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Evidential fusion of sensor data for activity recognition in smart homes

Xin Hong [a,*], Chris Nugent [a], Maurice Mulvenna [a], Sally McClean [b], Bryan Scotney [b], Steven Devlin [a]

[a] School of Computing and Mathematics and Computer Science Research Institute, University of Ulster, Jordanstown, BT37 0QB, UK

[b] School of Computing and Information Engineering and Computer Science Research Institute, University of Ulster, Coleraine, BT52 1SA, UK

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ABSTRACT

Advances in technology have provided the ability to equip the home environment with a layer of technology to provide a truly 'Smart Home'. These homes offer improved living conditions and levels of independence for the population who require support with both physical and cognitive functions. At the core of the Smart Home is a collection of sensing technology which is used to monitor the behaviour of the inhabitant and their interactions with the environment. A variety of different sensors measuring light, sound, contact and motion provide sufficient multi-dimensional information about the inhabitant to support the inference of activity determination. A problem which impinges upon the success of any information analysis is the fact that sensors may not always provide reliable information due to either faults, operational tolerance levels or corrupted data. In this paper we address the fusion process of contextual information derived from uncertain sensor data. Based on a series of information handling techniques, most notably the Dempster–Shafer theory of evidence and the Equally Weighted Sum operator, evidential contextual information is represented, analysed and merged to achieve a consensus in automatically inferring activities of daily living for inhabitants in Smart Homes. Within the paper we introduce the framework within which uncertainty can be managed and demonstrate the effects that the number of sensors in conjunction with the reliability level of each sensor can have on the overall decision making process.

1. Introduction

Smart Home technology offers the prospect of significant improvements in the quality of life and level of independence for elderly or disabled people. The alternative is the reliance on a form of formal or informal care or in certain cases a form of institutionalisation may be required. The desired effect is therefore to equip with the home environment with intelligent and autonomous technology which subsequently extends the period of time a person can remain within their own home. As we are currently witnessing demographic changes resulting in an increase in the median age of the population there is not only an opportunity for a widespread uptake of Smart Homes, but also a real need to manage the additional burden on health and social care services that are a result of these demographic changes.

Smart Homes equipped with centrally managed networked devices therefore have the ability to provide a means for independent but safe living, remote but effective caring, and professional but constant health-monitoring. One of the key supporting features offered by a Smart Home is the ability to monitor the activities of daily living. By being able to recognise and monitor activities of daily living for example making a drink, bathing, dressing etc., automatic detection of changes in patterns of behaviour is possible. This information can reveal a decline in health, risks in the environment, and emergency

* Corresponding author. Tel.: +44 2870324890.
E-mail address: x.hong@ulster.ac.uk (X. Hong).

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situations that may require the assistance of caregivers. This can be considered as perhaps one of the most important areas within which Smart Homes can have the largest impact from both user and carer perspectives.

Considerable research has been devoted towards activity recognition by using multiple sensors of different types, from visual sensors like cameras [1] to sensors which provide binary 'on' or 'off' outputs such as contact switch sensors that may be used to detect for example a door being opened or closed [2]. As opposed to sensors like cameras and microphones, small and simple sensors such as switch-on, pressure sensors, and movement detectors are less invasive and ensure the privacy and comfort of inhabitants within their home.

Context-aware activity recognition in a sensorised networked environment is built on low-level sensor data detecting contexts when the inhabitant interacts with the environment. The information generated can be used to identify the activity that the inhabitant is performing. Many sensors may provide information about the inhabitant's situation simultaneously. The main problem is that data obtained from sensors have different degrees of uncertainty [3]. This uncertainty may arise for a number of reasons. The question which is to be asked is if a sensor provides a value of 'on' or 'off' how sure can we be about this measurement and how can we accommodate for any uncertainty that may exist. For example it may be the case that the sensor is faulty, it may be that it can never be 100% accurate due to the nature of what it is measuring or it may be that the overarching management system has for some reason corrupted the data. In our current work we have aimed to investigate means by which such uncertainty could be accommodated for within Smart Homes. We have focused on the deployment of anonymous binary sensors including movement detectors, contact switch sensors, and pressure mats to monitor the rudimentary activities of daily living in Smart Homes.

Among numerical reasoning mechanisms, Bayesian methods and Evidence Theory of which the Dempster–Shafer theory of evidence (DS theory) is a major constituent are commonly used to handle uncertainty. Examples of applying Bayesian methods for activity recognition have been previously reported in [2,4–6]. As a generalised probability approach DS theory has distinct features compared with Bayesian theory: representing ignorance due to the lack of information and aggregating beliefs when new evidence is accumulated. This is a useful feature which can be used within the context of Smart Homes to manage the degree of uncertainty, which, until now has not been accommodated for. In this paper, we propose an evidential approach to reasoning under uncertainty in the monitoring and management of activities of daily living. The proposed approach is based on the use of DS theory through the fusion of contextual information inferred from uncertain sensor data. Within this paper we have shown how the framework can be established, how DS theory and other tools can be employed for information management and reasoning under uncertainty and in addition have shown the ability of the framework to distinguish between the different activities of daily living. The remainder of this paper is organised as follows. Section 2 briefly introduces the typical characteristics of the sensors used in Smart Homes and informally defines context for activity recognition and establishes the activities of daily living on a practical basis. This is supplemented with the presentation of an ontology hierarchy of context-aware activities. Evidential networks of activity inference are formalised being constructed from an activity hierarchy of ontology in Section 3. In Section 4 we propose a novel approach of inferring activities from sensed contexts with uncertainty by evidential reasoning on the basis of DS theory. Section 5 details the steps of evidential inference with a Case Study of the approach and presents a series of experiments which shows the effects of sensor deployment and reliability in the differentiation of a number of activities of daily living. Section 6 describes some related work and highlights special features of our approach. Finally the paper is concluded in Section 7.

2. Smart homes for the elderly

2.1. Simple anonymous sensors

Due to the constraints of building a Smart Home, such as privacy, cost, technical installation of retro-fits and practicability, careful consideration should be given towards the selection of sensors. One particular type of sensor which has received wide spread acceptance is the anonymous binary sensor as introduced in the previous section. These sensors have been reported as being commonly deployed within home security systems and to avoid some of the constraints within the wider context of sensor deployment are the preferable choice for use in a Smart Home environment. These sensors are unable to directly identify occupants and at any given time a binary value may be obtained from them. Whenever the state of a certain context (object, movement) associated with a binary sensor is changed, the value of the sensor changes to '1' from '0' when it is in a static state. Types of binary sensors chosen in this research include movement detectors, contact switches and pressure mats. Movement detectors (passive infrared) are usually mounted in the ceilings of the home and can be used to detect user presence throughout the house. Contact switches may be installed on the doors of cupboards, the fridge, the microwave, etc. Pressure mats may be discreetly installed in objects such as chairs, sofas, beds and in some instances may be used to locate specific movements within rooms by for example placing sensors in front of the sink in the kitchen or bathroom or at the side of the bed.

