Uncertain Information Management for ADL Monitoring in Smart Homes

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Summary. Smart Homes offer improved living conditions and levels of independence for the elderly population who require support with both physical and cognitive functions. Sensor technology development and communication networking have been well explored within the area of smart living environments to meet the demands for ageing in place. In contrast, information management still faces a challenge to be practically sound. In our current research we deploy the Dempster-Shafer theory of evidence to represent and reason with uncertain sensor data along with revision and merging techniques to resolve inconsistencies among information from different sources. We present a general framework for sensor information fusion and knowledge revision/merging especially for monitoring activities of daily living in a smart home.

Key words: Smart sensorised living environment, uncertainty, information fusion, belief revision, belief merging, DS theory, epistemic state, ordinal conditional function

1 Introduction

Demographic change is increasing the median age of the human population and the percentage of the population that is elderly. With 600 million people aged 60 and over in 2000, the number has been forecast to soar up to 1.2 billion by 2025 and 2 billion by 2050. It is also reported that in the developed world, the very old (age 80 and over) is the fastest growing population group [1]. Within this increase in the numbers of elderly comes an associated increase in the prevalence of chronic disease and disabilities.

As a result of the aforementioned demographic ageing challenges, there is a growing demand to develop and deploy technical solutions within the home environment to address these challenges and offer the desired effect of supporting elderly people to remain in their home for as long as they can [2]. Smart homes are viewed as one possible type of solution to this problem. They combine technological advancements in sensor technology, communication networking, and information management to offer elderly and disabled people the means to live independently and safely in their own homes. In addition, they move one step closer to help reduce the burden which is currently being placed on health and social care. Within the past few years attempts to produce solutions within the domain of assisted living have been prolific. These have varied from healthcare devices capable of measuring vital signs, to home automation systems to control lighting, heating, door opening/closing etc., and to highly sensorised Smart Home environments capable of monitoring a person's interaction within their own home [3, 4]. Although each of these areas has gained isolated success, larger scale challenges exist in the most effective means by which all of the information generated can be managed and used to deliver the most effective solution for people in their own homes and offer a level of independent living.

It is generally well appreciated that an elderly person's care requirements are complex. Hence, automating the process to deliver and manage care requires not only the collection of real time information from the environment related to the actions undertaken by the person, but also requires the correct modelling of both numerical information collected by sensors and the reasoning about this information using background knowledge and the knowledge (belief) related to the individual person.

The current study has aimed to develop a hybrid intelligent information management system to assist with elderly based homecare and to strengthen the lifestyle and health management of people within their own homes. This may involve the capability of integrating sensor information (e.g. motion, door open/close, water tap on/off, cooker on/off, etc.) and making use of this collective information and the knowledge about the care the person in their home requires. Background knowledge relating to an individual person's healthcare needs and lifestyle/general information is the typical type of information that is stored about the person and may be accessed to support the information management. In this paper we present a solution to model and reason with uncertain sensor data to predict the activities of the person being monitored. We then use background knowledge (such as a carer's diary) to resolve any inconsistencies between the predicted action and the actual activities as indicated by background knowledge (e.g., diary). Research in uncertain information management has been an active area of research for more than half a century and still remains a key topic in artificial intelligence and its applications. There are several methods that have been proposed to model and reason with uncertainty in either a numeric or symbolic format. Within our work we adopt the Dempster-Shafer (DS) theory of evidence to fuse uncertain information detected from sensors for activities of daily living (ADL) monitoring within a smart home and use ordinal conditional function based revision and merging approaches to handle inconsistencies within knowledge from different sources. The remainder of the paper is organised as follows. Section 2 briefly introduces the challenges posed by ageing and presents an overview of work in the area of assistive technologies and smart environments to support independent living. The notion of ADL monitoring is introduced as one of the most important aspects within the services offered by a smart home. Section 3 presents our evidence model of uncertain sensor data in inferencing daily living activities and in Section 4 we propose a method of belief revision and merging to handle possibly situations of conflict resulting from complex knowledge within the smart living environment. Finally the paper is concluded in Section 5 along with presentation of research plans for the future work.

2 Assistive Living Environments for the Elderly

2.1 Ageing in Place

It is now recognised that approaches which can effectively and efficiently support persons within their own are much required to combat the effects of the ageing population. As people become older it becomes more difficult for them to live on their own. Not only do they require certain assistance to live a normal life, but also support is required to ensure their safety and wellbeing. Traditional institutional services may be viewed as being expensive and by the elderly as not their preferred habitual location (they would prefer to live in their own homes). In addition, existing services have already been stretched in terms of resources in efforts to manage the needs of the increasing numbers of elderly within the population.

