.

Based on dynamic weights of the evidence, DWEN improves the GPT level of contextual information compared to previous works (i.e., [69, 68, 56]), which applied a static weight into the evidential fusion process within the given time t and location R. In order to model this goal, we divide each sensor's operation with two types of a context attribute: *Intrinsic* and *Optional*. An intrinsic context attribute is an attribute that changes the weight of a context attribute if its value at current time-indexed state (S_t) is not equal to that at previous time-indexed state (S_{t-1}). An optional context attribute is an attribute that assists in inferring the situation. Individual differences between two consecutive time-indexed states would not weaken the support for having the specific situation of the patient when the sensor between two consecutive time-indexed states activates continuously. We then recalculate and update the weight of each intrinsic context attribute using the proposed dynamic normalized weighting technique [127]. Finally, we fuse both intrinsic and optional context attributes, then, we apply them into Dynamic Weighting based Evidential Fusion Process (DWEFP) [70] so as to infer the situation of the patient based on temporal and relation dependency [67]. A temporal dependency distinguishes a false alarm from new sensor activations by comparing the measured belief mass distribution of three consecutive time-indexed states. A relation dependency represents the association or correlation of two consecutive time-indexed states. The index t is increased by one every time a new observation (e.g., sensory information) arrives. We consider a discrete-time stochastic process.

The rest of the chapter is organized as follows. The basics of dynamic weights of the evidence are introduced in section 5.2. We propose the DWEFP as a context

reasoning method in section 5.3. Finally, we perform a case study in order to compare the DWEFP with the DEFP [68] to show the improvement of the DWEFP approach compared to the DEFP approach in section 5.4.

5.2   Basics of Dynamic Weights of the Evidence

In this section, we introduce the basics of dynamic weight of the evidence. First, we pre-define rules of a context attribute based on the value of each sensor. Then, we determine the importance of the evidence in regarding to a specific situation of the patient using a normalized weighting technique that is similar to Simple Multi-Attribute Utility Theory (SMART) [127, 132].

5.2.1   Pre-defined Rule of a Context Attribute

First, we define a rule so as to represent dynamic weights of a context attribute as shown in Table 5.1. We assume that the ratio of total weights of optional context attributes $O(\sum \omega_i)$ is equal to that of intrinsic context attributes $I(\sum \omega_i)$ in order to apply the rule of combination. In evidential fusion networks, each context state has the same weight (e.g., the weight is equal to 0.5). We apply more $C(a_k^t)$, which reflects the increase or decrease degree of a particular context attribute, to the activated case (i.e., Emergency (4)) compared to the non-activated case (i.e., Warning (2 and 3) and Regular (1)), because the activated case is more important than the non-activated case in an emergency situation of the patient. In addition, we apply more $C(a_k^t)$ to the level increased case (i.e., $L(a_k^{t+1}) > L(a_k^t)$) compared to the level decreased case (i.e., $L(a_k^{t+1}) < L(a_k^t)$), where $L(a_k^t)$ reflects the level of a particular context attribute. The level increased case is also more important than the level decreased case in an emergency situation of the patient. Therefore, we calculate the weight of an intrinsic context attribute as below.

Table 5.1. Pre-defined Rules of a Context Attribute

Context Type	Sensor Type	Non-Activated			Activated
		Regular (1)	Warning (2)	Warning (3)	Emergency (4)
Intrinsic	Respiratory Rate	15~20 Hz	13~14 or 21~30 Hz	11~12 or 31~40 Hz	10 *below* or 41 *over* Hz
	Blood Pressure	120~90 mmHg	121~130 or 81~89 mmHg	131~140 or 71~80 mmHg	141 *over* or 61~70 mmHg
	Body Temperature	36.6~37 °C	36.1~36.5 or 37.1~38 °C	35.6~36 or 38.1~39 °C	35.5 °C below or 39.1 °C over
Optional	Location	The motion detector installed in the ceiling catches the RF signal attached on the patient			
	Motion	The motion detector installed in the door catches the RF signal attached on the patient			
	Pressure	The pressure sensor attached on the sofa catches the weight of the patient			

1. initial $O(\sum \omega_i) = I(\sum \omega_i) = 0.5$

2. if all $L(a_k^t) = L(a_k^{t+1})$, then $C(a_k^{t+1}) = 0$

3. else if $L(a_k^{t+1}) > L(a_k^t)$ and $L(a_k^{t+1}) \neq 4$, then $C(a_k^{t+1}) = 2\alpha$

4. else if $L(a_k^{t+1}) < L(a_k^t)$ and $L(a_k^t) \neq 4$, then $C(a_k^{t+1}) = -\alpha$

5. else if $L(a_k^{t+1}) > L(a_k^t)$ and $L(a_k^{t+1}) = 4$, then $C(a_k^{t+1}) = 3\beta$

6. else if $L(a_k^{t+1}) < L(a_k^t)$ and $L(a_k^t) = 4$, then $C(a_k^{t+1}) = -2\beta$

with two % values α and β (i.e., $\beta \geq \alpha$).

5.2.2   A Normalized Weighting Technique

We calculate the relative weight of a context attribute based on Multi-Attribute Utility Theory (MAUT) [127, 132] in order to setup the initial weight of a context attribute within a given context state. The weights are determined by their importance in regarding to a specific situation of the patient. In particular, we construct a scale representing the properties of the levels of a context attribute in order to evaluate context attributes. For instance, we assume that the scale from 0 (e.g., the least affection) to 55 (e.g., the most affection) for the situation serves as measure of the evaluation as shown in Table 5.2. We pre-defined the scale of a context attribute then we calculate the relative importance of a context attribute using eq. (5.1).

$$\tilde{\omega}_u = \omega_v / \sum_{w=1}^{N} (\omega_w) \tag{5.1}$$

where $\tilde{\omega}_u$ defines the relative weight of a context attribute, ω_v is the sum of the value of Scale-R and Scale-E for one sensor type, and $\sum_{w=1}^{N}(\omega_w)$ is the total sum of the value of Scale-R and Scale-E.

After calculating the relative weight of a context attribute, we redistribute the weight of a context attribute over time based on the pre-defined rule of a context attribute. Let ω_1, ω_2, $\cdots$, ω_k, $\cdots$, ω_{k+m}, $\cdots$, ω_N denote an initial relative weight

Table 5.2. An example of Relative Weight of a Context Attribute

Sensor Type	Regular	Emergency	Relative Weight $\tilde{\omega}_u$
Respiratory Rate	Scale-R (5)	Scale-E (15)	0.6
Blood Pressure	Scale-R (5)	Scale-E (15)	0.2
Body Temperature	Scale-R (5)	Scale-E (55)	0.2
Location	Scale-R (5)	Scale-E (10)	0.25
Motion	Scale-R (5)	Scale-E (10)	0.25
Pressure	Scale-R (5)	Scale-E (25)	0.50

associated with a given context state S_i^t for fusion process. A normalized weighting technique for individual difference between two time-indexed states is applied to each context attribute as below:

A Normalized Weighting Technique within the same location:

1. Repeat for each optional context attribute k:

   $\omega_k = \omega_i$, where i defines an initial weight

2. Repeat for each intrinsic context attribute k:

   if all $L(a_k^t) = L(a_k^{t+1})$ or all $C(a_k^{t+1})$ are equal,

   then all $\omega_k = \omega_i$

   else if any $L(a_k^t) \neq L(a_k^{t+1})$ or any $C(a_k^{t+1})$ is different,

   then $\hat{\omega}_k = \omega_i / \sum_{j=1}^{N}(\omega_j \pm C(a_j^{t+1}))$,

   where $\hat{\omega}_k$ defines a new weight for a context attribute

5.3 Dynamic Weighting based Evidential Fusion Process (DWEFP)

We perform context reasoning based on the dynamic weighting based evidential network (DWEN) that is constructed based on DEN with dynamic weights of the evidence in order to improve the GPT level of contextual information. In particu-
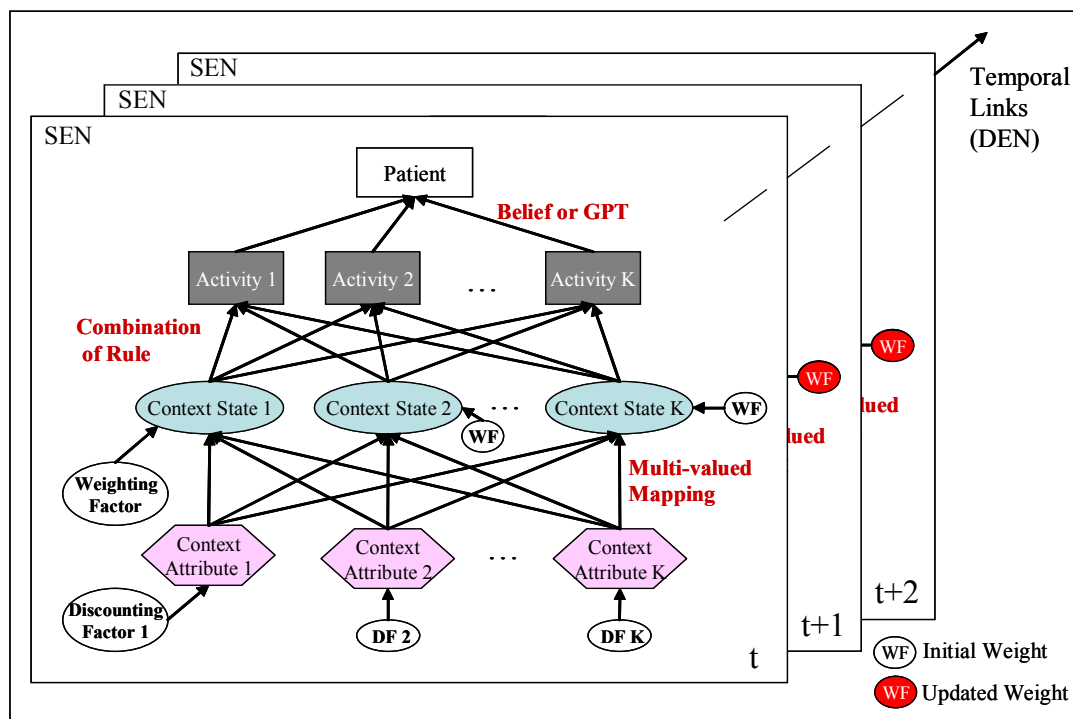
Figure 5.1. An example of the DWEN, which has updated weights.

lar, we propose the Dynamic Weighting based Evidential Fusion Process (DWEFP) approach by using a normalized weighting technique (e.g., SMART).

5.3.1 Evidential Operations with DWEN

Based on the proposed SEN with a temporal dimension as shown in Figure 4.2, the dynamic weighting based evidential network (DWEN) is constructed as shown in Figure 5.1. Within a DWEN, context reasoning is performed so as to make a high GPT level of the situation of the patient compared to the DEFP approach. We first calculate the GBBA of SEN initially using evidential operations (i.e., Chapter 3.3.2) at 1st time-indexed state. Second, we apply the updated weight into each context attribute from 2nd time-indexed state using the proposed normalized weighting technique. Finally, we calculate the confidence level (i.e., GPT) of contextual information then compare it with the DEFP approach (i.e., Chapter 4.3.2) in order to make a

correct decision about the situation of the patient. The procedures of the DWEFP approach, which is the 3rd proposed context reasoning method by applying dynamic weights into each context attribute over time, consist of seven steps.

5.3.2   DWEFP Approach

1. (**Measure a GBBA of SEN**): Initially, we measure a GBBA of SEN using evidential operations at time stamp t. The first prediction $(\hat{m}_{t_1,M}^{\Theta})$ is equal to measurement $(m_{t_1}^{\Theta})$ at time-indexed state t_1.