2.2. Context-aware activities of daily living

The term *context* has been used broadly with a variety of meanings for context-aware applications in pervasive computing [7]. When using the term activity recognition in conjunction with Smart Home technology, we refer to contexts as any

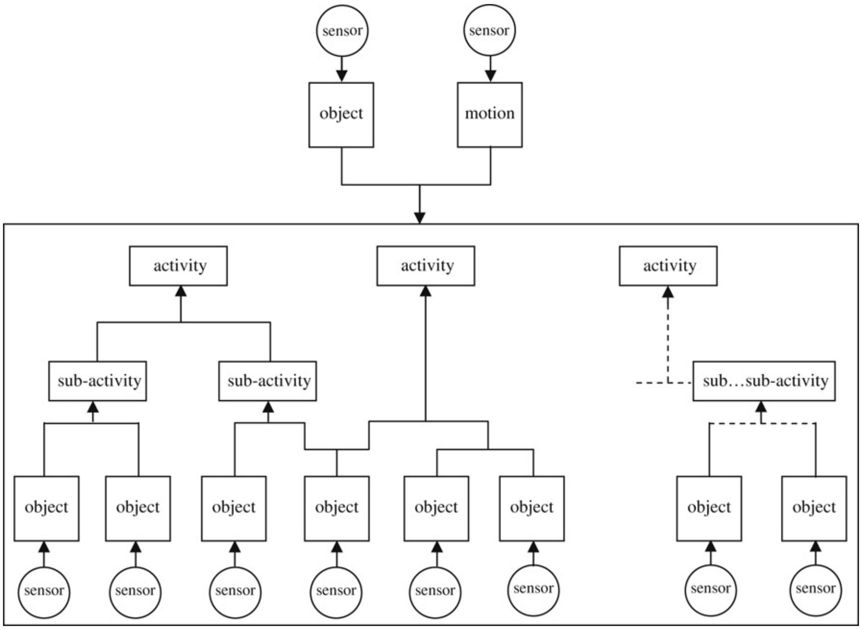


Fig. 1. A general ontology network of context-aware activities.

information that can be used to characterise the activity of the inhabitant, including the room that the inhabitant is in, objects that the inhabitant interacts with, whether the inhabitant is currently mobile, in addition to the time of the day when an activity is being performed. In terms of activity recognition in Smart Homes, context awareness can be considered to infer the activity using contextual information as detailed above. The state change of the context involved in an activity can be detected through low-level sensor readings. When the value of a sensor changes, the state of the associated context of that sensor is said to have changed. This indicates that the inhabitant has just interacted with contextual information related to an activity, which can then be used to infer the activity that the inhabitant is undertaking.

Numerous studies have cited typical scenarios [8,9] or descriptions of activities of daily living [4] which can be used to help further explain the requirements of the monitoring environment. Two activity scenarios which may be considered are Grooming and Preparing a drink. Each activity scenario may be comprised of a number of sub-activities. For example, Grooming is considered to be comprised of actions related to washing, brushing teeth and combing hair. In addition, an activity can mean one of many alternative activities, such as preparing a drink could be preparing a cold drink or preparing a hot drink. An activity is also performed by the inhabitant moving around and interacting with objects. For example, preparing a cold drink consists of going to the cupboard and getting a cup, going to the fridge, opening the fridge and taking out the juice and pouring the juice into the cup. To represent these sequence and structure of activities it is beneficial to design an ontology of activities.

2.3. Ontology hierarchy of context-aware activities

As previously introduced, activities of daily living can be measured by the inhabitant's interaction with objects within the environment and with them moving around in the environment [4]. The interaction with objects and movements involved in an activity are recorded by associated sensors which send signals to the central management system for processing. The interrelationships between sensors, contexts and activities can be represented by a hierarchical network of ontologies. In the first instance it is possible to recognise that a particular activity can be performed or associated with a certain room in the house. As our first attempt of introducing the hierarchy we therefore group activities of daily living according to the room they can be performed in. Each ontology represents hierarchical interrelationships between sensors, related contexts and relevant activities within a room location. On a hierarchical ontology, from the point of view of graphical presentation, a sensor is represented by a circular node. A square node represents context (an object or motion) with a rectangular node representing an activity. A sensor node is directly connected to a context node by an outbound arrow. A context node can be part of a set of contexts connected together and subsequently points to an activity. Given that some contexts are related to several activities, they can also be connected to a set of activities. An activity node can be a subset of a higher abstract activity which may be a few layers up the activity hierarchy. Fig. 1 shows a general ontology network of context-aware activities.

If we consider the scenario of identifying the type of a drink a user is making it is possible to further expand on the concept of the ontology network. If for the sake of simplicity we reduce the possible activities to making a hot or cold drink we can begin to consider a simplified kitchen environment and suite of sensors which would be required to gather

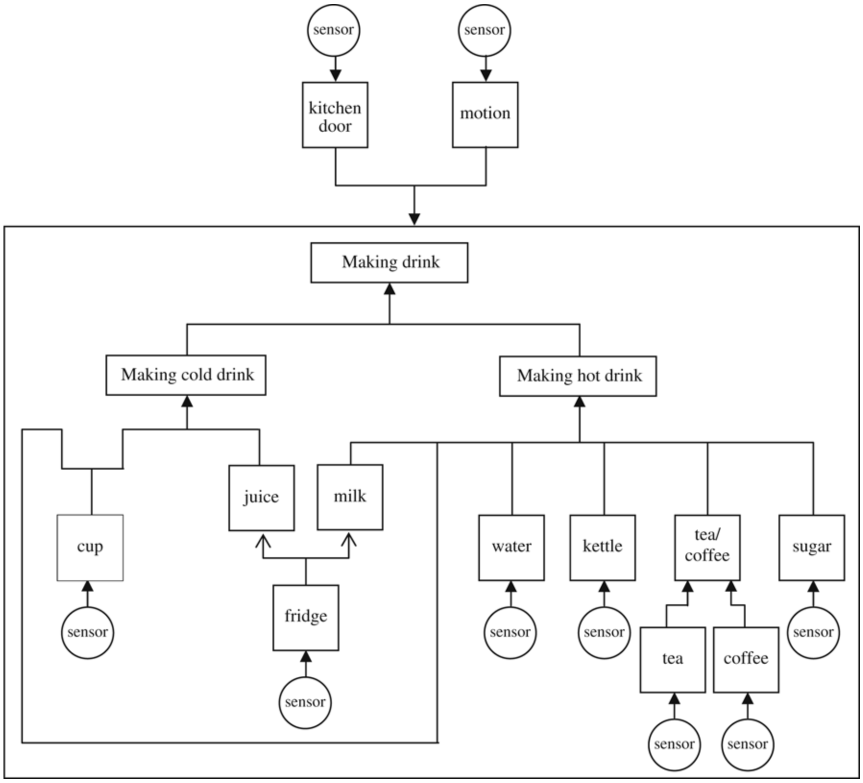


Fig. 2. A simplified ontology network of kitchen activities.

sufficient information to permit discrimination between these two activities. Contact sensors could be installed on the fridge, the cupboard, the tea/coffee jars, the sugar jar, and the water tap. A tilt sensor may also be mounted to the kettle. In this scenario we are also proposing that the fridge only stores juice and milk. An ontology hierarchy for the activities being performed in the kitchen can be constructed as shown in Fig. 2.