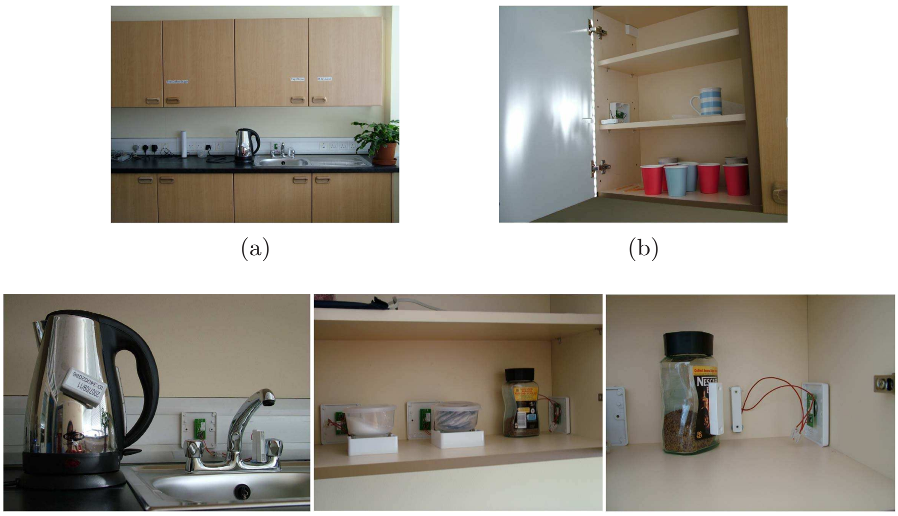
Modern assistive technologies attempt to provide a solution to compromise the imbalance between the growing needs and declined capability of caring for the elderly. Assisted living environments can provide supervision or assistance with ADLs, help with the coordinating of health care services and monitor people's activities to help ensure their health, safety, and well-being. Such environments are perceived to enable elderly people to remain living in their homes for longer periods of time and hence support the desired effect of 'ageing in place' [5]. This provides benefit not only to the elderly, however, also provides numerous benefits to their carers, families and even society as a whole.

2.2 Smart Sensorised Homes

Smart homes are a form of assisted living environments equipped with sensors/actuators, communication networks and information management systems. Sensors are the fundamental physical layer within the smart home hierarchy which have the ability to dynamically perceive changes within the environment.

Among the various sensor technologies currently available, anonymous binary sensors such as contact switches and pressure sensors are the most popular. They generate information in a non-intrusive manner about a person's interaction with domestic objects in addition to crudely profiling how the person moves around the house. At any given time binary sensors have the ability to present one of two possible values as an output. Whenever the state of a certain context (object, movement) associated with a sensor is changed, the value of the sensor is changed from '0' to '1' and hence reflects the fact that the context has been interacted as it has changed from a static state. For example, a contact switch sensor attached to the door of a fridge can tell the opening and closing of the fridge door when its value changes from '0' to '1'.

Fig. 1 shows a set of wireless binary sensors installed in a semi-functional kitchen within the smart laboratory in our department. These suite of sensors have the ability to assess if a person is preparing a simple drink and to subsequently identify if a hot or cold drink is being prepared[6].



(a) (b)

(c) (d) (e)

Fig. 1: Sensors within smart kitchen environment to assess the ADL of preparing a drink (a) picture of the semi-functioning kitchen, (b) cupboard with door sensor, (c) kettle with tilt switch and contact switch on tap, (d) contact sensors on sugar, tea and coffee jar and (e) contact sensor on coffee in 'on' state

2.3 Daily Living Activity Monitoring

Monitoring ADLs within the home environment can provide a means to assess an elderly person's wellbeing and in certain circumstances can be used to measure both cognitive and physical decline. The measurement of ADL performance in certain circumstances also allows the assessment of treatment effects, care-giver burden, the targeting of interventions and care packages along with the elucidation of the link between cognition and everyday functional ability [7].

ADLs refer to activities that reflect the person's capacity of self-care and hence reflects on their ability to live independently within the community. They can be activities that don't involve interactions with domestic objects and on the other hand those that do. The ADLs commonly monitored for assessing elder people include bathing, dressing, using the toilet, preparing meals, preparing drinks, taking medications, light housework, using the telephone, watching TV, etc. One of the key supporting features offered by a smart home is its ability to monitor ADLs through the deployment of sensor technology.

It is a common knowledge that people performing an ADL within the home need to move around the environment and interact with certain objects. For example, the ADL of 'preparing a simple drink' taking place in the kitchen involves the interactions of taking a cup from the cupboard, taking a tea bag or taking coffee, boiling the water in the kettle and pouring hot water into the cup. These activities may be followed by opening the fridge to take the milk if required and adding sugar if preferred. As such, monitoring people interacting with objects through observations of sensors installed in the home has become a very active approach in recognising and distinguishing ADLs which have been performed [8].

3 Sensor Uncertainty

In this section we first review Dempster-Shafer (DS) theory in representing and reasoning with uncertain information. The evidential network model of ADL recognition proposed in [9] is then reviewed briefly in the second part of this section.

3.1 Dempster-Shafer Theory

The DS theory of evidence originated in Dempster's work [10] and further formalised by Shafer in [11], is a generalization of traditional probability which allows us to better quantify uncertainty [12, 13].