2. (**Update the Weight of a Context Attribute**): We calculate the relative importance of a context attribute then we redistribute the weight of a context attribute over time based on the pre-defined rule of a context attribute. Then, we calculate individual difference between two time-indexed states using the proposed normalized weighting technique (i.e., eq. (5.1)). Finally, we apply the updated weight into each context attribute from 2nd time-indexed state so as to obtain the GPT of contextual information.

3. (**Prediction and Evolution**): We calculate prediction from the previous GBBA and model of evolution using the disjunctive rule of combination (i.e., eq. (4.1)). The disjunctive rule of combination is well suited for the model evolution under uncertainty because it does not allow to assign more belief to an hypothesis than does the previous GBBA. The GBBA of SEN at time stamp $t+1$ will be affected by prediction $(\hat{m}_{t+1,M}^{\Theta})$.

4. (**Learning**): We fuse $\hat{m}_{t+1,M}^{\Theta}$ and m_{t+1}^{Θ} using the conjunctive rule of combination so as to make a new GBBA. As a learning, if a conflict value (C_F) is greater than the pre-defined threshold (T), a new GBBA is adapted. Whereas, the previous learned GBBA is adapted as a new GBBA (i.e., eq. (4.8)).

5. (**Fading Memory Process**): We apply a fading memory process (F_a) with the defined time window size (W) so as to reduce the affection of long past information. After F_a is performed, the GBBA of $\hat{m}^{\Theta}_{t+w,M}$ is equal to the GBBA of m^{Θ}_{t+w} (i.e., eq. (4.9)). The previous GBBA of $\hat{m}^{\Theta}_{t+w-1,M}$ is ignored at time stamp $t+w$.

6. (**Update and Decision Making**): We calculate each GPT of the frame of discernment per time-indexed state (i.e., eq. (3.8)) by applying the updated rule then calculate differentiation (D_F) of two consecutive time-indexed states. Based on the mean of D_F (i.e., $\bar{D}_F$) and the pre-defined value for δ and γ, we can make a decision: No errors, False alarm, or Emergency progress (i.e., eq. (4.11)).

7. (**Comparison the GPT level**): Finally, we compare the GPT level of consecutive time-indexed states. If the GPT level is over the pre-defined threshold (Te), which represents the emergency situation, for four continuous time-indexed states, we make a decision about the situation of the patient as an emergency.

5.4 A Case Study

We make the same specific situation (i.e., fainting or sleeping) of the patient in the living room of the smart home as shown in Figure 3.3. We describe the DWEFP approach as a context reasoning method based on the applied scenario. Then, we compare the uncertainty level and GPT level of DWEFP with those of DEFP in order to show the improvement of the GPT level of the DWEFP approach. For making a simulation, we perform an evidential fusion process with a 95% confidence interval for 500 iterations.
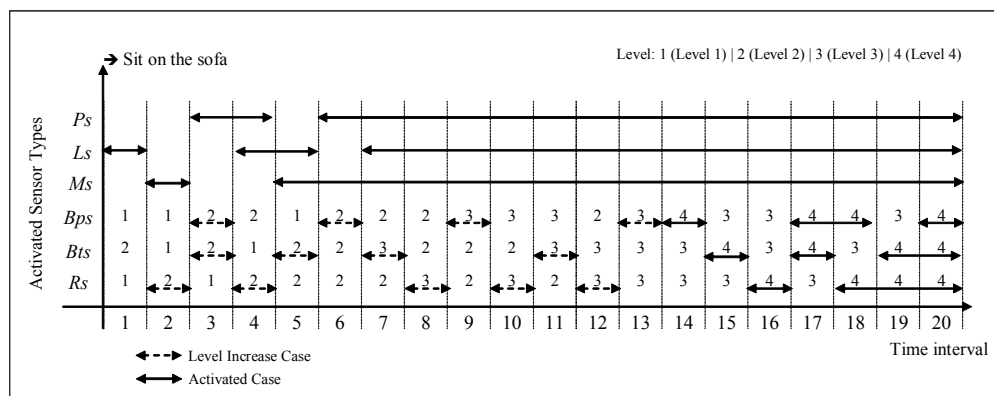
Figure 5.2. An example of emergency level changes based on time intervals.

Table 5.3. An example of the % values of α and β

% value	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
β	5 %	10 %	15 %	20 %	25 %	30 %
α	5 %	5 %	10 %	10 %	15 %	30 %

5.4.1 Applied Scenario

As mentioned in Chapter 3, many ambiguous situations of the patient can happen in home-based care. We suppose that the same situation (i.e., "sleeping" (Sl) or "fainting" (F)) of the patient can happen in smart home applications. In order to check dynamic emergency level changes based on time intervals, six types of a sensor are randomly activated during 20 time intervals as shown in Figure 5.2. Among six types of a sensor, three types of a sensor: blood pressure, body temperature and respiratory rate are involved in an intrinsic context attribute type. Whereas three types of a sensor: pressure, location and motion are involved in an optional context attribute type. Within Figure 5.2, we apply the level increased case and the activated case based on the data of Table 5.1. Initially, a discounting factor and a relative weight of each sensor are fixed so as to calculate the initial GBBA of SEN. In particular, we assume that a discounting factor of the environmental sensors, the location sensor,

Table 5.4. Comparison Case 1 in Table 5.3 without/with dynamic weights

Time	Without dynamic weight			With dynamic weight (Case 1)		
	B	T	R	B	T	R
1	0.2	0.2	0.6	0.2	0.2	0.6
2	0.2	0.2	0.6	0.190	0.181	0.629
3	0.2	0.2	0.6	0.208	0.198	0.594
4	0.2	0.2	0.6	0.199	0.179	0.622
5	0.2	0.2	0.6	0.187	0.196	0.617
6	0.2	0.2	0.6	0.202	0.192	0.606
7	0.2	0.2	0.6	0.198	0.207	0.595
8	0.2	0.2	0.6	0.189	0.188	0.623
9	0.2	0.2	0.6	0.210	0.190	0.600
10	0.2	0.2	0.6	0.199	0.179	0.622
11	0.2	0.2	0.6	0.201	0.200	0.599
12	0.2	0.2	0.6	0.182	0.190	0.628
13	0.2	0.2	0.6	0.197	0.187	0.617
14	0.2	0.2	0.6	0.220	0.181	0.599
15	0.2	0.2	0.6	0.197	0.208	0.596
16	0.2	0.2	0.6	0.184	0.175	0.641
17	0.2	0.2	0.6	0.214	0.203	0.583
18	0.2	0.2	0.6	0.200	0.171	0.628
19	0.2	0.2	0.6	0.179	0.196	0.625
20	0.2	0.2	0.6	0.201	0.191	0.608

and the medical body sensors are 20%, 10% and 5%, respectively. We can obtain an initial relative weight of each sensor using a scale representing method as shown in Table 5.2. In addition, we apply different % values of α and β (i.e., $\beta \geq \alpha$) as shown in Table 5.3 so as to check the variations of the weight depending on the selected degree of a level change $(C(a_k^{t+1}))$.

5.4.2   Updated Weights with the normalized weighting technique

In order to show the improvement of the GPT level of the DWEFP approach, we first calculate the updated weights of each context attribute by applying the
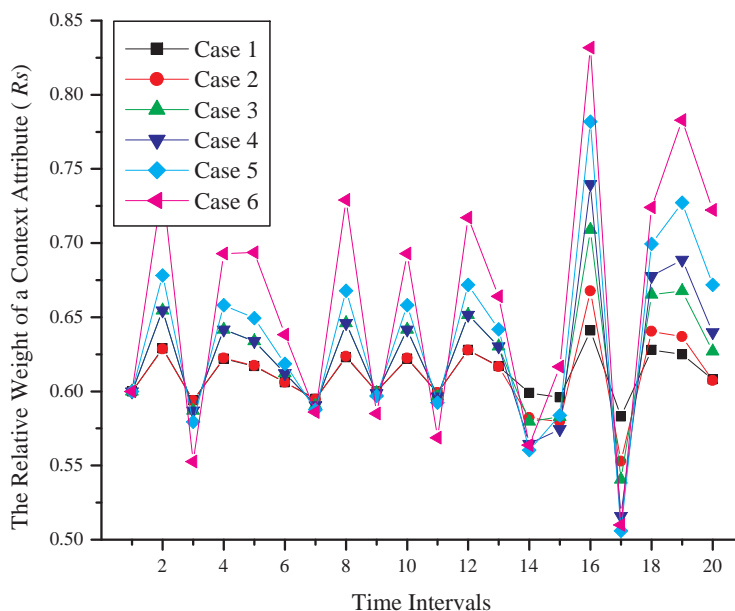
Figure 5.3. An example of updated weights of a context attribute (Rs) .

normalized weighting technique into the evidence. Then, we can obtain the updated weights for each intrinsic context attribute as shown in Table 5.4. In Table 5.4, we compare two cases: 1) Without dynamic weights and 2) With dynamic weights. In particular, we apply Case 1 in table 5.3 (e.g., $\alpha = \beta = 5\%$) into dynamic weights so as to update the weight of the evidence. Depending on the selected α and β, we can estimate which context attribute has a level increase case or an activation. For example, in Figure 5.3, we show the variations of the respiratory rate sensor based on different % values of α and β in Table 5.3. We can estimate which context attribute has a level increase or an activation by comparing an individual difference between two consecutive time-indexed states. The degrees of the variation of "Rs" until 13th time interval is smaller than those from 14th to 20th time interval. Based on these variations, we can distinguish the level increased case from the activated cases. An individual difference is more clear than the others when we consider Case 6 in Table 5.3.
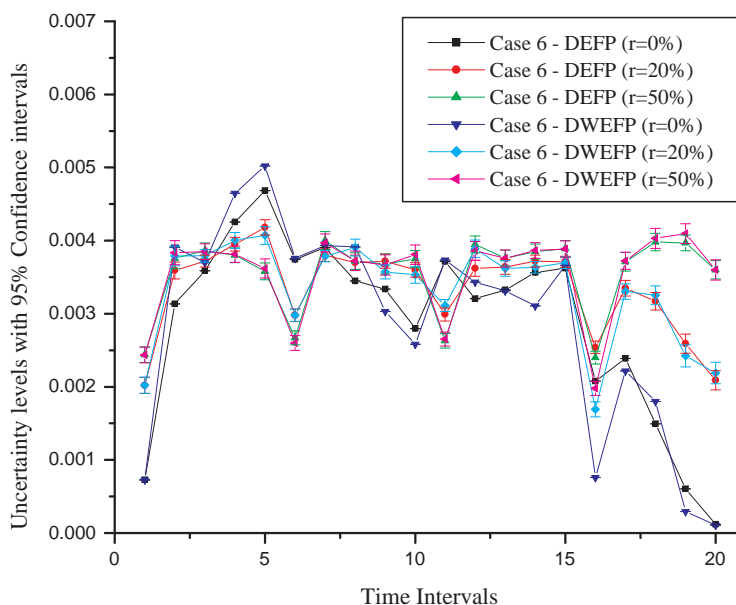
Figure 5.4. Uncertainty levels of DWEFP and DEFP with Case 6 in Table 5.2.

5.5 Comparison and Analysis

In this section, first, we compare the uncertainty level of DWEFP with that of DEFP. Second, we compare the GPT level of DWEFP with previous approaches such as SEFP, DEFP and DBNs [90, 141].