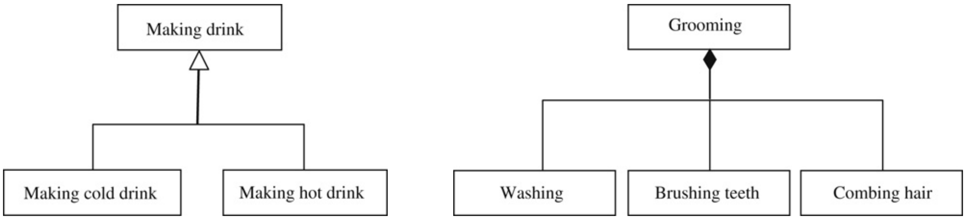
3. Evidential network of activity recognition

Sensors, once activated, present contextual evidence such as which room the inhabitant is in, which objects the inhabitant is interacting with and whether or not an inhabitant is moving around the home or room. All of this information provides valuable evidence which in turn can be considered indicative as to what activities the inhabitant is performing.

Based on the proposed concept of ontology networks of context-aware activities as presented in the previous section, we propose evidential networks of context-aware activity inference. Lower level activities can be considered as evidence of higher level activities where the lowest level activities are inferred from sensed contexts. As such there may be two types of evidential networks: activities–activity and sensors-contexts-activity.

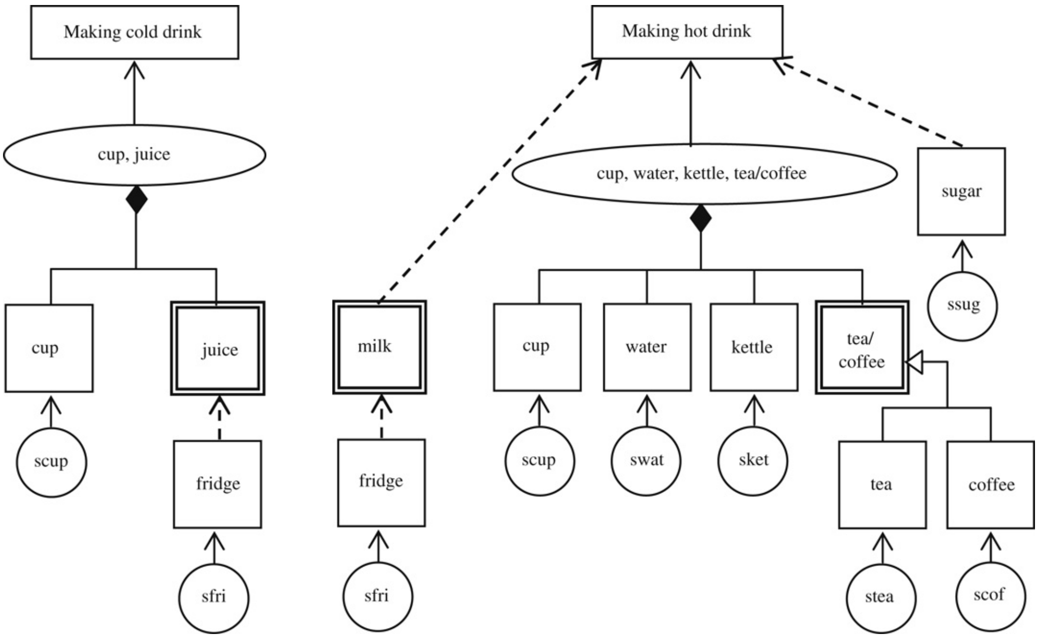
An activities–activity network contains only activities in a tree hierarchy. An activity can have several sub-activities at the layer below. An activity may also be a sub-activity to another activity. There are two types of connections between an activity and its sub-activities. For the first type of connection within our activities–activity network where sub-activities are alternatives to each other, the activity is said to be carried out only when any of its sub-activities have been performed. Such a network is drawn as a tree in which the connections between an activity and its sub-activities are represented by lines coming from the sub-activities which then merge into a single line with a hollow triangle at the activity side. For example, the network shown in Fig. 3a indicates that Making drink (activity) can be either the Making cold drink sub-activity or the Making hot drink sub-activity. With the second type of connection within our activities–activity network an activity is deemed to consist of several sub-activities. In this instance the activity is only considered complete when all sub-activities have been performed. In a network tree this type of connection is shown by lines from the sub-activities which all merge into a single line with a solid diamond end stopping at the activity. Fig. 3b shows an example of such a network for the Grooming activity.

An evidential network of sensors-contexts-activity is also represented as a tree hierarchy in which the sensors, the object contexts and the activity are represented by circle, square and rectangular nodes respectively. A sensor node is connected with a line with an arrowhead to a context node. With different involvements of object contexts in performing a given activity it is possible to divide contexts into two groups: core and accessory. Core contexts are the compulsory contexts



(a) Making drink. (b) Grooming.

Fig. 3. Examples of evidential networks of activities–activity. (The graphical notations are summarised in Table 1.)



(a) Making cold drink. (b) Making hot drink.

Fig. 4. Examples of evidential networks of sensors-contexts-activity. Sensor abbreviations: sfri—fridge, swat—water tap, sket—kettle, scup—cup, stea—tea, scof—coffee, ssug—sugar. (The graphical notations are summarised in Table 1.)

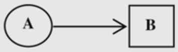
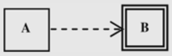
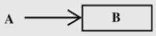
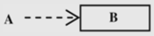
which must be interacted with when performing a certain activity. Accessory contexts can be considered as optional and may or may not be involved in the performance of a specific activity. Performing an activity may involve interacting with several core and many accessory contexts. An additional context is introduced as the composite of all core contexts related to the activity and shown as an eclipse node in the network. The relations between the composite context and its core context components are represented by a line joining the composite node to a core context node, with a solid diamond on the line near the composite node. The newly added composite context node and any accessory contexts are connected to the activity node separately by a solid and dashed line with an arrowhead respectively. Some square nodes are marked with a double outline to represent contexts that are not directly associated with a sensor but rather deduced from a sensed context. In the network a dashed line with a hollow triangle end links a sensed context to a context node deduced with uncertainty. Fig. 4 displays two examples of evidential networks of sensors-contexts-activity in the kitchen: Making cold drink and Making hot drink. It is upon the ability to formalise the representation of ontology networks that we can now proceed and manage uncertainty within sensed contexts.