Basic Concepts

At the core of DS theory is the concept of the frame of discernment. The *frame of discernment* refers to the exhaustive set of mutually exclusive values that a variable can hold, denoted Θ. It contains a set of hypotheses about values that the variable may hold.

Once the frame of discernment is established a number between 0 and 1 can be assigned to represent the degree of belief on the observation called evidence in a form of mass functions. A *mass function* is a function mapping 2^Θ to [0, 1] and represents the distribution of a unit of belief over Θ, satisfying the following two conditions:

$$\begin{array}{llll} (1) & m(\emptyset) = 0 & \emptyset: & \text{the empty set;} \\ (2) & \sum_{A\subseteq\Theta} m(A) = 1 & A: & \text{a subset of } \Theta. \end{array}$$

Based on a mass function the *belief* (Bel) and *plausibility* (Pls) functions are defined. Bel and Pls are the lower and upper bounds of the probability that are distinctly used in DS theory to represent uncertainty. They can be calculated from a mass function as follows.

$$Bel(A) = \sum_{B\subseteq A} m(B) \text{ and } Pls(A) = \sum_{B\supseteq A} m(B).$$

Bel represents the total weight of evidence in supporting A and Pls on failing to refute A, which can be used to determine the amount of support on A. They can be used to induce rules based on the belief distributions and may thus be regarded as providing pessimistic and optimistic measures of how strong a rule might be [14].

One feature of DS theory is that it can accumulate evidence from independent sources by the *Dempster's rule of combination.* Let m_1 and m_2 be mass functions on 2^Θ. Combining m_1 and m_2 gives a new mass function m called the orthogonal sum of m_1 and m_2 as:

$$m(C) = (m_1 \oplus m_2)(C) = \frac{\sum_{A\cap B=C} m_1(A)m_2(B)}{1-\sum_{A\cap B=\emptyset} m_1(A)m_2(B)}$$

Extended Concepts

Many research efforts have aimed to extend DS theory to provide widely applicable solutions in real world applications.

Discount rate was first defined in [15], by which the evidential function may be discounted in an effort to reflect the reliability of the evidence itself. Let r $(0 \leq r \leq 1)$ be a discount rate. The discounted mass function can then be represented in the following way:

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

where

(a) $r = 0$ the source is absolutely reliable
(b) $0 < r < 1$ the source is reliable with a discount rate r
(c) $r = 1$ the source is completely unreliable

Translation [15] operation is used to determine the impact of evidence originally appearing on a frame of discernment Θ_E upon elements of a compatibly related frame of discernment Θ_H through a *multivalued mapping* $\Gamma : \Theta_E \rightarrow 2^{\Theta_H}$ as follows:

$$m_{\Theta_H}(H_j) = \sum_{\Gamma(e_i)=H_j} m_{\Theta_E}(e_i)$$

where $e_i \in \Theta_E$, $H_j \subseteq \Theta_H$.

Propagation [16] is the generalised form of translation, in which relationships betweeen evidence space Θ_E and hypothesis space Θ_H can be certain or uncertain. In [17] *evidential mapping* was proposed to represent such complex relationships. The evidential mapping generalises the multivalued mapping by assigning an element of e_i of Θ_E a set of subset-mass pairs rather than a set of subsets as the multvalued mapping does in the following way:

$$\Gamma^*(e_i) = \{(H_{ij},\ f(e_i \rightarrow H_{ij})),\ ...,\ (H_{im},\ f(e_i \rightarrow H_{im}))\}$$

where $e_i \in \Theta_E$, $H_{ij} \subseteq \Theta_H$, $i = 1,\ ...,\ n$, $j = 1,\ ...,\ m$, satisfying

(a) $H_{ij} \neq \emptyset,\ j = 1,\ ...,\ m$;
(b) $f(e_i \rightarrow H_{ij}) > 0,\ j = 1,\ ...,\ m$;
(c) $\sum_{j=1}^{m} f(e_i \rightarrow H_{ij}) = 1$;
(d) $\Gamma^*(\Theta_E) = \{(\Theta_H, 1)\}$.

A piece of evidence on Θ_E can then be propagated to Θ_H through the evidential mapping Γ^* as follows:

$$m_{\Theta_H}(H_j) = \sum_i m_{\Theta_E}(e_i) f(e_i \rightarrow H_{ij})$$

where $h_i = \{H_{i1},\ ...,\ H_{im}\}$, and $H_j \in h_j$, $\Gamma^*(e_i) = \{(H_{i1}, f(e_i \rightarrow H_{i1})), ..., (H_{im}, f(e_i \rightarrow H_{im}))\}$, $f(e_i \rightarrow H_j) \in [0,\ 1]$.

Equally weighted sum operator [9] is the extension of the operator originally defined in [12] for integrating aggregates from different samples in a distributed database. Let $\Theta_A = \{A, \neg A\}$ and $\Theta_B = \{B, \neg B\}$ are two frames of discernment. We call the frame of discernment $\Theta = \{(A, B), \neg(A, B)\}$ the composite frame of Θ_A and Θ_B. If we have two mass functions m_1 and m_2 on the composite frame Θ originated from Θ_A and Θ_B, then a new mass function can be formed by using equally weighted sum operator in the following way:

$$m(C) = m_1 \overline{\oplus}\, m_2(C) = \frac{m_1(C) + m_2(C)}{2}$$

where $C \subseteq \Theta$.