5.5.1 Uncertainty levels of DWEFP and DEFP

After obtaining updated weights of context attributes, we apply a TBF using eqs. (4.1), (4.4), (4.5) and (4.6) in order to compare the uncertainty level of DWEFP with that of DEFP. We assume that the pre-defined threshold (T) for the conflict value (C_F) is equal to zero. Thus, we apply the model evolution process continuously. As shown in Figure 5.4, the degrees of uncertainty of DWEFP can not easily distinguish from those of DEFP when we apply different error rates (i.e., 0%, 20% and 50%) into the evidential fusion process with a 95% confidence interval. Thus, we compare the uncertainty level of DWEFP with that of DEFP using paired observations by applying
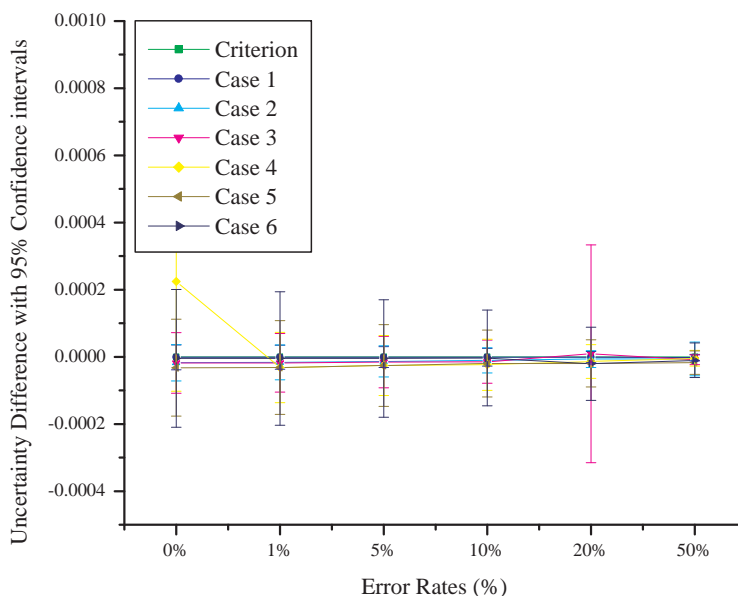
Figure 5.5. Comparison Uncertainty levels of DWEFP and DEFP.

different error rates (r) (i.e., 0%, 1%, 5%, 10%, 20% and 50%). As shown in Figure 5.5, the 95% confidence interval of paired observations includes zero so we can not distinguish which one has the better performance than the other so as to reduce the conflicting mass in uncertainty level of contextual information. The uncertainty level of the DWEFP approach and that of DEFP approach has no different in performance analysis.

5.5.2 GPT levels of DWEFP and DEFP

5.5.2.1 GPT levels of DWEFP, DEFP, SEFP, and DBNs

We compare the GPT level of DWEFP, which applies the updated weights into the evidential operations, with those of DEFP, SEFP and DBNs. We utilize the same underlying model (i.e., Shafer model [114]), which assumes exclusivity between elements of the Θ [69], so as to compare the DWEFP approach with the others. We deal with the level increased case as the activated case so as to calculate the GPT
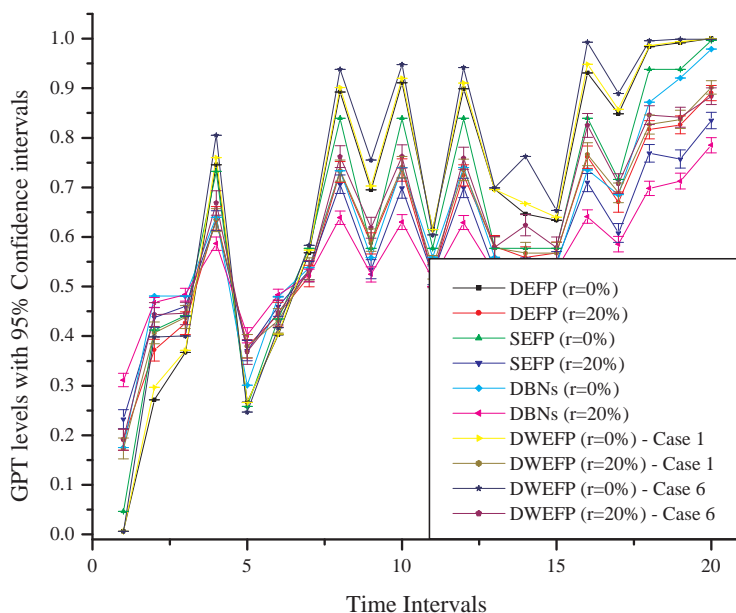
Figure 5.6. GPT levels of DEFP, SEFP, DBNs and DWEFP (Case 1 and 6).

level. We apply a fading memory process (F_a) into the evidential fusion process such as DEFP and DWEFP with pre-defined threshold for a conflict value (i.e., $T=0$) and time window size (i.e., $W=5$). We also apply two error rates (i.e., 0% and 20%) into the evidential fusion process with a 95% confidence interval. Based on the result of Figure 5.6, the GPT level of DBNs is higher than others when optional context attributes only activate, because DBNs does not consider the ignorance [84] of different pieces of the evidence. In addition, the GPT level of DWEFP seems like a higher than others when both intrinsic and optional context attributes activate. However, there exists ambiguity among DEFP and DWEFP, because of the confidence intervals of the two fusion processes DEFP and DWEFP. Thus, we compare the GPT level of DWEFP with that of DEFP using paired observations as shown in Figure 5.7. In this case, we compare the GPT levels of DWEFP with those of DEFP based on different error rates (i.e., 0%, 1%, 5%, 10%, 20% and 50%) and different % values of α and β (i.e., from Case 1 to Case 6 in Table 5.2). As shown in Figure 5.7, the confidence
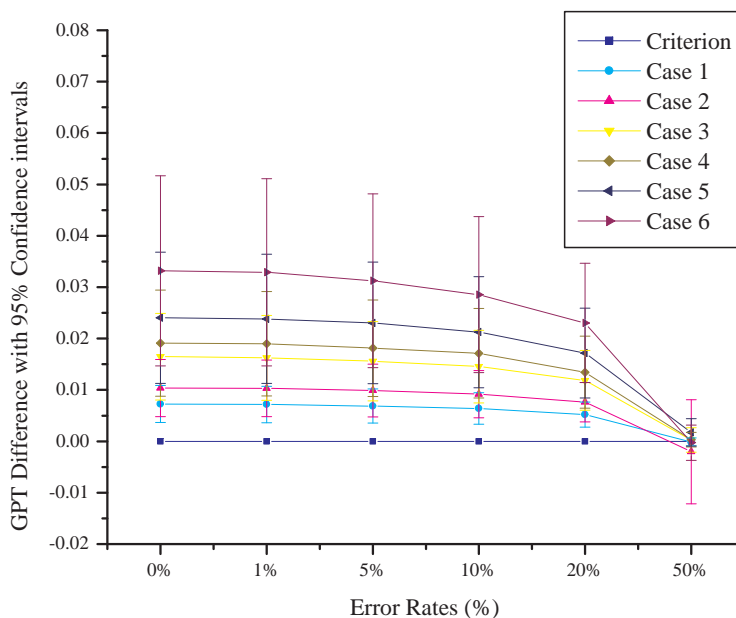
Figure 5.7. Comparison GPT levels of DWEFP and DEFP.

intervals does not include zero except for the error rate is 50% case. Therefore, the GPT level of DWEFP is higher than that of DEFP. We know that we improve the GPT level using the DWEFP approach compared to the DEFP approach.

5.5.2.2 Comparison with different discounting factors (D)

We apply different discounting factors (D) with selected error rates (r) (i.e., 0%, 5%, 10%, 20% or 50%) into context attributes as shown in Table 5.5 in order to calculate the GPT levels of DEFP and those of DBNs. We apply updated weights into each sensor by calculating the % values of α and β as shown in Case 1 and Case 6 of Table 5.2, because the % value of α and β is the smallest and the biggest in Table 5.2, respectively. In the previous chapter, the evidential fusion process with a 95% confidence interval show various degrees of GPT that depends on different discounting factors. Thus, we compare the GPT level of DWEFP and with that of DEFP by using

Table 5.5. Different discounting factors (D) with selected error rates (r)

No.	S	L	H	Bp	Bt	R
Case 1 - error rate 0%	0%	0%	0%	0%	0%	0%
Case 2 - error rate 0%	5%	5%	5%	5%	5%	5%
Case 3 - error rate 5%	5%	5%	5%	5%	5%	5%
Case 4 - error rate 5%	10%	10%	10%	10%	10%	10%
Case 5 - error rate 10%	10%	10%	10%	10%	10%	10%
Case 6 - error rate 10%	20%	20%	20%	20%	20%	20%
Case 7 - error rate 20%	20%	20%	20%	20%	20%	20%
Case 8 - error rate 20%	50%	50%	50%	50%	50%	50%
Case 9 - error rate 50%	50%	50%	50%	50%	50%	50%

paired observations directly. In order to compare the two fusion processes, we assume that a threshold for conflict value is equal to zero $(T = 0)$ and time window size is equal to five $(W = 5)$ in TBF algorithm. According to Figure 5.8, the confidence intervals do not include zero except for the error rate is 50% case. With a 50% error rate case, we can not prove anything, because an error make the wrong simulation operation then it is nothing. We can not believe the sensor activation or deactivation at that time-indexed state. Therefore, the GPT of DWEFP is higher than that of DEFP in this scenario. We improve the degree of GPT using the DWEFP approach compared to the DEFP approach.

In addition, we can infer the situation of the patient by using the mean of the D_F (i.e., $\bar{D}_F$) and pre-defined rule of a decision. We assume that a pre-defined threshold (Te) for an emergency situation is equal to 0.7. For instance, if the degree of GPT is over 0.7 for four time-indexed states continuously, we estimate that the situation of the patient is an emergency. This is helpful to make a decision about the situation of the patient in home-based care.
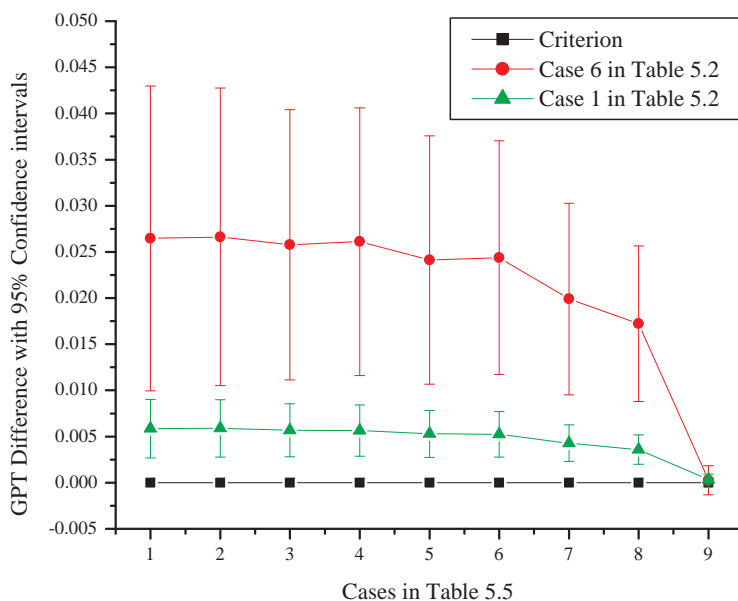
Figure 5.8. Comparison GPT levels of DWEFP and DEFP with different D.

5.6 Summary

Correctly designing the quality of a context is an important factor so as to improve the GPT level of contextual information. However, it is difficult in defining the absolute weight of the evidence. We considered both relative and individual weight of the evidence in order to apply dynamic weights to the evidence over time. This helped to make a reliable decision about the situation of the patient based on time progress. We then compared the uncertainty level and GPT level of the DWEFP approach with the DEFP approach using paired observations. Finally, we knew that we can not distinguish the better one when we compared the uncertainty level of DWEFP with that of DEFP. However, we improve the GPT level when we utilized DWEFP compared to DEFP. Until now, we compared the uncertainty level and GPT level of contextual information based on different fusion processes such as BNs, DST, SEFP, DEFP and DWEFP from chapter 3 to chapter 5. In particular, we utilized paired observations in order to compare two fusion processes within the

same framework. Based on the results of the paired observations, we knew that the uncertainty level of DEFP or DWEFP is lower than that of SEFP and DST. The GPT (i.e., pignistic probability) level of DWEFP is higher than that of others. Therefore, in this dissertation, we improved the reliability of contextual information using the PCR5 combination rule, the TBF algorithm, and the normalized weighting technique.