4. Evidential reasoning of activities

4.1. Uncertainty in sensed contexts

Sensed context is usually highly dynamic and prone to noise and sensing errors [7]. In many situations sensors can provide uncertain contexts. One situation may be that the sensor over-senses the contexts. For example a movement detector's range can fall outside the room that it is monitoring, so the detector might sense people as they move outside. Another example may be that a malfunctioning sensor gives invalid readings that incorrectly reflect the state change of the context it is

Table 1
Summary of the graphical notation used in Figs. 3 and 4

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

associated with. For instance the contact switch sensor installed on the door of a fridge may have an intermittent technical problem. As such the zero reading does not necessarily mean that the inhabitant has not opened the fridge as it would whenever it is functioning correctly. In another situation the connection between the central monitoring facility and the sensor fails resulting in a missing sensor reading along with an unknown state of the associated context.

Smart Homes aim to be equipped with as many sensors as possible. Tagging every single item in the household is desirable but simply impracticable. Some sensor readings give information about contexts only at an abstract level. For example, a contact switch sensor is installed on the door of the fridge. There are many contents contained in the fridge such as milk, juice, butter, jam, ready-to-cook meals to name but a few. When the fridge sensor is triggered, the state of the fridge context is changed which indicates the inhabitant interacts with the fridge (opening the fridge and getting food out of the fridge). However, it is not possible to infer what food is removed from the fridge by simply considering the current state of the fridge door. If the inhabitant wants to make a cold drink, it is more likely that the juice is removed. If the inhabitant wants to make a hot drink, then it is more likely that they will remove milk from the fridge. Mapping from the sensed fridge (context at the abstract level) to the item removed from the fridge (context at the detailed level) is dynamic and uncertain. In addition, inferring from a context to an activity can also include uncertainty to some extent. Some people have tea/coffee with sugar, and some do not. Mapping from taking sugar to the activity of making tea is certainly not as obvious as that from having removed a cup from the cupboard, boiled water and placed a tea bag in the cup.

4.2. Dempster–Shafer theory of evidence

The Dempster–Shafer (DS) theory of evidence originated from Dempster's work [10] and further extended by Shafer [11], is a generalisation of traditional probability which allows us to better quantify uncertainty. The theory is based on a number of key propositions which are summarised as follows.

Frame of discernment: A sensor can have either a value of one (active) or zero (inactive). The two values comprise the exhaustive set of mutually exclusive values that the sensor can hold. In DS theory, the set is called the frame of discernment of the sensor, denoted by Θ. For example, $\{scup, \neg scup\}$ is the frame of discernment for sensor *scup* in which *scup* represents the sensor is active and $\neg scup$ represents the sensor is inactive.

Mass function: Many factors surrounding the sensor have an impact on the quality of the sensor's observation. For example, the inhabitant in the hallway passing the open door of the kitchen may activate the motion sensor in the kitchen giving a false result. The observation of the sensor is inherently evidential. DS theory uses a number in the range [0, 1] to represent the degree of belief in the observation. The distribution of a unit of belief over the frame of discernment is called evidence. A function m: $2^{\Theta} \rightarrow [0, 1]$ is called a mass function, representing the distribution of belief and satisfying the following two conditions:

$$(1)\ m(\emptyset) = 0 \qquad \emptyset: \text{ the empty set}$$
$$(2)\ \sum_{A \subseteq \Theta} m(A) = 1 \quad A: \text{a subset of } \Theta.$$

A mass value can be committed to either a singleton or a subset of Θ. This property makes DS theory more expressive than probability theory. When a mass value is committed to a subset that has more than one element, it is explicitly stating that there is not enough information to distribute this belief more precisely to each individual element in the subset. In particular, the total belief is assigned to the whole frame of discernment, $m(\Theta) = 1$, when there is no evidence about Θ at all. In contrast, probability theory lacks this ability by dividing the total belief equally among elements of Θ. If $m(A) > 0$, the subset A of Θ is called a focal element of the belief distribution.

Belief and plausibility: Dempster used a range of probability rather than a single probabilistic number to represent uncertainty. The lower and upper bounds of the probability are called the belief and plausibility respectively, which can be defined by mass functions as follows.

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

Bel represents the degree of belief to which the evidence supports A. *Pls* describes the degree of belief to which the evidence fails to refute A, that is, the degree of belief to which it remains plausible.

4.3. Evidential operations

The following evidential operations may be involved when inferring activities along evidential networks.

Reliability discounting [12]: Some sensors are more vulnerable to misreading or malfunctioning due to their type and location and where they are installed. The impact of evidence is discounted to reflect the sensor's credibility, in terms of *discount rate* r $(0 \le r \le 1)$. The discounted mass function is defined as follows:

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

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.

Belief distributions on sensor nodes of evidence are reflected onto an activity node of hypothesis through the translation or propagation operations by a multivalued mapping or an evidential mapping respectively.

Multivalued mapping: Dempster used a multivalued mapping to reflect the relationship between two frames of discernment both representing evidence to the same problem but from different views. For two frames of discernment Θ_E and Θ_H, a *multivalued mapping* Γ describes a mapping function $\Gamma : \Theta_E \leftarrow 2^{\Theta_H}$, assigning to each element e_i of Θ_E a subset $\Gamma(e_i)$ of Θ_H.

An alternative definition for a multivalued mapping is a *compatibility relation* [12,13]. A **compatibility relation** simply describes which elements from the two frames can be true simultaneously. The compatibility relation between frames Θ_E and Θ_H is a subset of the Cartesian product of the two frames: $\Theta_{E,H} \subseteq \Theta_E \times \Theta_H$.

The compatibility relation $\Theta_{E,H}$ is related to the multivalued mapping Γ by: $\Theta_{E,H} = \{(e_i, h_j)|h_j \in \Gamma(e_i)\}$, $\Gamma(e_i) = \{h_j|(e_i, h_j) \in \Theta_{E,H}\}$.

Translation [12]: The evidential operation called translation can be used to determine the impact of evidence originally appearing on a frame of discernment upon elements of a compatibly related frame of discernment. Suppose the frame of discernment Θ_E carries a mass function m, the translated mass function over the compatibly related frame of discernment Θ_H is:

$$m'(H_j) = \sum_{\Gamma(e_i)=H_j} m(e_i)$$

where $e_i \in \Theta_E$, $H_j \subseteq \Theta_H$, and $\Gamma : \Theta_E \to 2^{\Theta_H}$ is a multivalued mapping.

Evidential mapping: The relationship between an element e_i of Θ_E and a subset H_{ij} of Θ_H may not be certain. To represent such uncertain relationships an evidential mapping [14] $\Gamma^* : \Theta_E \to 2^{2^{\Theta_H}\times[0,1]}$ assigns to an element e_i of Θ_E instead of a set of subsets, a set of subset-mass pairs:

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

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

(*a*) $H_{ij} \ne \emptyset, \quad j = 1, \dots, m;$
(*b*) $f(e_i \to H_{ij}) > 0, \quad j = 1, \dots, m;$
(*c*) $\Sigma_{j=1}^{m} f(e_i \to H_{ij}) = 1;$
(*d*) $\Gamma^*(\Theta_E) = \{(\Theta_H, 1)\}.$

Propagation [15]: When a relationship is uncertain, a piece of evidence on Θ_E is propagated to Θ_H through an evidential mapping Γ^*.

$$m'(H_j) = \sum_i m(e_i) f(e_i \to H_j)$$

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

Translation is a special case of propagation, in which relationships between evidence space Θ_E and hypothesis space Θ_H are certain.