The equally weighted sum operator satisfies both the commutative and associative laws. It can be applied to sum up n mass functions.

Maximization [9] is defined to aggregate mass functions on the frame of discernment to which the frames' masses originally come from are alternative. Frames $\Theta_A = \{A,\ \neg A\}$ and $\Theta_B = \{B,\ \neg B\}$ are said to be alternative in relation to the frame $\Theta_C = \{C,\ \neg C\}$ if the followings are satisfied:

(1) if $< \{A\}$ is true $>$ or $< \{B\}$ is true $>$, then $< \{C\}$ is true $>$;
(2) if $< \{\neg A\}$ is true $>$ and $< \{\neg B\}$ is true $>$, then $< \{\neg C\}$ is true $>$;
(3) if $< \Theta_A$ is true $>$ and $< \Theta_B$ is true $>$, then $< \Theta_C$ is true $>$.

If m_1 and m_2 are two mass functions over Θ_C originally from Θ_A and Θ_B, the new mass function over Θ_C can be formed in the following way:

$$m_{\Theta_C} = max(m_1, m_2).$$

In the form of belief and plausibility functions, this maximization operation can also be represented as follows:

$$Bel_{\Theta_C} = max(Bel_1,\ Bel_2),\ \text{and}\ Pls_{\Theta_C} = max(Pls_1,\ Pls_2).$$

3.2 Representing and Reasoning with Uncertain Sensor Data

Sensor Evidence Representation

In a sensorised smart home, sensor activations detected provide evidence about which activities have been performed. With DS theory evidence can be represented in the form of mass functions.

Example 1 *Between 2:30pm and 2:40pm, the system detects nothing apart from two sensors on the doors of the cupboard and the fridge (denoted as scup and sfri) in the kitchen were triggered. These two sensor activations can be described as follows:*

$$m_{\Theta_{scup}}(\{scup\}) = 1,\ m_{\Theta_{sfri}}(\{sfri\}) = 1$$

where $\Theta_{scup} = \{scup,\ \neg scup\}$, $\Theta_{sfri} = \{sfri,\ \neg sfri\}$

Many practical issues such as the type of a sensor, distance between a sensor and its receiver, previous reliability and the place where a sensor is installed make the sensor vulnerable to misreading or malfunctioning. Discounting allows these to be taken into account to reflect the reliability of the sensor.

Example 2 *(Example 1 continued) Sensor scup and sfri both are door contact switch sensors. Sensor scup has been replaced with a new battery recently. However, sensor sfri has been installed for over 5 months which is near to the end of its battery's life time of 6 months. We consider sfri is less reliable than scup. If we assume that scup works 98 out of 100 times and sfri does 90 out of 100, scup and sfri activation evidence given in Example 1 can then be revaluated by discounting in the following way:*

$$r_{scup} = 2\% \ \Rightarrow\ m^r_{\Theta_{scup}}(\{scup\}) = 0.98,\ m^r_{\Theta_{scup}}(\{\Theta_{scup}\}) = 0.02;$$

$$r_{sfri} = 10\% \ \Rightarrow\ m^r_{\Theta_{sfri}}(\{sfri\}) = 0.90,\ m^r_{\Theta_{sfri}}(\{\Theta_{sfri}\}) = 0.10.$$

ADL Evidential Networks

Performing an activity in a sensorised smart home involves a series of interactions with objects, in turn activations of sensors associated with the objects.

Example 3 *'Preparing a simple drink' can be 'preparing a cold drink' or 'preparing a hot drink'. If it is the latter it is possible to categorise this further to establish if the drink is tea or coffee. Within the setup of the smart kitchen described in Fig. 1 in Section 2.2, we can identify the necessary interactions involved with the preparation of each drink and mapped these onto an array of sensors (as shown in Table 1) that would be required to monitor in order to distinguish between which activity was actually being performed.*

Table 1: Summary of sensor technology used for the ADL of preparing a simple drink (O - Optional, Y - Yes, N - No)

	Sensor name	**Description**	**Tea**	**Coffee**	**Cold drink**
1.	Fridge (sfri)	Detects if the fridge is opened	O	O	Y
2.	Cupboard (scup)	Detects if a cup or glass is removed from the cupboard	Y	Y	Y
3.	Coffee (scof)	Detects if coffee is taken	N	Y	N
4.	Tea (stea)	Detects if tea is taken	Y	N	N
5.	Sugar (ssug)	Detects if sugar is taken	O	O	N
6.	Water tap (swat)	Detects if the tap on the sink is turned on	O	O	N
7.	Kettle (sket)	Detects if water is poured from the kettle	Y	Y	N

Upon the collection of knowledge about performing an activity along with object interactions and sensor activations, evidential networks are built for inferring which activity has been performed. An evidential network is a graphical representation of ADL inference hierarchy, which contains the following contents.