In the next chapter, we will introduce recent related works about data fusion method in ubiquitous or pervasive computing area.

CHAPTER 6

RELATED WORK

6.1 Introduction

This chapter presents recent research works related to context awareness, context modeling, context reasoning and decision making in general or more specifically to context reasoning method under uncertainty in pervasive computing area. In section 6.2, the most important pioneering projects which help to define the notion of activity monitoring and had great influence on the development of this field are briefly introduced. In section 6.3, different types of context modeling is compared to lead the reason of our selection of context modeling concept and to make our context modeling. In section 6.4, some context reasoning method, which helps to improve the quality of contextual information, is introduced. In particular, dynamic situation reasoning under uncertainty is treated as a specific in order to compare it with our approach. In section 6.5, we introduce the simple multi-attribute rating technique which helps to make a decision using ranking concept. Finally, we summarize the related work in section 6.6.

6.2 Projects

In recent years, research conducted within the area of context awareness in ubiquitous or pervasive computing area has become very active due to the demands for smart environments technology so as to improve the quality of life for individuals with disabilities and those wishing to age in place [26]. Thus, several research projects have studied the use of multi-sensor based technologies in order to facilitate

an assisted living environment. Among them, MavHome [27, 138, 137] is a project motivated to support ambient intelligent systems into the smart environments. In MavHome project, motion sensors are deployed so as to determine the location of the inhabitant then this location based information is subsequently considered with other sensory based information such as temperature, moisture measurement, and so on. The combined information of the ambient intelligent system that controls the devices automatically and reduces the interaction of the inhabitant is used in order to make an inference about the situation of the inhabitant in smart environment. This combined information of multi-sensor devices is similarly used in this dissertation. The Adaptive Home [87, 88] is another research project that uses sensors so as to determine ideal settings for lights and HVAC within the home by using a feed-forward neural network and by learning the habits of the user by using reinforcement learning algorithm. As the Adaptive Home project that can save resources then support users by learning their behavior and automating simple task, this dissertation also uses a similar learning algorithm in order to predict the user's status over time in smart environments. The Aware Home is built as a living laboratory for empirical research on ubiquitous computing with the goal to sense contextual information about itself and its inhabitants by using the developed Context Toolkit [63, 35]. It is a very flexible framework for abstracting context sensing from applications in a distributed heterogeneous network environments. However, the Aware Home project does not support continuous context and does not deal with unreliable sensory information that is mainly dealt with in this dissertation.

A limited number of research projects have been studied for the management of uncertainty of the sensor in smart environments. In [102], RFID tags, which are similarly used as a medical body sensor device, are placed on objects of interests so as to detect object interactions. This RFID tag can be envisaged for activity recognition

in conjunction with activities of daily living. Nevertheless, the constraints imposed through the RFID reader glove that has to be worn to sense tags makes it potentially less desirable to the patient to use such a glove. To recognize activities performed by an inhabitant, a set of simple sensors based on the identification of patterns [124] and simultaneous room-level tracking system [131] are developed to check the movement of the inhabitant. The systems are limited to whether or not an inhabitant is moving. These projects [131, 102, 124, 125] use a probabilistic reasoning method in order to deal with uncertainty in sensory information for context-aware activity recognition in a sensory network environment. However, they still have a potential drawback that the fact studies of behavioral patterns require large amount of activity history data then this limitation does not solve the uncertainty of sensory data. Therefore, in this dissertation, we utilize the bottom-up reasoning structure [56, 110] for recognizing contextual information in smart environments. It can model uncertainty at a low sensor level and has the ability of managing the reliability of the system in order to help correct decision making of the contexts.

6.3   Context Modeling

Contextual information is gathered from a variety of the pieces of evidence that differ in the quality of information they produce and that are often failure prone. The pervasive computing community increasingly understand that developing context-aware applications should be supported by adequate contextual information modeling and reasoning techniques. These techniques reduce the complexity of context-aware applications and improve their maintainability and evolvability [16]. For instance, context aware applications use contextual information in order to evaluate whether there is a change to the user and computing environment context then they take a decision whether any adaptation to that change is necessary often requires reasoning

capabilities. It is therefore important that context modeling techniques are able to support both consistency verification of the model and context reasoning techniques. In addition, due to its dynamic and heterogeneous nature, contextual information may be of variable quality. In fact, it may even be incorrect since most sensors feature an inherent inaccuracy and this inaccuracy increase over time. Contextual information may be incomplete or conflicting with other contextual information. Thus, a good context modeling approach must include modeling of contextual information quality so as to support reasoning about context. In this section, we introduce different context modeling based on context information types, their relationships and dependencies, context histories, context qualities and context abstractions describing real world situations using context information facts.

6.3.1   Object-role based Models

The object-role based model (ORM) [49, 48] was developed for conceptual modeling of databases. Context Modeling Language (CML) is the representative of ORM. The CML was described in a preliminary form by [53, 52]. CML provides a graphical notation designed in order to support different sources of context, imperfect information and constraints of context. For instance, CML is able to support querying over uncertain information using the alternative construct (i.e., three-valued logic). This logic expression combines any number of basic expressions using logical connectives and special forms of the universal and existential quantifiers. It can support runtime representation and querying for high-level context abstractions. However, CML has several weaknesses. All context types are uniformly represented as atomic facts in CML. If a hierarchical structure is needed or one particular dimension of context is dominant, this model is not adaptable. In addition, CML emphasizes the development of context models for particular applications or application domains, which do

not provide the interoperability. Thus, there are some attempts to create a hybrid model that combines the respective advantages of CML and ontology-based model in [123, 55]. In this dissertation, we utilize the graphical model for describing the occupant-centered pragmatic approach that provides primary context attributes such as location, time, people and facilities and devices, in section 2.4.1.

6.3.2 Spatial Models

Space is an important context in many context-aware applications and most spatial context models organize their contextual information by physical locations (e.g., the boundary of room, the location of the sensor, or the associated location as metaphor) [113, 32, 100]. Spatial context models are well suited for context-aware applications that are mainly location-based. In particular, a spatial organization of contextual information may be beneficial in many mobile information systems due to their inherent mobility. Thus, spatial context models allow reasoning about the location and spatial relationships of objects. Such relations cover the inclusion in a distinct area or range and the distance to other entities (e.g., position, range and nearest neighbor [14, 45]. In addition, their efficient processing highly depends on the underlying context information management system that uses different types of contextual information based on the location. For instance, geometric and geographic locations offer simple mapping to map data and sensor data, while symbolic and relational locations are easier to build up and represent a simple perception of space [93]. However, this spatial model keeps the location data of contextual information up to date. In this dissertation, we consider a spatial contextual information in order to reason the situation of the inhabitant. We then assume that a spatial contextual information is no importance when the related sensor operation does not changed.

6.3.3 Ontology-based Models

Context can be considered as a specific kind of knowledge. Ontology-based context model exploits the representation and reasoning of this knowledge so as to describe complex context that can not be represented by simple context models [10]. In ontology-based models with OWL-DL formalism [57], a particular set of instances of a basic context data and their relationships reveals the presence of more abstract context characterization (e.g., user's activity). It is possible to automatically derive a new knowledge about the current context and to detect possible inconsistencies in the context information of pervasive environments [24, 140, 18]. Compared to the other context models, an ontology-based model provides clear advantages both in terms of heterogeneous and interoperability. However, it is difficult to support modeling temporal aspect in ontology and the operators provided by OWL-DL, which makes a computational expensive reasoning, are sometimes inadequate to define complex descriptions [8]. Hence, the possibility of augmenting the expressivity of ontological languages through an extension with rules has been investigated by the Semantic Web community and brought to the definition of logic languages [23]. In this dissertation, we only use a classification concept of ontology for defining a context classification, because our context modeling method such as the relation-dependency approach is more focused on temporal-related contextual information.

6.3.4 Hybrid Models

In order to obtain more flexible and general systems, different models and reasoning tools need to be integrated with each other. For instance, a hybrid approach combines ontologies with the fact-based approach provided by the CML so as to handle ambiguous and imperfect contextual information with interoperability in [55]. In addition, the integration of above three models has been presented in [9, 15] in order to

support the scalability requirements of pervasive computing services that can derive high-level context data on the basis of raw one. In particular, a hierarchical hybrid model composed of sensor data fusion, context data representation and semantics of context terms is considered so as to make context modeling [85, 82]. However, it still has an open issue (e.g., how to integrate the open-world semantics of ontologies with the closed-world semantics of DB-based models and logic programming and how to reconcile probabilistic reasoning with languages not supporting uncertainty. Thus, in this dissertation, we defined our context modeling, which is similar to the combination of spatial and object context models, in order to derive probabilistic context reasoning under uncertainty based on sensor data fusion.

6.4   Context Reasoning

In context-aware applications, situations [43, 32] are external semantic interpretations of low-level sensor data by permitting a higher-level specification of human behavior and the corresponding system services and the way of changing situation is called context reasoning and interpretation [77]. It means that we need reasoning context models that can adapt the situation definitions based on discovered changes with changing environments and changing user needs [60]. However, both the physical world itself and our measurements of it are prone to uncertainty. Thus, different types of entities in the pervasive environment must be able to reason about uncertainty. In order to solve this problem, a number of mechanisms have been proposed in the literature for reasoning on uncertainty and there are two main purposes for reasoning on uncertainty: 1) improving the quality of contextual information and 2) inferring new kinds of contextual information. Reasoning to improve the quality of contextual information typically takes the form of multi-sensor fusion where data from different sensors are used so as to increase confidence, resolution or any other context quality

metrics. Reasoning to infer new contextual information typically takes the form of deducing higher-level contexts (e.g., activity of a user) or situations from lower-level contexts (e.g., location information of a user), because we can not directly sense the higher-level contexts. These contexts may be associated with a certain level of uncertainty depending on both the accuracy of the sensed information and precision of the deduction process [16, 73]. Therefore, in this section, we introduce some context reasoning approaches such as Fuzzy logic, Probabilistic logic, Bayesian Networks (BNs), Hidden Markov Models (HMMs), Kalman Filtering Models (KFMs), Dynamic Bayesian Networks (DBNs) and Dempster-Shafer Theory (DST) of the evidence in order to compare them with our context reasoning approach.

6.4.1 Puzzy Logic, Probabilistic Logic and BNs

In fuzzy logic, a degree of membership represented by a pair (A:m) where A is a set and m is a possibility distribution in real unit interval [0,1] is used so as to show an imprecise notion such as confidence values [139, 75]. The elements of two or more fuzzy sets can be combined in order to create a new fuzzy set with its own membership function then it is used for reasoning models which need more than the probabilistic theory with uncertainty. For instance, the fuzzy logic is used so as to capture a clinical uncertainty in medical data of pervasive computing applications in [7]. In addition, fuzzy logic is well suited for describing subject contexts by resolving conflicts between different contexts (e.g., Actuator's operation in [66]). In this dissertation, we assume that the environmental sensors are operated based on the fuzzy logic of the selected sensors.

As mentioned in section 3.2.1, probabilistic logic and Bayesian networks (BNs) can be used for improving the quality of contextual information through multi-sensor fusion as well as for deriving the higher-level probabilistic contexts. They also can be

used for resolving conflicts between contextual information obtained from different sources. According to [105, 46], the probabilistic logic is used for encoding access control policies and the BNs is used for combining uncertain information from a large number of sources and deducing higher-level contexts. However, these rules can not represent the ignorance [84], which manages the degree of uncertainty, caused by the lack of information.