Belief distributions on the same frame can be combined by Dempster's rule of combination if they are from several different evidence sources. Alternatively they may be summed up through the equally weighted sum operator if they are from sources that are components of the frame.

Dempster's rule of combination: A belief distribution presents a probability opinion over Θ. When several belief distributions are obtained through distinct sources over the same Θ, a new belief distribution representing the consensus of those disparate opinions can be produced by the Dempster's rule of combination. Let m_1 and m_2 be mass functions on Θ representing two bodies of evidence from independent sources. A and B represent focal elements of m_1 and m_2 respectively. A new mass function m is formed by combining m_1 and m_2: $m = m_1 \oplus m_2$.

$$m(C) = \frac{\sum\limits_{A\cap B=C} m_1(A)m_2(B)}{1 - \sum\limits_{A\cap B=\emptyset} m_1(A)m_2(B)} = \frac{\sum\limits_{A\cap B=C} m_1(A)m_2(B)}{\sum\limits_{A\cap B\neq\emptyset} m_1(A)m_2(B)}.$$

The combination rule is associative and commutative.

Equally weighted sum operator: In Fig. 3b, the activity Grooming is the composite of the sub-activity Washing, Brushing teeth and Combing hair. The three sub-activities all contribute beliefs to Grooming. However, the belief distributions do not satisfy the condition of being independent so they cannot be aggregated by using Dempster's combination rule. A weighted sum operator was first proposed by McClean and Scotney [16] for integrating aggregates that represent different samples in a distributed database. Here we use an equally weighted sum operator to sum belief distributions on a composite node contributed by its non-independent component nodes.

$$m(A) = m_1 \hat{\oplus} \cdots \hat{\oplus} m_N(A) = \frac{1}{N}\sum_{i=1}^{N} m_i(A)$$

where $A \subseteq \Theta$.

The equally weighted sum operator is still a mass function, and both commutative and associative.

Maximization: "Making cold drink" and "Making hot drink" are two alternative sub-activities of "Making drink" activity. Inspired by the union operation of membership functions in the fuzzy set theory [17], we define the maximization operation to calculate the aggregated belief values on an activity contributed from its alternative sub-activities.

$$Bel(C) = \max(Bel(A), Bel(B)), \quad \text{and} \quad Plc(C) = \max(Pls(A), Pls(B))$$

where C is the composite of alternatives A and B.

The maximization operator also applies to mass calculation on an object context that is deduced from alternative sensed object contexts.

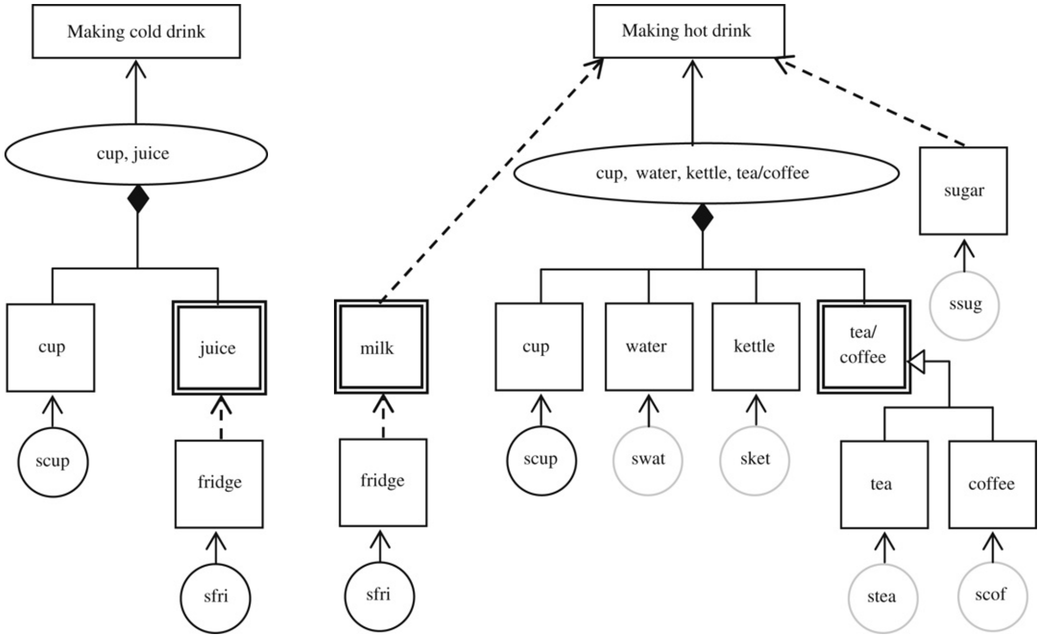
5. Evidential inference of activities

Based on the simplified kitchen arrangement as previously introduced in Section 2.3, we draw a scenario which will be used throughout this section to help illustrate the underlying concepts and evidential operations.

Case study: In the first instance the kitchen door sensor has been triggered and the motion sensor is currently active within the kitchen. The system then detects that two sensors Cup and Fridge become active. After about two minutes, the door sensor is triggered again and the motion sensor in the kitchen turns inactive. During the two minutes no other sensors in any of the other rooms were activated. What really happened in the kitchen?

Two high level sensors: kitchen door sensor and motion sensor in the kitchen limit activities to be recognised in the kitchen. There are many activities that can be performed in the kitchen, such as "Making drink" ("Making cold drink" or "Making hot drink"), "Making breakfast" ("Making cereal", or "Making toast", or "Frying eggs", etc.) and so on. Based on the simplified ontology of activities in the kitchen as shown in Fig. 2, we can derive the evidential networks for "Making cold drink", "Making hot drink" and "Making drink" as shown in Fig. 5a, b, Fig. 3a respectively. Inference through the evidential networks can then find out what activity is most likely to have been performed in the kitchen.

Observations occur at the sensor nodes as shown in Fig. 5. Sensor *scup* and *sfri* were triggered and have been represented as activated sensors shown as the visible nodes in the Figure. The other sensors were not activated and have been represented as faded nodes on the diagram. The activity "Making cold drink" in Fig. 5a, the activity "Making hot drink" in Fig. 5b and the activity "Making drink" in Fig. 3a are the hypotheses to be deduced.



(a) Making cold drink. (b) Making hot drink.

Fig. 5. Example case of evidential networks of context-aware activities.