Nodes

Nodes represent sensors, objects and activities. There are four types of nodes represented in different shapes.

Circular nodes are sensor nodes which bear evidence of sensor activations on performing an activity.

Square nodes are objects which performing an activity needs to interact with. Some objects are not associated with a sensor, that means their interactions can not be detected directly through sensors' activations but may be deduced from other objects' interactions. In the network such a node is outlined by double lines to distinguish from an object associated with a sensor outlined by a single line.

Eclipse nodes are composite nodes which are formed from the object nodes below whose involvements are compulsory in consideration of performing an activity.

Rectangle nodes represent activities to be inferred or to be used to infer a higher level activity.

Edges

An edge linking two nodes represents a relation between the two nodes.

Certain relation in the form of a solid line with an arrowhead is a simple relationship between two nodes in terms of multivalue mapping.

Heuristic relation in the form of a dashed line with an arrowhead represents an uncertain relationship between two nodes in terms of evidential mapping.

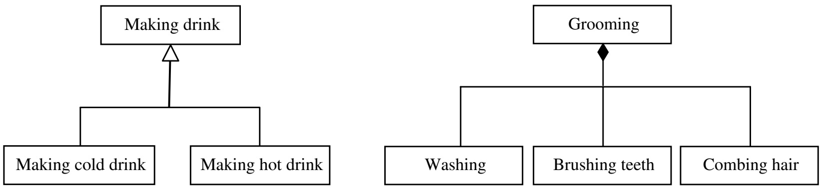
Alternation relations exist between nodes at a layer (e.g. layer A) and a node at one layer above them (e.g. layer B). The nodes at layer A are alternative in relation to the node at layer B when their existence satisfies the definition given in Section 3.1. Alternative relations are represented by a line joining the nodes at layer A to the node at layer B ending with a hollow triangle.

Composition relations describe compulsory existence of some nodes in relation to another node. Such relation is represented by a line joining the composite node to its compulsory nodes, with a solid diamond at the end.

There are two types of evidential networks: sensors-objects-activity and activities-activity networks. A sensors-objects-activity network contains sensor, object and activity nodes, which can infer which activity is performed according to object interactions evidenced by sensor activations. An activities-activity network containing only activity nodes represents a higher level of activity inference, which identifies an abstract activity from detailed sub-activities.

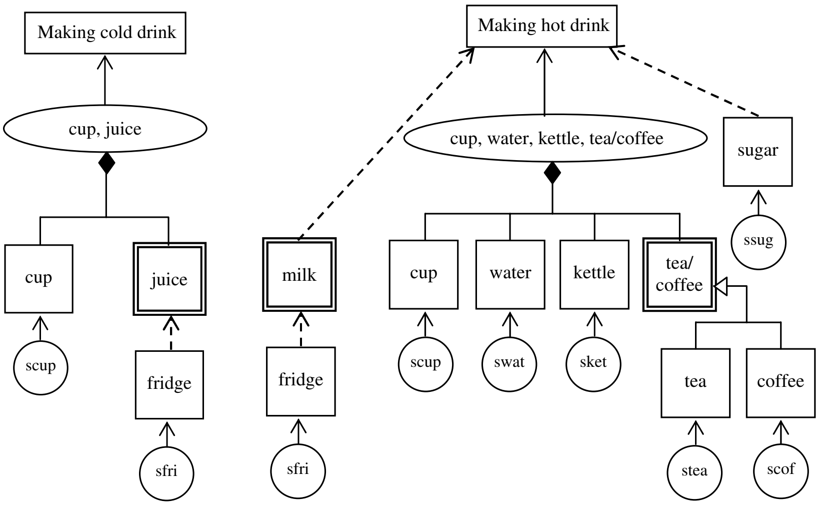
Example 4 *Continued from Example 3, we can draw the evidential networks of two types as given in Fig. 2 and 3. An additional example of activities-activity network is given in Fig. 2b to cover more connecting relations possibly existing in an evidential network.*

Once evidential networks are constructed and new sensor evidence is collected, activity inference can then be carried out to achieve a decision of the activity performed. The sensor evidence is processed along the directions of links in the network through discounting, translation, propagation, equally



(a) Making drink (b) Grooming

Fig. 2: Examples of evidential networks of activities-activity



(a) Cold drink (b) Hot drink

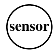
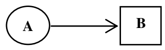
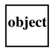
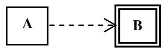
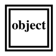
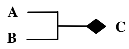
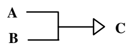
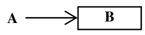
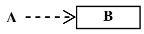
Fig. 3: Examples of evidential networks of sensors-objects-activity
Sensor abbreviations: sfri - fridge, swat - water tap, sket - kettle, scup - cup, stea - tea, scof - coffee, ssug - sugar

weighted sum, maximisation and combination. At last an activity with the highest belief above a threshold will be identified as the activity most possibly performed.