6.4.2 HMMs, KFMs and DBNs

In order to deal with unpredictable temporal changes in sensory information, Hidden Markov Models (HMMs) [31, 95, 120], Kalman Filtering Models (KFMs) [86, 130] or Dynamic Bayesian Networks (DBNs) [39, 90, 141] are utilized as fusion techniques. In terms of probabilistic networks, HMMs represent stochastic sequences as Markov chains; the states are not directly observed, but are associated with observable evidences, and their occurrence probabilities depend on the hidden states. This model can be used for location prediction by using a hierarchical Markov model that can learn and infer a user's daily movements [76]. KFMs represent the state of the system refers to a set of variables that describe the inherent properties of the system at a specific instant of time. This is a useful technique for estimating, or updating the previous estimate of, a system's state by using indirect measurements of the state variables and using the covariance information of both state variables and indirect measurements [94]. However, DBNs, which were proposed as a generalization of HMMs and KFMs, have some distinct features. DBNs allow much more general graph structures compared with HMMs or KFMs. DBNs represent the hidden state in terms of a set of random variable compared with HMMs, which represent the state space with a single random variable. DBNs allow general hybrid and nonlinear conditional probability densities (CPDs) compared with KFMs, which require all CPDs

to be linear-Gaussian. This is a useful feature to manage the causality between random variables as well as time series data. For instance, a high level user behavior is inferred from low level sensor data by adding knowledge of real-world constraints to user location data in [101]. A variant of DBNs is used in an unsupervised way in order to predict transport routes based on GPS data. By adding constraints on the routes that could be learned by the training algorithm, the prediction accuracy was significantly improved.

DBNs are made up of the interconnected two time-indexed states of a static Bayesian Network (BN) and the transition of a static BN between two consecutive time t and $t+1$ satisfies the Markov property [96] as shown in Figure 6.1. DBNs can be implemented by keeping in memory two states at any one time-indexed state, representing a previous time-indexed state and current time-indexed state, respectively. In Figure 6.1, the two time-indexed states, which have an associated conditional probability, are such rotated that old states are dropped and new states are used as time progress. The arcs between two time-indexed states reflect temporal causality and they are parameterized by transitional probabilities. The joint distribution from the initial moment of time $(t = 1)$ until the time boundary $(t = T)$ is then given by

$$P(S_{1:T}) = \prod_{t=1}^{T} \prod_{i=1}^{n} P(S_i^t | k(S_i^t)) \tag{6.1}$$

where S_i^t is the ith node at time t and $k(S_i^t)$ stands for the parents of a node S_i^t at time t. They can either be in the same time-indexed state or in the previous time-indexed state. In this dissertation, we use the Markov property, which is similar to DBNs, in order to represent temporal and state links between two consecutive time-indexed states of a Static Evidential Network (SEN) (i.e., Dynamic Evidential Network (DEN)) then compare it with the original process of DBNs.
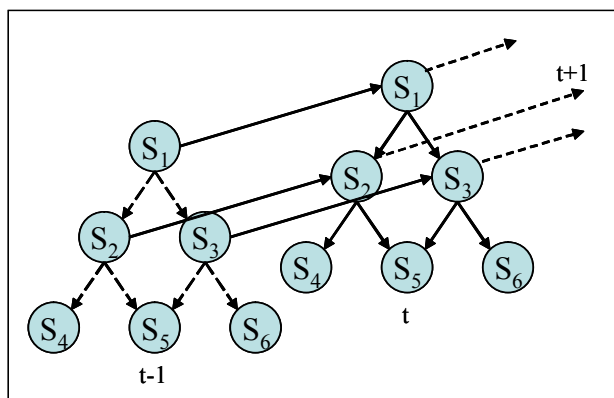
Figure 6.1. An example of Dynamic Bayesian Networks (DBNs).

6.4.3 Dempster-Shafer Theory (DST)

As mentioned in section 3.2.2, the DST is a mathematical theory of the evidence based on belief and plausible reasoning, which is used to combine separate pieces of information in order to calculate the probability of the event. It is often used method of sensor fusion so as to deal with uncertainty associated with context reasoning by combining the independent observations of multiple sensors (e.g., the user's activity monitoring in smart home) [133, 56]. However, DST has limitations and weaknesses. In particular, the Dempster's combination rule has limitations. The results of the combination has low confidences when a conflict becomes important between sources. Thus, in this dissertation, we use the Dezert-Smarandache Theory (DSmT), which is an extended DST, as a context reasoning method. No one applies the DSmT into the ubiquitous or pervasive computing area. Our research first attempts the DSmT into the pervasive computing applications (e.g., home-based care application) in order to reduce the conflicting mass in uncertainty level of contextual information compared to the DST approach and improve the confidence (i.e., GPT) level of contextual information compared to the fusion process based on BNs in emergency situation of the patient in [71].

6.5   Making Decisions

Decision making is the study of identifying and choosing alternatives based on the values and preferences of the decision maker. Making a decision implies that there are alternative choices to be considered, and in such a case we want not only to identify as many of these alternatives as possible but to choose the one that best fits with our goals, objectives, desires, values, and so on [50, 127, 58]. In addition, all decision problems have multiple alternatives and criteria then the weights associated with the criteria can properly reflect the relative importance of the criteria only if the scores a_{ij} are from a common, dimensionless scale in most of the approaches based on the Multi-attribute Utility Theory (MAUT) [20, 62], which uses utility functions that can be applied to transform the raw performance values of the alternatives against diverse criteria, both factual (objective, quantitative) and judgmental (subjective, qualitative), to a dimensionless scale. In the practice, the intervals [0,1] or [0,100] are used for fusing data obtained from different sensor into one single utility value (e.g., confidence). This confidence is used to reason the occurrence of a situation. As one of a MAUT, Simple Multi-Attribute Rating Technique (SMART) [13, 80], which is an extension to MAUT that employs ranking procedure to rank the contextual elements (e.g., context attributes), is the simplest form of the MAUT methods. The ranking value x_j of alternative A_j is obtained simply as the weighted algebraic mean of the utility values associated with it, i.e.

$$x_j = \sum_{i=1}^{m} w_i a_{ij} / \sum_{i=1}^{m} w_i, \qquad j = 1, \ldots, n. \tag{6.2}$$

where w_i represents the relative importance of a criteria and a_{ij} reflects the values of a decision table.

To apply SMART, first, the decision makers assign values so as to measure the performance of the alternatives on each criterion. Second, the relative importance of

the criteria in the value needs to be established by ranking the relative importance of the criteria. Not all of the criteria will be equally important. Finally, the decision makers aggregate weights and values for all criteria for that alternatives by using the normalized weighting, which is calculated by dividing the value by the total for all values. For instance, [60] computes a dynamic situation based on ranked context attribute using this approach. In this dissertation, we also utilize the similar method (i.e., the proposed normalized weighting technique) so as to process the dynamic weight of the evidence (i.e., an intrinsic context attribute) over time.

6.6   Summary

In ubiquitous or pervasive computing environments, various entities are required to work together in order to achieve the goal of anywhere anytime computing. Context awareness, which is composed of the information ranging from user location, user history and user preferences to environmental conditions and changes in the environment, is a key factor that facilitates coordination between various entities in these environments. In addition, it allows entities to adapt to changing situation in the environment that helps them in their reasoning process in pervasive environments. To make this goal, dynamic context reasoning under uncertainty based on context model is needed as one of the fundamental features. Therefore, in this chapter, we briefly introduced the related projects, several context modeling, context reasoning methods and decision makings so as to reduce uncertainty of contextual information and infer new kinds of contextual information by improving the confidence level of the contexts.

As related projects, we treated MavHome [27, 138, 137], Adaptive Home [87, 88], and AwareHome [63, 35]. Several projects [102, 124, 131] are introduced so as to manage uncertainty of sensory information in smart environments. In particular,

[131, 102, 124, 125] used a probabilistic reasoning method in order to deal with uncertainty in sensory information. However, they still had a potential drawback, we also introduced [56, 110], which used the bottom-up reasoning method. It can model uncertainty at a low sensor level and had the ability of managing the reliability of the system.

As related context modelings, we categorized four context models such as object-role based model (e.g., fact-based model) [49, 48, 53, 52], spatial-based model [113, 32, 100, 14, 45, 93], ontology-based model [10, 57, 24, 140, 18], and hybrid model [55, 9, 15, 85, 82]. In particular, the hybrid model that integrated different types of model is more frequently used in recent years, because each model had limitations to represent all aspects of the contexts. For instance, object-role based model can express dynamic and heterogeneous contextual information, histories and high-level context abstractions (e.g., the activity monitoring of the patient). However, it can less support a hierarchical context description compare to the ontology-based model. The spatial-based model can provide efficient procedures for the execution of typical spatial query. However, if more complex spatial domains are modeled, interoperability can be more easily obtained by a shared ontology of location. Finally, ontology-based model can support for interoperability and heterogeneity. Thus, it can well suited for the representation of complex relationships and dependencies among context data then can recognize the high-level context abstractions. However, it is difficult to recognize the simpler context data (e.g., basic physical activities) and user's dynamic adaptive preferences. The above considerations seemed to suggest that different models need to be integrated with each other. In this dissertation, we used a hybrid model that is similar to the combination of spatial and object context models in order to make our context modeling.

As related context reasoning methods, we introduced some approaches such as Fuzzy logic [139, 75, 7, 66], Probabilistic logic and Bayesian Networks (BNs) [105, 46, 84], Hidden Markov Models (HMMs) [31, 95, 120, 76], Kalman Filtering Models (KFMs) [86, 130, 94], Dynamic Bayesian Networks (DBNs) [39, 90, 141, 101], and Dempster-Shafer Theory (DST) of the evidence [133, 56]. In particular, the advantages and disadvantages of fuzzy logic, probabilistic logic, BNs and DST are compared so as to deal with uncertainty of contextual information and improve the quality of contextual information. In addition, HMMs, KFMs and DBNs are compared so as to deal with unpredictable temporal changes in sensory information. Based on the related context reasoning methods, in this dissertation, we adapted the Dezert-Smarandache Theory (DSmT), which is an extended DST, as a context reasoning method, because it can reduce the uncertainty level then can improve the confidence (i.e., GPT) level of contextual information [71].

Finally, we introduced the SMART [13, 80], which is an extension to MAUT that employed ranking procedure to rank the contextual elements (e.g., context attributes), as a decision making method. This approach computed a dynamic situation based on ranked context attribute by fusing data obtained from different sensor into one single utility value (e.g., confidence), which is used to reason the occurrence of a situation. In this dissertation, we used a similar method so as to deal with dynamic weights of the evidence over time in pervasive environments. In summary, we made a similar or improved context reasoning method by adapting the new context modeling, context reasoning and decision making techniques compared to related works.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1   Conclusion

In this dissertation, we proposed context reasoning under uncertainty based on evidential fusion networks in home-based care in order to support both consistency verification of the model and context reasoning techniques. The proposed reasoning technique improved the quality of contextual information and inferred new kinds of contextual information.

First, we defined a pragmatic context classification in order to provide reliable contextual information in smart spaces such as in home-based care. In smart pervasive environments, an information description vocabulary set for a given application is carefully pre-specified in context classification so as to make a practical solution by adopting two approaches: 1) occupant-centered pragmatic approach and 2) relation-dependency approach. Based on the defined context classification, we proposed a state-space based context modeling with an evidential form as a generalized context modeling in order to represent the situation of the patient, to improve the quality of a given piece of contextual information by reducing uncertainty, and to infer new kinds of contextual information. Given context modeling consists of a hierarchical interrelationship among multi-sensors, related context and relevant activities within a selected region, we reasoned the context models that can adapt the situation definitions based on discovered changes with changing environments and changing user needs over time.