Table 2
Examples of frames of discernment

Name	Type	Frame of discernment
scup	Sensor	$\{scup, \neg scup\}$
cup	Context	$\{cup, \neg cup\}$
Making cold drink	Activity	$\{\textit{Making cold drink, Making cold drink}\}$

Table 3
Examples of multivalued mappings

Relationship	Multivalued mapping
$scup \to cup$	$\{scup\} \to \{cup\}$; $\{\neg scup\} \to \{\neg cup\}$; $\{scup, \neg scup\} \to \{cup, \neg cup\}$.
$cup \to (cup,\ juice)$	$\{cup\} \to \{(cup,\ juice)\}$; $\{\neg cup\} \to \{\neg(cup,\ juice)\}$; $\{cup, \neg cup\} \to \{(cup,\ juice), \neg(cup,\ juice)\}$.
$(cup,\ juice) \to$ *Making cold drink*	$\{(cup,\ juice)\} \to \{\textit{Making cold drink}\}$; $\{\neg(cup,\ juice)\} \to \{\neg\textit{Making cold drink}\}$; $\{(cup,\ juice), \neg(cup,\ juice)\} \to \{\textit{Making cold drink}, \neg\textit{Making cold drink}\}$.
Making cold drink $\to$ *Making drink*	$\{\textit{Making cold drink}\} \to \{\textit{Making drink}\}$; $\{\neg\textit{Making cold drink}\} \to \{\neg\textit{Making drink}\}$; $\{\textit{Making cold drink}, \neg\textit{Making cold drink}\} \to \{\textit{Making drink}, \neg\textit{Making drink}\}$.

5.1. Evidential network representation

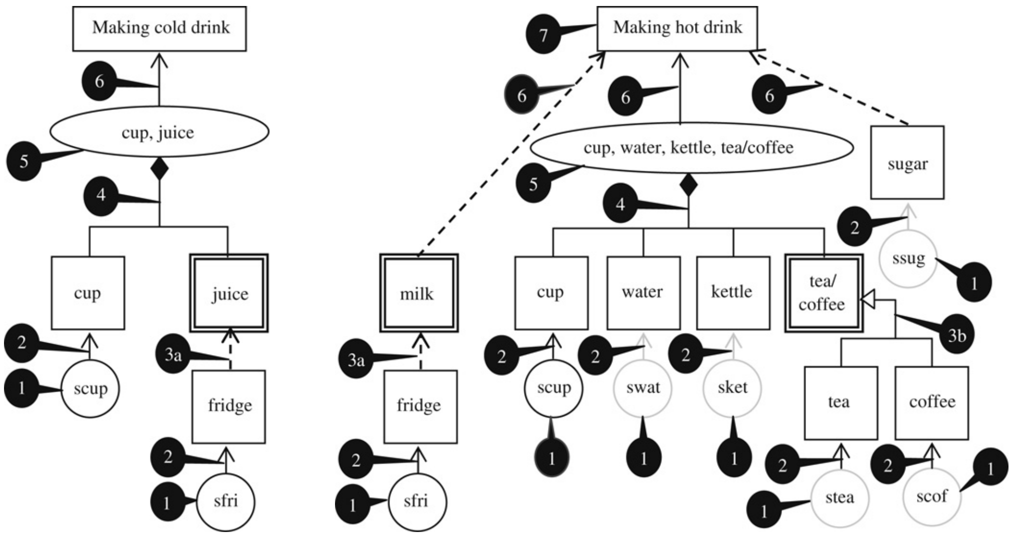
Inferring activities starts from representing the evidential networks in evidential forms. Each node is represented by the frame of discernment. For the case study, Table 2 shows an example of the frame of discernment for each type of node. Sensor nodes can have two values: active and inactive, hence the frame of discernment for a sensor is comprised of two elements. For example, $\{swat, \neg swat\}$ is the frame of discernment for the water tap sensor, in which *swat* means the sensor is active and $\neg swat$ means an inactive sensor. A context node can be interacted with or remain intact. For an activity node the frame is made up of two elements: performing the activity, not performing the activity.

Each arc in an evidential network represents the relationship between one node to another, which can be represented by a multivalued mapping or an evidential mapping.

In the evidential networks of the case study, all relationships between a sensor and its associated context node, a composite context and its component contexts, a composite context and an activity, and an activity and its sub-activity are compatible. Given this compatibility they are represented by multivalued mappings. Table 3 shows an example of multivalued mappings between different pairs of nodes.

Table 4
Evidential mappings

Relationship	Evidential mapping
fridge → *juice*	{*fridge*} → {({*juice*}, 0.9), ({*juice*, ¬*juice*}, 0.1)}; {¬*fridge*} → {({¬*juice*}, 1.0)}; {*fridge*, ¬*fridge*} → {({*juice*, ¬*juice*}, 1.0)}.
fridge → *milk*	{*fridge*} → {({*milk*}, 0.1), ({*milk*, ¬*milk*}, 0.9)}; {¬*fridge*} → {({¬*milk*}, 1.0)}; {*fridge*, ¬*fridge*} → {({*milk*, ¬*milk*}, 1.0)}.
milk → *Making hot drink*	{*milk*} → {({*Making hot drink*}, 0.7), ({*Making hot drink*, ¬*Making hot drink*}, 0.3)}; {¬*milk*} → {({*Making hot drink*, ¬*Making hot drink*}, 1.0)}; {*milk*, ¬*milk*} → {({*Making hot drink*, ¬*Making hot drink*}, 1.0)}.
sugar → *Making hot drink*	{*sugar*} → {({*Making hot drink*}, 0.4), ({*Making hot drink*, ¬*Making hot drink*}, 0.6)}; {¬*sugar*} → {({*Making hot drink*, ¬*Making hot drink*}, 1.0)}; {*sugar*, ¬*sugar*} → {({*Making hot drink*, ¬*Making hot drink*}, 1.0)}.



(a) Making cold drink. (b) Making hot drink.

Fig. 6. Examples of activity inference on sensors–contexts–activity networks Key: solid callouts show steps of inference on nodes or link arcs.

In the case study, opening the fridge can only mean removing juice or milk. Given the cup and nothing else is involved in the scenario it is more likely that only the juice has been taken out, and very unlikely that milk has been removed from the fridge. Suppose that the inhabitant puts milk in their tea/coffee 7 times out of ten and adds sugar 4 times out of ten. Table 4 gives the details of their heuristic relationships in the form of evidential mappings.

5.2. Activity inference on evidential networks

From the bottom up the activity inference starts with the evidential networks of sensors-contexts-activity, followed by reasoning on activities–activity networks.

In a sensors-contexts-activity network, evidence appears on a sensor node associated with an object context, which in turn may deduce objects in detail, or be summed up onto a composite context node by an equally weighted sum operation that is then translated to the relevant activity node, or propagated to a connected activity node by an evidential mapping. On an activity node, several belief distributions can be combined by Dempster's combination rule.

Fig. 6 shows the inference procedure on the evidential networks in Fig. 5 set by the case study. At the beginning of inference, evidence on sensor nodes are represented by mass functions as follows.

$$m_{scup}(\{scup\}) = 1; \quad m_{sfri}(\{sfri\}) = 1;$$
$$m_{swat}(\{\neg swat\}) = 1; \quad m_{sket}(\{\neg sket\}) = 1;$$
$$m_{stea}(\{\neg stea\}) = 1; \quad m_{scof}(\{\neg scof\}) = 1; \quad m_{ssug}(\{\neg ssug\}) = 1.$$

The inference procedure consists of seven steps of evidential operations.