4 Revision and Merging Based Inconsistency Handling

In a smart home environment, information from different sources often becomes conflict. Most typically, information generated from ADLs inferred from sensor evidence (in short ADLs throughout this section) and some kind of background knowledge such as a diary plan is not always consistent. If we consider one source of information is more reliable than another, then we can resort to a revision process, while if we cannot tell which piece of information

Table 2: Summary of Graphical Notations used in Fig. 2 and Fig. 3

Node	Context	Link	Relation
	sensor		sensor A is associated with object B
	object (associated with a sensor)		object A derives object B
	object (derived from other object)		A and B are compulsory to C; A, B and C can be objects or activities
	object (a set of compulsory objects)		A and B are alternative to C; A, B and C can be objects or activities
	activity		A is compulsory to activity B; A can be an object, a compound object, or an activity
			A is optional to activity B; A can be an object, or an activity

is more reliable, then a merging process is needed. In this section, we will explore the revision and merging based inconsistency handling techniques.

4.1 Belief Revision

Knowledge/Belief revision ([18, 19, 20]) is one of the fundamental activities of an intelligent agent in which an agent revises its beliefs upon receiving new evidence (if new evidence is treated as being more important). Often, new information is conflicting with its current beliefs. Therefore, belief revision is a framework to characterize the process of belief change in order to revise the agent's current beliefs to accommodate new evidence and to reach a new consistent set of beliefs. One of the fundamental assumptions in belief revision is that new information is believed more reliably than old beliefs, so new information must be taken into account in order to reflect the true state of the object being observed.

The AGM postulates [18] formulated in the propositional setting in [19] characterize what a revision operator shall comply with regard to belief change and they are successful for one-step revision activities. However, it has been pointed out that these postulates are too weak for iterated belief revision where a counterintuitive result may emerge after a sequence of new information is observed and a belief set is revised accordingly [20].

To overcome this problem, revision by epistemic states (instead of belief set) has been investigated and gradually becomes a mainstream, especially for iterated belief revision ([20, 21, 22, 23], etc). However, these papers do not provide a explicitly and clear definition of epistemic states[1].

In contrast to the above approaches to epistemic state revision derived from AGM revision framework in logics, epistemic state revision has also been studied in numerical settings. The well known probability distributions can be viewed as an instantiation of epistemic states and probability updating is thus considered as revision by epistemic states. In [24], ordinal conditional functions (OCFs) are introduced to render the dynamics of the change of epistemic states (i.e., epistemic state revision). In [25], a possibility counterpart was proposed by Dubois and Prade. Remarkably, a generalized model for the dynamics (strategies) of epistemic state revision under the framework of plausibility measures introduced by Friedman and Halpern [26] is proposed in [27], which takes probability distributions, OCFs and possibility measures as its special cases.

To illustrate the revision strategies, we introduce the following notations. Let W denote a non-empty set of possible worlds, let A be a subset of W denoting the new evidence. $\forall A \subseteq W$, $\overline{A} = W \setminus A$.

For probability distributions, the revision strategy is commonly referred to as Jeffrey's Rule [28], and it is described as follows.

Let P be a prior probability distribution on W, and a new piece of evidence is provided as $P'(A) = \alpha$ and $P'(\overline{A}) = 1 - \alpha$ where P' is also a probability distribution on W but up to now, $P'(w), \forall w \in W$ is unknown. The responsibility of revision is to rationally assign values to $P'(w), \forall w \in W$ based on P, $P'(A)$ and $P'(\overline{A})$.

$$P'(w) = \begin{cases} \frac{\alpha P(w)}{P(A)} \text{ for } \quad w \in A \\ \frac{1-\alpha P(w)}{P(\overline{A})} \text{ for } w \in \overline{A} \end{cases} \tag{1}$$

An *ordinal conditional function* [24], also known as a *ranking function* [29] or a *kappa*-function, commonly denoted as κ, is a function from W to the set $N \cup \{+\infty\}$ where N is the set of ordinal numbers.

Function κ is normalized (consistent) if there exists at least one possible world w such that $\kappa(w) = 0$. Value $\kappa(w)$ is understood as the degree of *disbelief* of world w. So the smaller the value, the more plausible the world is. The ranking value of a set A is defined as:

$\kappa(A) = min_{w \in A} \kappa(w)$

The conditioning of ordinal conditional function is defined as:

$$\kappa(B|A) = min_{w \in A \cap B}(\kappa(w)) - \kappa(A) = \kappa(A \cap B) - \kappa(A).$$

Note that in [24], $\kappa(\emptyset) = \infty$. So when $A \cap B = \emptyset$, $\kappa(B|A) = \infty$.