Second, we proposed a static evidential fusion process (SEFP) as a context reasoning method in order to obtain a high confidence (i.e., GPT) level of contextual information. In particular, we processed data obtained from multi-sensors with an evidential form based on Dezert-Smarandache Theory (DSmT). The DSmT reduced the uncertainty level and obtained a rational decision of contextual information using the proportional conflict redistribution no. 5 (PCR5) combination rule and a generalized pignistic transformation (GPT). This approach had better performance for uncertainty analysis in decision making as to the ability to measure the probability, belief, or uncertainty levels in multi-sensor based networks compared to the existing and contemporary methods based on Bayesian Networks (BNs) or Dempster-Shaper Theory (DST).

Third, we proposed a dynamic evidential fusion process (DEFP) as the 2nd context reasoning method in order to deal with dynamic metrics such as preference, temporal consistency and relation-dependency of the context using the autonomous learning process (ALP) and the temporal belief filtering (TBF). The DEFP approach improved the confidence level of contextual information so as to reduce the ambiguity of the consecutive time-indexed states in unpredictable temporal changing environments, then, provide a correct decision making about the situation of the patient in emergency environments. In particular, this approach had better confidence levels compared to Dynamic Bayesian Networks (DBNs) by considering six steps: 1) Checking a temporal dependency of two consecutive time-indexed states, 2) Finding an optimal threshold (T) for a conflict value (C_F) in TBF algorithm, 3) Finding an optimal time window size (W), 4) Calculating the GPT level with static weights and different error rates (r) of the evidence, 5) Calculating the GPT level with different weights of the evidence and 6) Calculating the GPT level with different discounting factors (D) of the evidence.
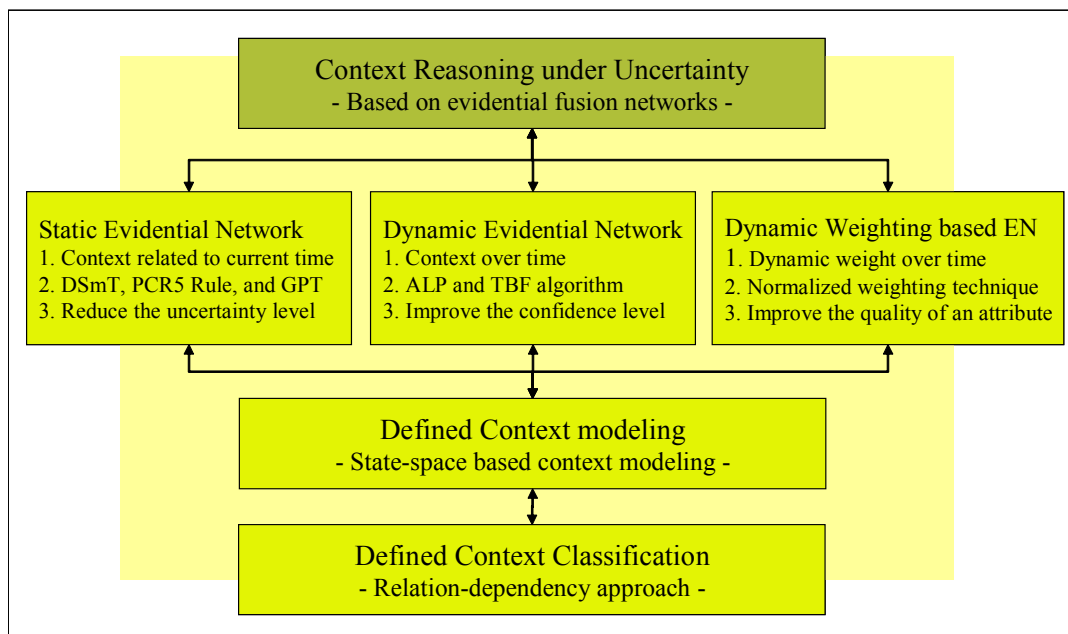
Figure 7.1. The proposed approach as context reasoning under uncertainty.

At the end, we proposed a dynamic weighting based evidential fusion process (DWEFP) as the 3rd context reasoning method in order to deal with both relative and individual importance of the evidence in the given context attribute using the proposed normalized weighting technique. The DWEFP approach obtained an optimal weight of the evidence over time that improved the quality of contextual information in the emergency progress of the patient. In particular, this approach had better confidence levels compared to the previous approaches such as the fusion process based on SEFP, DEFP or DBNs that applied a static weighting factor into the given context attribute.

Therefore, we summarized our proposed approach as context reasoning under uncertainty based on evidential fusion networks in home-based care as Figure 7.1.

7.2   Future Work

A diversity of things can influence a person's user experience [65] defined as "a person's perceptions and responses that result from the use or anticipated use of a product, system or service" with a system. To address the variety, factors influencing user experience have been classified into three main categories: user's state, system properties and context (e.g., situation) [51]. Studying typical users and contexts helps designing the system then improve the decision making in pervasive computing environments [12]. In the future, we will continuous work on user experience in order to adapt the user's feelings stemming both from pragmatic and hedonic aspects of the system into the pervasive healthcare monitoring system (PHMS).

REFERENCES

[1] Core body temperature sensor (http://www.hqinc.net/pages/products.html).

[2] Neurotech (http://www.neurotechreports.com).

[3] Sayaka (http://www.rfamerica.com/syayka/index.html).

[4] Verichip (http://www.verichipcorp.com/content/company/rfidtags/implantable.html).

[5] Vitalsense (http://www.minimitter.com/products/vitalsense/index.html).

[6] F. Adelstein, S. K. S. Gupta, G. R. III, and L. Schwiebert. *Fundamentals of Mobile and Pervasive Computing.* McGraw-Hill, 2004.

[7] S. Agarwal, A. Joshi, T. Finin, Y. Yesha, and T. Ganous. A pervasive computing system for the operating room of the future. *Mobile Networks and Applications*, 12(2):215–228, 2007.

[8] A. Agostini, C. Bettini, and D. Riboni. Experience report: Ontological reasoning for context-aware internet services. In *Proc. of the 4th IEEE Intl. Workshop on Pervasive Computing and Communications (PerCom'06)*, pages 8–12, Pisa, Italy, 2006.

[9] A. Agostini, C. Bettini, and D. Riboni. Hybrid reasoning in the care middleware for context-awareness. *International Journal of Web Engineering and Technology*, 5(1):3–23, 2009.

[10] F. Baader, D. Calvanese, D. L. McGunness, D. Nardi, and P. F. Pate-Schneider. *The Description Logic Handbook: Theory, Implementation, and Applications.* Cambridge University Press, 2003.

[11] C. Baker, K. Armijo, S. Belka, M. Benhabib, V. Bhargava, N. Burkhart, A. Minassians, G. Dervisoglu, L. Gutnik, M. Haick, C. Ho, M. Koplow, J. Mangold,

129

S. Robinson, M. Rosa, A. Schwartz, C. Sims, H. Stoffregen, A. Waterbury, E. Leland, T. Pering, and P. Wright. Wireless sensor networks for home health care. In *Proc. of the Intl. Workshop on Advanced Information Networking and Applications (AINA'07)*, pages 832–837, Washington DC, USA, 2007.

[12] C. A. Barnum and L. A. Palmer. More than a feeling: understanding the desirability factor in user experience. In *Proc. of the 28th ACM Intl. Conf. on Human factors in computing systems (CHI'10)*, pages 4703–4716, Atlanta, Georgia, USA, 2010.

[13] F. H. Barron and B. E. Barrett. The efficiency of smarter-simple multi-attribute rating technique extended to ranking. *Acta Psychologica*, 93(1):23–36, 1996.

[14] C. Becker and F. Durr. On location models for ubiquitous computing. *Personal and Ubiquitous Computing*, 9(1):20–31, 2005.

[15] C. Becker and D. Nicklas. Where do spatial context-models end and where do ontologies start? a proposal of a combined approach. In *Proc. of the 1st Intl. Workshop on Advanced Context Modeling and Reasoning and Management*, Univ. of Southampton, Nottingham, UK, 2004.

[16] C. Bettini, O. Brdiczka, K. Henricksen, J. Indulska, D. Nicklas, A. Ranganathan, and D. Riboni. A survey of context modeling and reasoning techniques. *Pervasive and Mobile Computing*, 6(2):161–180, 2009.

[17] 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). *Journal of Advanced in Information Fusion*, 1(2):122–139, 2006.

[18] P. Bouquet, F. Giunchiglia, F. van Harmelen, L. Serafini, and H. Stuckenschmidt. Contextualizing ontologies. *Journal of Web Semantics*, 1(4):325–343, 2004.

[19] N. Bricon-Souf and C. R. Newman. Context awareness in healthcare: A review. *International journal of Medical Informatics*, 76(1):2–12, 2007.

[20] J. Butler, D. J. Morrice, and P. W. Mullarkey. A multiple attribute utility theory approach to ranking and selection. *Management Science*, 47(6):800–816, 2001.

[21] M. Campos, J. M. Juarez, J. Salort, J. Palma, and R. Marin. Reasoning in dynamic systems: From raw data to temporal abstract information. *Neurocomputing*, 72:871–878, 2009.

[22] E. Cayirci and T. Coplu. Sendrom: Sensor networks for disaster relief operation management. *Wireless Networks*, 13(3):409–427, 2007.

[23] T. Chaari, E. Dejene, F. Laforest, and V. Scuturici. A comprehensive approach to model and use context for adapting applications in pervasive environments. *International Journal of Systems and Software*, 80(12):1973–1992, 2007.

[24] H. Chen, F. Perich, T. W. Finin, and A. Joshi. Soupa: Standard ontology for ubiquitous and pervasive applications. In *Proc. of the 1st Intl. Conf. on Mobile and Ubiquitous Systems (MobiQuitous'04)*, pages 258–267, Boston, Massachusetts, USA, 2004.

[25] D. J. Cook and S. K. Das. *Smart Environment: Technology, Protocols and Applications.* John Wiley & Sons, Univ. of Texas at Arlington, TX, 2004.

[26] D. J. Cook and S. K. Das. How smart are our environments? un updated look at the state of the art. *Pervasive and Mobile Computing*, 3:53–73, 2007.

[27] D. J. Cook, G. M. Youngblood, E. Heierman, K. Gopalrantnam, S. Rao, A. Litvin, and F. Khawaja. Mavhome: An agent-based smart home. In *Proc. of the IEEE Intl. Conf. on Pervasive Computing and Communications (PerCom'03)*, pages 521–524, Dallas-Fort Worth, Texas, 2003.

[28] J. Coutaz, J. L. Crowley, S. Dobson, and D. Garlan. Context is key. *Communication of the ACM*, 48(3):49–53, 2005.

[29] P. Dai, H. Di, L. Hong, L. Tao, and G. Xu. Group interaction analysis in dynamic context. *IEEE Trans. Syst., Man, Cybern. B*, 38(1):34–42, 2008.

[30] M. Danninger and R. Stierelhagen. A context-aware virtual secretary in a smart office environment. In *Proc. of the 16th ACM Intl. Conf. on Multimedia*, pages 529–538, 2008.

[31] W. Dargie. The role of probabilistic schemes in multisensor context-awareness. In *Proc. of the 5th IEEE Intl. Conf. on Pervasive Computing and Communications Workshops*, pages 27–32, 2007.

[32] A. K. Dey. Understandings and using context. *Personal and Ubiquitous Computing*, 5(1):4–7, 2001.

[33] A. K. Dey and G. D. Abowd. Towards a better understandings of context and context-awareness. In *Proc. of the Intl. Workshop on The What, Who, Where, When, Why and How of Context-Awareness*, volume 1707, pages 304–307, London, UK, 2000.