Step 1 — *Discounting sensor evidence*. Sensors in the kitchen have been installed recently and manufacturer statistics show sensors are working correctly at different rates: 95% for contact switch sensors including cup, fridge, tea, coffee, and sugar sensors, 85% for water tap sensor, and 70% for kettle sensor. So a discount rate of 5% is assigned to sensor cup, fridge, tea, coffee and sugar, 15% is assigned to sensor water tap, and 30% to kettle sensor. The discounted mass functions can be calculated,

$$m^r_{scup}(\{scup\}) = 0.95,\ m^r_{scup}(\{scup,\ \neg scup\}) = 0.05;$$
$$m^r_{sfri}(\{sfri\}) = 0.95,\ m^r_{sfri}(\{sfri,\ \neg sfri\}) = 0.05;$$
$$m^r_{swat}(\{\neg swat\}) = 0.85,\ m^r_{swat}(\{swat,\ \neg swat\}) = 0.15;$$
$$m^r_{sket}(\{\neg sket\}) = 0.70,\ m^r_{sket}(\{sket,\ \neg sket\}) = 0.30;$$
$$m^r_{stea}(\{\neg stea\}) = 0.95,\ m^r_{stea}(\{stea,\ \neg stea\}) = 0.05;$$
$$m^r_{scof}(\{\neg scof\}) = 0.95,\ m^r_{scof}(\{scof,\ \neg scof\}) = 0.05;$$
$$m^r_{ssug}(\{\neg ssug\}) = 0.95,\ m^r_{ssug}(\{ssug,\ \neg ssug\}) = 0.05.$$

Step 2 — *Translating mass functions from sensors to associated object contexts*. A sensor being active indicates the associated object context has been interacted with. A sensor and the associated context maintain a compatible relationship which can be represented by a multivalued mapping as the examples shown in Table 3. The mass function on a sensor node can then be translated to the associated object context node by using the multivalued mapping.

$$m_{cup}(cup) = m^r_{scup}(\{scup\}) = 0.95,$$
$$m_{cup}(\{cup,\ \neg cup\}) = m^r_{scup}(\{scup,\ \neg scup\}) = 0.05;$$
$$m_{fridge}(\{fridge\}) = m^r_{sfri}(\{sfri\}) = 0.95,$$
$$m_{fridge}(\{fridge,\ \neg fridge\}) = m^r_{sfri}(\{sfri,\ \neg sfri\}) = 0.05;$$
$$m_{water}(\{\neg water\}) = m^r_{swat}(\{\neg swat\}) = 0.85,$$
$$m_{water}(\{water,\ \neg water\}) = m^r_{swat}(\{swat,\ \neg swat\}) = 0.15;$$
$$m_{kettle}(\{\neg kettle\}) = m^r_{sket}(\{\neg sket\}) = 0.70,$$
$$m_{kettle}(\{kettle,\ \neg kettle\}) = m^r_{sket}(\{sket,\ \neg sket\}) = 0.30;$$
$$m_{tea}(\{\neg tea\}) = m^r_{stea}(\{\neg stea\}) = 0.95,$$
$$m_{tea}(\{tea,\ \neg tea\}) = m^r_{stea}(\{stea,\ \neg stea\}) = 0.05;$$
$$m_{coffee}(\{\neg coffee\}) = m^r_{scof}(\{\neg scof\}) = 0.95,$$
$$m_{coffee}(\{coffee,\ \neg coffee\}) = m^r_{scof}(\{scof,\ \neg scof\}) = 0.05;$$
$$m_{sugar}(\{\neg sugar\}) = m^r_{ssug}(\{\neg ssug\}) = 0.95,$$
$$m_{sugar}(\{sugar,\ \neg sugar\}) = m^r_{ssug}(\{ssug,\ \neg ssug\}) = 0.05.$$

Step 3 — *Inferring from a sensed context node to a deduced context node*.

(a) The contexts "juice" and "milk" are masked by the context "fridge" of which the state can be detected by the associated sensor. The relationships of "fridge" with "juice" and "milk" are heuristic, which are represented by an evidential mapping as given in Table 4. The mass function on "fridge" is propagated to "juice" and "milk" by the evidential mappings. From this step we can derive the mass functions on "juice" and "milk".

$$\begin{aligned} m_{juice}(\{juice\}) &= m_{fridge}(\{fridge\}) * m(\{fridge\} \to \{juice\}) \\ &= 0.95 \times 0.9 = 0.855, \end{aligned}$$

$$\begin{aligned} m_{juice}(\{juice,\ \neg juice\}) &= m_{fridge}(\{fridge\}) * m(\{fridge\} \to \{juice, \neg juice\}) + m_{fridge}(\{fridge, \neg fridge\}) \\ &\quad * m(\{fridge, \neg fridge\} \to \{juice, \neg juice\}) \\ &= 0.95 \times 0.1 + 0.05 \times 1 = 0.145; \end{aligned}$$

$$\begin{aligned} m_{milk}(\{milk\}) &= m_{fridge}(\{fridge\}) * m(\{fridge\} \to \{milk\}) \\ &= 0.95 \times 0.1 = 0.095, \end{aligned}$$

$$\begin{aligned} m_{milk}(\{milk, \neg milk\}) &= m_{fridge}(\{fridge\}) * m(\{fridge\} \to \{milk, \neg milk\}) + m_{fridge}(\{fridge, \neg fridge\}) \\ &\quad * m(\{fridge, \neg fridge\} \to \{milk, \neg milk\}) \\ &= 0.95 \times 0.9 + 0.05 \times 1 = 0.905. \end{aligned}$$

(b) The contexts "tea" and "coffee" are the two alternatives of context "tea/coffee". The mass function on "tea/coffee" can be calculated by the maximization operator as follows.

$$\begin{aligned} m_{tea/coffee}(\{\neg tea/coffee\}) &= \max(m_{tea}(\{\neg tea\}), m_{coffee}(\{\neg coffee\})) \\ &= \max(0.95,\ 0.95) = 0.95, \end{aligned}$$

$$\begin{aligned} m_{tea/coffee}(\{tea/coffee,\ \neg tea/coffee\}) &= \max(m_{tea}(\{tea,\ \neg tea\}), m_{coffee}(\{coffee,\ \neg coffee\})) \\ &= \max(0.05,\ 0.05) = 0.05. \end{aligned}$$

Step 4 — *Translating from a core context node to the composite context node by a multivalued mapping*. In Fig. 5a, "cup, juice" is the composite node of "cup" and "juice". The relationships between them are certain and represented by a multivalued mapping. Mass functions on "cup" and "juice" are therefore translated onto "cup, juice".