In [24], the (A, α)-conditionalization, also commonly regarded as (A, α)-revision, is proposed as follows. Let an agent's current belief be represented

[1] In these paper, to some extent an epistemic state is implicitly considered as constructed from plausibility orderings between possible worlds which is dated back to Spohn's ordinal conditional function [24], but there are no explicit definitions.

by an OCF κ, and let new evidence concerning event A be given as $\kappa'(A) = 0$ and $\kappa'(\overline{A}) = \alpha$, then the revision of κ by κ' is defined as:

$$\kappa'(w) = \begin{cases} \kappa(w|A) & \text{for } w \in A \\ \alpha + \kappa(w|\overline{A}) & \text{for } w \in \overline{A} \end{cases} \tag{2}$$

A possibility distribution π is a mapping from W to $[0, 1]$. It induces a possibility measure $\Pi : 2^W \to [0, 1]$ and a necessity measure $N : 2^W \to [0, 1]$ as follows:

$$\Pi(A) = max_{w \in A}\pi(w) \text{ and } N(A) = 1 - \Pi(\overline{A}).$$

$\Pi(A)$ estimates to what extent an agent believes the truth value is in the subset A while $N(A)$ estimates the degree the agent believes the truth value should be necessarily in A.

There are several conditioning methods in possibility theory, and we adopt the following one in this paper [25].

$$\Pi(B|A) \stackrel{def}{=} \frac{\Pi(B \cap A)}{\Pi(A)} \tag{3}$$

A counterpart of Spohn's (A, α)-conditionalization was suggested in [25] in possibility theory such that if new evidence suggests that $\Pi'(A) = 1$ and $\Pi'(\overline{A}) = 1 - \alpha$ (which implies that $N'(A) = \alpha$), then the belief change of an agent's current belief π can take the following form

$$\pi'(w) = \begin{cases} \pi(w|A) & \text{for } w \in A \\ (1 - \alpha)\pi(w|\overline{A}) & \text{for } w \in \overline{A} \end{cases} \tag{4}$$

where $\pi(w|A) = \pi(w)/\Pi(A)$ which can be derived from Equation 3 with B being a singleton, i.e., $B = \{w\}$.

Example 5 *Suppose that information from a diary is always considered as more reliable than information generated from ADLs. Let us look at the following simple scenarios.*

Scenario 1: Information by ADLs shows that the person is using the telephone while the diary records that the person is attending the doctor's appointment. Let i denote that the person is at home, $\neg i$ denote otherwise, u denote using the telephone, and d denote at the doctor's appointment.

If we use a logical approach[2]*, that is, the less reliable information is u, and the more reliable one is d. As $u \models i$ and $d \models \neg i$, we know that u and d are inconsistent (i.e., $d \models \neg u$). Then a revision of u by d, denoted as $u \circ d$, results in d. That is, revision supports that the agent is at the doctor's, then the information of using the telephone might be either*

1. *the phone sensor made a bad recording (so the related sensors are ill-functional),*

[2] Here we mean classical propositional logic. Lowercase letters are used to represent propositions. $a \models b$ means that a implies b.

2. or it is not the person but his carer who is making the call.

If we use ordinal conditional functions for belief revision, that is, assuming information by ADLs is provided as (The person is using the telephone, at least more possibly at home than not)

$$\kappa_1(u) = 0, \kappa_1(i \wedge \neg u) = 10, \kappa_1(\neg i) = 100,$$

and the diary gives (The person is at the doctor's, at least more possibly outside than at home)

$$\kappa_2(d) = 0, \kappa_2(\neg i \wedge \neg d) = 10, \kappa_2(i) = 100,$$

then the revision result is

$$\kappa(d) = 0, \kappa(\neg i \wedge \neg d) = 10, \kappa(u) = 100, \kappa(i \wedge \neg u) = 110.$$

This result shows that the person is at the doctor's, at least more possible outside than at home, and if he is at home, he is more possibly using the telephone.

Scenario 2: Information by ADLs shows that the person is preparing a drink while the diary gives that the person is in the kitchen having lunch. Let p *denote that the person is preparing a drink,* l *denote that the person is having lunch. Note that preparing a drink is a step of having lunch, i.e.,* $p \models l$.

If we use a logical approach, that is, the less reliable information is p, *and the more reliable one is* l. *As* $p \models l$, *we know that* p *and* l *are consistent. Then a revision of* p *by* l, *denoted as* $p \circ l$, *results in* p[3]. *That is, belief revision further supports the information generated from ADLs based on the diary information.*

If we use ordinal conditional functions for belief revision, that is, assuming information by ADLs is provided as

$$\kappa_1(p) = 0, \kappa_1(\neg p \wedge l) = 10, \kappa_1(\neg l) = 20,$$

and the diary gives

$$\kappa_2(l) = 0, \kappa_2(\neg l) = 10,$$

then the revision result is

$$\kappa(p) = 0, \kappa(\neg p \wedge l) = 10, \kappa(\neg l) = 20.$$

This result shows that the consistent information is retained after revision.

[3] In fact, if two pieces of information a, b are consistent, then belief revision postulates [19, 20] make $a \circ b = a \wedge b$.