[34] A. K. Dey, G. D. Abowd, and D. Salber. A context-based infrastructure for smart environments. In *Proc. of the 1st Intl. Workshop on Managing Interactions in Smart Environments (MANSE'99)*, pages 114–128, 1999.

[35] A. K. Dey, D. Salber, and G. D. Abowd. A conceptual framework and a toolkit for supporting the rapid prototyping of context-aware applications. *Human Computer Interaction (HCI)*, 16(2-4):97–166, 2001.

[36] J. Dezert and F. Smarandache. *Advances and Applications of DSmT for Information Fusion, Vol. 1*. American Research Press, Rehoboth, 2004.

[37] J. Dezert and F. Smarandache. *Advances and Applications of DSmT for Information Fusion, Vol. 2*. American Research Press, Rehoboth, 2006.

[38] J. Dezert and F. Smarandache. *Advances and Applications of DSmT for Information Fusion, Vol. 3*. American Research Press, Rehoboth, 2009.

[39] J. Dezert, F. Smarandache, and M. Daniel. The generalized pignistic transformation. In *Proc. of the 7th Intl. Conf. on Information Fusion*, pages 384–391, 2004.

[40] J. Esteban, A. Starr, R. Willetts, P. Hannah, , and P. Bryanston-Cross. A review of data fusion models and architectures: Towards engineering guidelines. *Neural Computing and Applications*, 14(4):273–281, 2005.

[41] D. Estrin, D. Culler, K. Pister, and G. Sukhatme. Connecting the physical world with pervasive networks. *IEEE Pervasive Computing*, 1(1):59–69, 2002.

[42] T. Fulford-Jones, G. Wei, and M. Welsh. A portable, low-power, wiereless two-lead ekg system. In *Proc. of the 26th IEEE Intl. Conf. on EMBS (EMBS'04)*, pages 1–5, San Francisco, CA, 2004.

[43] H. W. Gellersen, A. Schmidt, and M. Beigl. Multi-sensor context-awareness in mobile devices and smart artifacts. *Mobile Networks and Applications*, 7(5):341–351, 2002.

[44] L. Grajales and I. V. Nicolaescu. Wearable multisensor heart rate monitor. In *Proc. of the Intl. Workshop on Wearable and Implantable Body Sensor Networks (BSN'06)*, pages 154–157, Washington DC, USA, 2006.

[45] M. Grossmann, M. Bauer, N. Honle, U. Kappeler, D. Nicklas, and T. Schwarz. Efficiently managing context information for large-scale scenarios. In *Proc. of the 3rd IEEE Intl. Conf. on Pervasive Computing and Communications (PerCom'05)*, pages 331–340, Kauai Island, Hawaii, USA, 2005.

[46] T. Gu, H. K. Pung, and D. Q. Zhang. A bayesian approach for dealing with uncertain contexts. In *Proc. of the 2nd Intl. Conf. on Pervasive Computing*, pages 205–210, Austrian Computer Society, 2004.

[47] D. L. Hall and J. Llinas. An introduction to multisensor data fusion. *IEEE*, 85(1):6–23, 1997.

[48] T. A. Halpin. *Conceptual Schema and Relational Databases Design, 2nd Edition.* Prentice Hall, Australia, 1995.

[49] T. A. Halpin. *Information Modeling and Relational Databases: From Conceptual Analysisto Logical Design.* Morgan Kaufman, San Francisco, 2001.

[50] R. Harris. *Introduction to Decision Making.* VirtualSalt, 2009.

[51] M. Hassenzahl and N. Tractinsky. User experience-a research agenda. *Behaviour and Information Technology*, 25(2):91–97, 2006.

[52] K. Henricksen. *A framework for context-aware pervasive computing applications.* Ph. D. Thesis, Univ. of Queensland, 2003.

[53] K. Henricksen and J. Indulska. Developing context-aware pervasive computing applications: Models and approach. *Pervasive and Mobile Computing*, 2(1):37–64, 2006.

[54] K. Henricksen, J. Indulska, and A. Rakotonirainy. Modeling context information in pervasive computing systems. In *Proc. of the 1st Intl. Conf. on Pervasive Computing*, pages 167–180, London, UK, 2002.

[55] K. Henricksen, S. Livingstone, and J. Indulska. Towards a hybrid approach to context modeling, reasoning and interoperation. In *Proc. of the 1st Intl. Workshop on Advanced Context Modeling, Reasoning and Management*, pages 54–61, Univ. of Southampton, Nottingham, UK, 2004.

[56] 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 and Mobile Computing*, 5(3):236–252, 2009.

[57] I. Horrocks, P. F. Patel-Schneider, and F. van Harmelen. From shiq and rdf to owl: The making of a web ontology language. *Journal of Web Semantics*, 1(1):7–26, 2003.

[58] V. N. Hyunh, Y. Nakamori, T. B. Ho, and T. Murai. Multiple-attribute decision making under uncertainty: the evidential reasoning approach revisited. *IEEE Trans. Syst., Man, Cybern. A*, 36(4):804–822, 2009.

[59] R. Jain. *The Art of Computer Systems Performance Analysis Techniques for Experimental Design, Measurement, Simulation, and Modeling*. John Wiley & Sons, Inc., Digital Equipment Corporation, Littleton, Massachusetts, 1991.

[60] P. P. Jayaraman, A. Zaslavsky, and J. Delsing. Dynamic situation modeling and reasoning under uncertainty. In *Proc. of the Intl. Conf. on Pervasive Services (ICPS'09)*, pages 113–122, London, UK, 2009.

[61] G. Jin, X. Lu, and M. Park. An indoor localization mechanism using active rfid tag. In *Proc. of the IEEE Intl. Conf. on Sensor Networks, Ubiquitous, and Trustworthy Computing (SUTC'06)*, pages 40–43, Washinton DC., USA, 2006.

[62] C. Kahraman and S. Cebi. A new multi-attribute decision making method: Hierarchical fuzzy axoimatic design. *Expert Systems with Applications*, 36(3):4848–4861, 2009.

[63] C. D. Kidd, R. Orr, G. D. Abowd, C. G. Atkeson, I. A. Essa, B. MacIntyre, E. D. Mynatt, T. Starner, and Newstetter. The aware home: A living laboratory for ubiquitous computing research. In *Proc. of the 2nd Intl. Workshop on the Cooperative Buildings, Integrating Information, Organization, and Architecture (CoBuild'99)*, pages 191–198, 1999.

[64] Y. Kim and D. Kim. Healthcare service with ubiquitous sensor networks for the disabled and elderly people. *LNCS, Computers Helping People with Special Needs*, 4061:716–723, 2006.

[65] E. Law, V. Roto, M. Hassenzahl, and A. Vermeeren. Understanding, scoping and defining user experience: A survey approach. In *Proc. of the 27th ACM Intl. Conf. on Human factors in computing systems (CHI'09)*, pages 719–728, Boston, MA, USA, 2009.

[66] H. Lee, J. Choi, and R. Elmasri. A conflict resolution architecture for the comfort of occupants in intelligent office. In *Proc. of the 4th IET Intl. Conf. on Intelligent Environments (IE'08)*, pages 1–8, University of Washington, Seatle, 2008.

[67] H. Lee, J. Choi, and R. Elmasri. A classification and modeling of the quality of contextual information in smart spaces. In *Proc. of the 6th IEEE Intl. PerCom Workshop. on Context Modeling and Reasoning (CoMoRea'09)*, pages 1–5, Galveston, TX, 2009.

[68] H. Lee, J. Choi, and R. Elmasri. A dynamic evidential network for multisensor context reasoning in home-based care. In *Proc. of the 8th IEEE Intl. Conf. on Systems, Man, and Cybernetics (SMC'09)*, pages 4994–4999, San Antonio, TX, 2009.

[69] H. Lee, J. Choi, and R. Elmasri. Sensor data fusion using dsm theory for activity recognition under uncertainty in home-based care. In *Proc. of the 23th IEEE Intl. Conf. on Advanced Information Networking and Applications (AINA'09)*, pages 517–524, Bradford, UK, 2009.

[70] H. Lee, J. Choi, and R. Elmasri. A dynamic normalized weighting based context reasoning in home-based care. In *Proc. of the 24th IEEE Intl. Conf. on Advanced Information Networking and Applications (AINA'10)*, pages 804–811, Perth, Australia, 2010.

[71] H. Lee, J. Choi, and R. Elmasri. A static evidential netowrk for context reasoning in home-based care. *IEEE Trans. Syst., Man, Cybern. A*, 40(5):1–12, 2010.

[72] H. Lee, D. Kim, K. Basu, and S. Das. A carbon footprint reduction and an inhabitant's comfort maximization by controlling different levels of lighting and thermostat in smart home. In *Proc. of the 5th Intl. Conf. on Smart Homes and Health Telematics (ICOST'07)*, Nara, Japan, 2007.

[73] H. Lee, B. Lee, K. Park, and R. Elmasri. Fusion techniques for reliable information: A survey. *JDCTA: International Journal of Digital Content Technology and its Applications*, 4(2):74–88, 2010.

[74] H. Lee, K. Park, B. Lee, J. Choi, and R. Elmasri. Issues in data fusion for healthcare monitoring. In *Proc. of the 1st ACM Intl. Conf. on Pervasive Technologies Related to Assistive Environments (PETRA'08)*, pages 1–8, Athens, Greece, 2008.

[75] A. Lemmi and G. Betti. Capability approach and fuzzy set theory: description, aggregation and inference issues. *Fuzzy set approach to multidimensional proverty measurement*, 3:93–113, 2006.

[76] L. Liao, D. J. Patterson, D. Fox, and H. Kautz. Learning and inferring transportation routines. *Artificial Intelligence*, 171(5-6):311–331, 2007.

[77] S. Loke. On representing situations for context-aware pervasive computing: Six ways to tell if you are in a meeting. In *Proc. of the 4th IEEE Intl. Workshop on Pervasive Computing and Communications (PerCom'06)*, pages 35–39, Pisa, Italy, 2006.

[78] R. Luo, C. Yih, and K. Su. Multisensor fusion and integration: approaches, applications, and future research directions. *IEEE Sensors Journal*, 2(2):107–119, 2002.

[79] J. Luprano, J. Sola, Dasen, J. M. Koller, and O. Chetelat. Combination of body sensor networks and on-body signal processing algorithm: The practical case of myheart project. In *Proc. of the Intl. Workshop on Wearable and Implantable Body Sensor Networks (BSN'06)*, pages 76–79, Washington DC, USA, 2006.

[80] D. M. Lyons and D. F. Hsu. Combining multiple scoring systems for target tracking using rank-score characteristics. *Information Fusion*, 10(2):124–136, 2009.

[81] D. Macii, A. Boni, M. D. Cecco, and D. Petri. Tutorial 14: Multisensor data fusion. *IEEE Instrumentation and Measurement Magazine*, 11(3):24–33, 2008.

[82] M. Mamei and F. Zambonelli. Programming pervasive and mobile computing applications with the tota middleware. In *Proc. of the 2nd IEEE Intl. Conf. on Pervasive Computing and Communications (PerCom'04)*, pages 263–273, 2004.

[83] D. Mandic, D. Obradovic, A. Kuh, T. Adali, U. Trutschel, M. Golz, P. Wilde, J. Barria, A. Constantinides, and J. Chambers. Data fusion for modern engineering applications: An overview. In *Proc. of the Intl. Conf. on Artificial Neural Networks*, volume 3697, pages 715–721, 2005.

[84] S. Maskell. A bayesian approach to fusing uncertain, imprecise and conflicting information. *Information Fusion*, 9(2):259–277, 2008.

[85] B. Mathieu, M. Song, M. Brunner, M. Stiemerling, M. Cassim, A. Galis, L. Cheng, K. Jean, , R. Ocampo, Z. Lai, and M. Kampmann. Autonomic management of context-aware ambient overlay networks. In *Proc. of the 2nd Intl. Conf. on Communications and Networking in China*, pages 727–733, 2007.

[86] P. S. Maybeck. *Stochastic Models, Estimation, and Control.* New York: Academic, 1979.

[87] M. C. Mozer. The neural network house: An environment that adapts to its inhabitants. In *Proc. of the American Association for Artificial Intelligence Spring Symposium on Intelligent Environments*, pages 110–114, 1998.

[88] M. C. Mozer. *Lessons from an adpative home in Smart Environments: Technology, Protocols, and Applications*. Wiley, 2004.

[89] C. K. Murphy. Combining blief functions when evidence conflicts. *Decision Support Systems*, 29:1–9, 2000.

[90] K. Murphy. *Dynamic Bayesian Networks: Representation, Inference and Learning*. Ph. D. Disseration, Univ. of California, Berkeley, 2002.

[91] J. W. Ng. Ubiquitous healthcare localization schemes. In *Proc. of the 7th Intl. Workshop on Enterprise ntworking and Computing in Healthcare Industry (HEALTHCOM'05)*, pages 156–161, 2005.

[92] L. Ni, Y. Liu, Y. Lau, and A. Patil. Landmarc: indoor location sensing using active rfid. *Wireless Networks*, 10(6):701–710, 2004.

[93] D. Nicklas, M. Grossmann, J. Minguez, and M. Wieland. Addig high-level reasoning to efficient low-level context management: A hybrid approach. In *Proc. of the 6th IEEE Intl. Workshops on Pervasive Computing and Communications*, pages 447–452, 2008.

[94] R. Olfati-Saber. Distributed kalman filtering for sensor networks. In *Proc. of the 46th IEEE Intl. Conf. on Decision and Control*, pages 5492–5498, 2007.

[95] N. Oliver and E. Horvitz. A comparison of hmms and dynamic bayesian networks for recognizing office activities. *LNCS, User Modeling*, 3538:199–209, 2005.

[96] S. Padhraic. Belief networks, hidden markov model, and markov random field: A unifying view. *Pattern Recognition letters*, 18:1261–1268, 1997.

[97] A. Padovitz, S. W. Loke, A. Zaslavsky, and C. Bartolini. An approach to data fusion for context awareness. In *Proc. of the 5th Intl. Conf. on Modeling and Using Context*, pages 353–367, 2005.

[98] F. Paganelli and D. Giuli. A context-aware service platform to support continuous care networks for home-based assistance. *LNCS, Univeral Access in Human-Computer Interaction (HCI), Ambient Interaction*, 6:168–177, 2007.

[99] 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. of the 4th Intl. Workshop on Wearable and Implantable Body Sensor Networks (BSN'07)*, volume 13, pages 208–212, 2007.

[100] J. Pascoe. The stick-e note architecture: Extending the interface beyond the user. In *Proc. of the 1st Intl. Conf. on Intelligent User Interfaces*, pages 261–264, 1997.

[101] D. J. Patterson, L. Liao, D. Fox, and H. Kautz. Inferring high-level behavior from low level sensors. In *Proc. of the 5th Intl. Conf. on Ubiquitous Computing (UbiComp'03)*, volume 2864, pages 73–89, 2003.

[102] M. Philipose, K. P. Fishkin, M. P. Patterson, D. Fox, H. Kautz, and D. Hahnel. Inferring activities from interactions with objects. *IEEE Pervasive Computing*, 3(4):50–57, 2004.

[103] 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. *Information Fusion*, 9(1):83–95, 2008.

[104] E. Ramasso, M. Rombaut, and D. Pellerin. A temporal belief filter improving human action recognition in videos. In *Proc. of the IEEE Intl. Conf. on Acoustics, Speech, and Signal Processing (ICASSP'06)*, volume 2, pages 141–144, 2006.

[105] A. Ranganathan, J. Al-Muhtadi, and R. H. Campbell. Reasoning about uncertain contexts in pervasive computing environments. *IEEE Pervasive Computing*, 3(2):62–70, 2004.

[106] M. A. Razzaque, Simon Dobson, and Paddy Nixon. Classification and modeling of the quality of contextual information. *IEEE TCAAS Letters*, 2007.

[107] B. Ristic and P. Smets. Target identification using belief functions and implication rules. *IEEE Transactions on Aerospace and Electronic Systems*, 41(3):1097–1103, 2005.

[108] G. L. Rogova and V. Nimier. Reliability in information fusion: literature survey. In *Proc. of the 7th Intl. Conf. on Information fusion*, pages 1158–1165, Stockholm, Sweden, 2004.

[109] J. Roy. From data fusion to situation analysis. In *Proc. of the 4th Intl. Conf. on Information Fusion*, pages 3–10, 2001.

[110] N. Roy. *A Context-Aware Learning, Prediction and Mediation Framework for Resource Management in Smart Pervasive Environments.* Ph. D. Disseration, Univ. of Texas, Arlington, 2008.

[111] N. Roy, A. Roy, S. Das, and K. Basu. A cooperative learning framework for mobility-aware resource management in multi-inhabitant smart homes. In *Proc. of the 2nd IEEE Intl. Conf. on Mobile and Ubiquitous Systems: Networking and Services (Mobiquitous'05)*, pages 393–403, 2005.

[112] M. Satyanarayanan. Pervasive healthcare. *IEEE Computer*, 8(4):10–17, 2001.

[113] B. Schilit, N. Adams, and R. Want. *Context-aware Computing Applications.* Xerox Corp., Palo Alto Research Center, 1994.

[114] G. Shafer. *A Mathematical Theory of Evidence.* Princeton Univ. Press, Princeton, New Jersey, 1976.

[115] E. Shahbazian, G. Rogova, and P. Valin. *Data fusion for situation monitoring, incident detection, alert and response management.* NATO Science Series, 2005.

[116] V. Shnayder, B. Chen, K. Lorincz, T. Fulford-Jones, and M. Welsh. Sensor networks for medical care. In *Proc. of the 3rd ACM Intl. Conf. on Embedded Networked Sensor Systems (SenSys'05)*, pages 314–328, New York, NY, 2005.

[117] F. Smarandache and J. Dezert. Information fusion based on new proportional conflict redistribution rules. In *Proc. of the 8th Intl. Conf. on Information Fusion*, volume 2, pages 907–914, 2005.

[118] P. Smets. Data fusion in the transferable belief model. In *Proc. of the 3rd Intl. Conf. on Information Fusion*, pages 21–33, 2000.

[119] P. Smets and R. Kennes. The transfer belief model. *Artificial Intelligence*, 66:191–234, 1994.

[120] C. Soyer, H. I. Bozma, and Y. Isterfanopulos. Attentional sequence-based recognition: Markovian and evidential reasoning. *IEEE Trans. Syst., Man, Cybern. B*, 33(6):937–950, 2003.

[121] A. Srinivasan and J. Wu. *A survey on secure localization in wireless sensor networks.* Encyclopedia of Wireless and Mobile Communications, B. Furht, 2008.

[122] J. Stankovic, Q. Cao, T. Doan, L. Fang, Z. He, R. Kiran, S. Lin, S. Son, R. Stoleru, and A. Wood. Wireless sensor networks for in home healthcare: Potential and challenges. In *Proc. of the Workshop on High Confidence Medical Device Software and Systems (HCMDSS'05)*, pages 2–3, Philadelphia, PA, 2005.

[123] T. Strang, C. Linnhoff-Popien, and K. Frank. Cool: A context ontology language to enable contextual interoperability. In *Proc. of the Intl. Conf. on Distributed Applications and Interoperable Systems (DAIS'03)*, volume 2893, pages 236–247, 2003.

[124] E. M. Tapia, S. S. Intille, and K. Larson. Activity recognition in the home using simple and ubiquitous sensors. In *Proc. of the Intl. Conf. on Pervasive Computing*, volume 3001, pages 1–17, 2004.

[125] D. T. Tran, D. Q. Phung, H. H. Bui, and S. Venkatesh. A probabilistic model with parsimonious representation for sensor fusion in recognizing activity in pervasive environment. In *Proc. of the 18th Intl. Conf. on Pattern Recognition*, pages 158–175, 2006.

[126] D. Trossen, D. Pavel, G. Platt, J. Wall, P. Valencia, C. A. Graves, M. S. Zamarripa, V. M. Gonzalez, J. Favela, E. LAvquist, and Z. KulcsAar. Sensor networks, wearable computing, and healthcare applications. *IEEE Pervasive Computing*, 6(2):58–61, 2007.

[127] G. Valiris, P. Chytas, and M. Glykas. Making decisions using the balanced scorecard and the simple multi-attribute raitng technique. *Performance Measurement and Metrics*, 6(3):159–171, 2005.

[128] U. Varshney. Pervasive healthcare. *IEEE Computer*, 36(12):138–140, 2003.

[129] K. Venkatasubramanian, G. Deng, T. Mukherjee, J. Quintero, V. annamalai, and S. K. S. Gupta. Ayushman: A wireless sensor network based health monitoring infrastructure and testbed. *LNCS, Distributed Computing in Sensor Systems*, 3560:406–407, 2005.

[130] G. Welch and G. Bishop. *An Introduction to the Kalman Filter*. UNC-Chapel Hill, TR 95-041, 2006.

[131] D. Wilson and C. Atkeson. Simultaneous tracking and activity recognition (star) using many anonymous, binary sensors. In *Proc. of the 3rd Intl. Conf. on Pervasive Computing*, pages 8–13, 2005.

[132] D. Winterfeld and W. Edwards. *Decision Analysis and Behavioral Research*. Cambridge, University Press, Cambridge, UK, 1986.

[133] H. Wu. *Sensor data fusion for context-aware computing using dempster-shafer theory.* Ph. D. Disseration, CMU, 2004.

[134] H. Wu, M. Siegel, and S. Ablay. Sensor fusion using dempster-shafer theory ii: static weighting and kalman filter-like dynamic weighting. In *Proc. of the 20th IEEE Instrumentation and Measurement Technology Conference*, volume 2, pages 907–912, Vail, CO, 2003.

[135] N. Xiong and P. Svensson. Multi-sensor management for information fusion: issues and approaches. *Information Fusion*, 3(2):163–186, 2002.

[136] G. Z. Yang. *Body Sensor Networks.* Springer, Imperial College London, UK, 2006.

[137] G. M. Youngblood and D. J. Cook. Data mining for hierarchical model creation. *IEEE Trans. Syst., Man, Cybern. C*, 37(4):561–572, 2007.

[138] G. M. Youngblood, L. B. Holder, and D. J. Cook. Managing adpative versatile environment. *Pervasive and Mobile Computing*, 1(4):373–403, 2005.

[139] L. A. Zadeh. Fuzzy sets as a basis for a theory of possibility. *Fuzzy Sets and Systems*, 100(1):9–34, 1999.

[140] D. Zhang, T. Gu, and X. Wang. Enabling context-aware smart home with semantic technology. *International Journal of Human-friendly Welfare Robotic Systems*, 6(4):12–20, 2005.

[141] Y. Zhang and Q. Ji. Active and dynamic information fusion for multisensor systems with dynamic bayesian networks. *IEEE Trans. Syst., Man, Cybern. B*, 36(2):467–472, 2006.

BIOGRAPHICAL STATEMENT

Hyun Lee is a Ph. D. student of the Department of Computer Science and Engineering at the University of Texas at Arlington since 2004. He received B. E. and M. S. degrees in the Department of Computer Science and Engineering at Sunmoon University (Asan, South Korea) in 1998 and 2002, respectively. His research interests include issues related to sensor fusion techniques and the integration of heterogeneous sensors and RFID systems for reducing the uncertainty and increasing the reliability of contextual information in pervasive computing areas.