4.2 Belief Merging

In many applications, there is a need to combine possibly conflicting information from different sources in order to get coherent knowledge. This is the origin of information/data fusion problem. As a very important part of the data fusion problem, in the last two decades, the merging of knowledge bases (especially in propositional logic) has attracted significant attention.

Knowledge bases (or belief bases) can be flat or stratified/ranked. In a flat knowledge base, all the logical formulae are viewed as equally important. In stratified knowledge bases, however, formulae are assigned with different levels of importance (priority). A formula at a higher level is viewed as more important than those at a lower level, while in a ranked knowledge base, each formula is attached to a rank (e.g., an ordinal number). A formula with a higher rank is more preferred than those with lower ranks.

Konieczny and Pino-Perez [30] gave a systematic examination on all the possible postulates for merging flat knowledge bases. It includes a basic set of six postulates (usually mentioned as KP postulates) and an extra set of postulates such as the majority postulate and the arbitrary postulate. The relations of these postulates are studied and some concrete merging operators are provided to show the consistency of these postulates.

Meyer and his coworkers studied the epistemic state merging [31, 32]. Meyer extends the KP postulates to the epistemic state version and gives some concrete examples. But no systematic examination on the epistemic merging postulates is given. The merging of stratified ranked knowledge bases has been studied in many papers such as, [33, 34, 35, 36, 37]. The prioritized merging postulates proposed by Delgrande, Dubois and Lang [36] can be induced by flat merging operators. It also shows that iterated revision can be seen as a kind of prioritized merging. However, these prioritized merging postulates only consider the knowledge bases and no systematic examination is provided.

Here we also introduce the merging of ordinal conditional functions.

The merging of two ordinal conditional functions κ_1 and κ_2 is defined in [38] as

$$(\kappa_1 \widehat{\oplus} \kappa_2)(w) = \kappa_1(w) + \kappa_2(w) - min_{w \in W}(\kappa_1(w) + \kappa_2(w)) \qquad (5)$$

This rule is applicable only when $min_{w \in W}(\kappa_1(w) + \kappa_2(w)) < +\infty$.

Example 6 *Suppose that information from different sources is of equal reliability. Let us look at the following simple scenarios.*

Scenario 3: Information by ADLs shows that the person is taking medicine while the diary gives that the person is also within 10 minutes of the expected time the person was to take medicine. Let t denote that the person is taking medicine, a denote that medicine has already been taken, $n = \neg t \wedge \neg a$ denote the person does not take medicine.

Here we use ordinal conditional functions. Assuming information by ADLs is provided as (The person is taking medicine)

$$\kappa_1(t) = 0, \kappa_1(a) = \kappa_1(n) = 100,$$

and the diary gives (The person has already taken medicine, but as 10 minutes is a relative small amount of time, it is also very likely he is taking medicine or has not)

$$\kappa_2(a) = 0, \kappa_2(t) = \kappa_2(n) = 10,$$

then the merging result is

$$\kappa(t) = 0, \kappa(a) = 90, \kappa(n) = 100.$$

This result shows that the person is taking medicine, and more possibly has taken than not.

Scenario 4: Information by ADLs shows that the bathroom door sensor is activated at 8:00 while the diary gives that the person usually gets out of bed at 8:00. Let b *denote that the person is in the bathroom,* g *denote that the person has already got out of bed. Note that* b *implies* g*, i.e.,* $b \models g$*.*

Obviously, this scenario is a bit similar to scenario 2 in Example 5. In that scenario, we use belief revision to deal with it and get a satisfactory result. In fact, we can also use belief merging. In a logical approach, the merging of b *and* g*, denoted as* $b \widehat{\oplus} g$*, results in* b[4]*. That is, if pieces of information are consistent, then belief revision and belief merging lead to the same result.*

If we use ordinal conditional functions here, that is, assuming information by ADLs is provided as

$$\kappa_1(b) = 0, \kappa_1(\neg b) = 100,$$

and the diary gives

$$\kappa_2(g) = 0, \kappa_2(\neg g) = 10,$$

then the merging result is

$$\kappa(b) = 0, \kappa(\neg b \wedge g) = 100, \kappa(\neg g) = 130.$$

This result shows that the consistent information is also retained after merging.

From the examples, we find that if pieces of information are totally inconsistent, we may resort to belief revision to get a consistent knowledge. If pieces of information are totally consistent, then belief revision and belief merging are both suitable approaches. If pieces of information are partially consistent but a bit differs in time, like scenario 3, then it is better to use belief merging.

[4] In fact, if two pieces of information a, b are consistent, then belief merging postulates [30] make $a \hat{\oplus} b = a \wedge b$.

5 Conclusion

Comparing the well developed state of sensorising technologies within smart homes, information management is far behind to change the vision of smart homes into a practical concept. In this paper we proposed solutions to infer ADLs with uncertain sensor data and manage inconsistency of ADLs with knowledge from other sources.

We are currently investigating the implementation of the solutions in a set of scenarios extracted from clinical simulation within our smart laboratory environment. With assistive living environments being constructed in relation to the project we are involved, we also expect to test the solutions in a real practical setup at a complex scale.

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