$$m1_{(cup,\ juice)}(\{cup,\ juice\}) = m_{cup}(\{cup\}) = 0.95,$$
$$m1_{(cup,\ juice)}(\{(cup,\ juice), \neg(cup,\ juice)\}) = m_{cup}(\{cup, \neg cup\}) = 0.05;$$
$$m2_{(cup,\ juice)}(\{cup,\ juice\}) = m_{juice}(\{juice\}) = 0.855,$$
$$m2_{(cup,\ juice)}(\{(cup,\ juice), \neg(cup,\ juice)\}) = m_{juice}(\{juice, \neg juice\}) = 0.145.$$

The same is for the composite node "cup, water, kettle, tea/coffee" (in short "cwkt/c") with the context node "cup", "water", "kettle" and "tea/coffee" as the components on the evidential network of "Making hot drink".

$$m1_{cwkt/c}(\{cwkt/c\}) = m_{cup}(\{cup\}) = 0.95,$$
$$m1_{cwkt/c}(\{cwkt/c, \neg cwkt/c\}) = m_{cup}(\{cup, \neg cup\}) = 0.05;$$
$$m2_{cwkt/c}(\{\neg cwkt/c\}) = m_{water}(\{\neg water\}) = 0.85,$$
$$m2_{cwkt/c}(\{cwkt/c, \neg cwkt/c\}) = m_{water}(\{water, \neg water\}) = 0.15;$$
$$m3_{cwkt/c}(\{\neg cwkt/c\}) = m_{kettle}(\{\neg kettle\}) = 0.70,$$
$$m3_{cwkt/c}(\{cwkt/c, \neg cwkt/c\}) = m_{kettle}(\{kettle, \neg kettle\}) = 0.3;$$
$$m4_{cwkt/c}(\{\neg cwkt/c\}) = m_{tea/coffee}(\{\neg tea/coffee\}) = 0.95,$$
$$m4_{cwkt/c}(\{cwkt/c, \neg cwkt/c\}) = m_{tea/coffee}(\{tea/coffee, \neg tea/coffee\}) = 0.05.$$

Step 5 — *Summing up on a composite context node*. On the evidential network "Making cold drink", "cup, juice" is the composite node formed by "cup" and "juice". The two mass functions translated from "cup" and "juice" onto "cup, juice" as calculated in the previous step are then summed up by the equally weighted sum operator. The same applies to node "cup, water, kettle, tea/coffee" on the evidential network "Making hot drink".

$$\begin{aligned} m_{(cup,\ juice)}(\{(cup,\ juice)\}) &= \frac{1}{2}(m1_{(cup,\ juice)} + m2_{(cup,\ juice)})(\{(cup,\ juice)\}) \\ &= \frac{1}{2}(0.95 + 0.855) = 0.903, \end{aligned}$$
$$\begin{aligned} m_{(cup,\ juice)}(\{(cup,\ juice), \neg(cup,\ juice)\}) &= \frac{1}{2}(m1_{(cup,\ juice)} + m2_{(cup,\ juice)})(\{(cup,\ juice), \neg(cup,\ juice)\}) \\ &= \frac{1}{2}(0.05 + 0.145) = 0.097; \end{aligned}$$
$$\begin{aligned} m_{cwkt/c}(\{cwkt/c\}) &= \frac{1}{4}(m1_{cwkt/c} + m2_{cwkt/c} + m3_{cwkt/c} + m4_{cwkt/c})(\{cwkt/c\}) \\ &= \frac{1}{4}(0.95 + 0 + 0 + 0) = 0.238, \end{aligned}$$
$$\begin{aligned} m_{cwkt/c}(\{\neg cwkt/c\}) &= \frac{1}{4}(m1_{cwkt/c} + m2_{cwkt/c} + m3_{cwkt/c} + m4_{cwkt/c})(\{\neg cwkt/c\}) \\ &= \frac{1}{4}(0 + 0.85 + 0.7 + 0.95) = 0.625, \end{aligned}$$
$$\begin{aligned} m_{cwkt/c}(\{cwkt/c, \neg cwkt/c\}) &= \frac{1}{4}(m1_{cwkt/c} + m2_{cwkt/c} + m3_{cwkt/c} + m4_{cwkt/c})(\{cwkt/c, \neg cwkt/c\}) \\ &= \frac{1}{4}(0.05 + 0.15 + 0.3 + 0.05) = 0.137. \end{aligned}$$

Step 6 — *Translating from a composite context node or propagating from an accessory context node, to an activity node*. On network "Making cold drink", the mass function on "cup, juice" is translated to "Making cold drink". On network "Making hot drink", the mass function on "cup, water, kettle, tea/coffee" is translated to "Making hot drink", but the mass functions on "milk" and "sugar" is propagated by the evidential mappings to "Making hot drink".

$$m_{Making\ cold\ drink}(\{Making\ cold\ drink\}) = m_{(cup,\ juice)}(\{(cup,\ juice)\}) = 0.903,$$
$$m_{Making\ cold\ drink}(\{Making\ cold\ drink, \neg Making\ cold\ drink\}) = m_{(cup,\ juice)}(\{(cup,\ juice), \neg(cup,\ juice)\}) = 0.097;$$
$$m1_{Making\ hot\ drink}(\{Making\ hot\ drink\}) = m_{cwkt/c}(\{cwkt/c\}) = 0.238,$$
$$m1_{Making\ hot\ drink}(\{\neg Making\ hot\ drink\}) = m_{cwkt/c}(\{\neg cwkt/c\}) = 0.625;$$
$$m1_{Making\ hot\ drink}(\{Making\ hot\ drink, \neg Making\ hot\ drink\}) = m_{cwkt/c}(\{cwkt/c, \neg cwkt/c\}) = 0.137;$$
$$\begin{aligned} m2_{Making\ hot\ drink}(\{Making\ hot\ drink\}) &= m_{milk}(\{milk\}) * m(\{milk\} \rightarrow \{Making\ hot\ drink\}) \\ &= 0.095 \times 0.7 = 0.067, \end{aligned}$$

$$\begin{aligned}
& m2_{Making\ hot\ drink}(\{Making\ hot\ drink, \neg Making\ hot\ drink\}) \\
& \quad = m_{milk}(\{milk\}) * m(\{milk\} \to \{Making\ hot\ drink, \neg Making\ hot\ drink\}) \\
& \qquad + m_{milk}(\{\neg milk\}) * m(\{\neg milk\} \to \{Making\ hot\ drink, \neg Making\ hot\ drink\}) \\
& \qquad + m_{milk}(\{milk, \neg milk\}) * m(\{milk, \neg milk\} \to \{Making\ hot\ drink, \neg Making\ hot\ drink\}) \\
& \quad = 0.095 \times 0.3 + 0 \times 1 + 0.905 \times 1 = 0.933; \\
& m3_{Making\ hot\ drink}(\{Making\ hot\ drink\}) \ = \ m_{sugar}(\{sugar\}) * m(\{sugar\} \to \{Making\ hot\ drink\}) = 0 \times 0.4 = 0, \\
& m3_{Making\ hot\ drink}(\{Making\ hot\ drink, \neg Making\ hot\ drink\}) \\
& \quad = m_{sugar}(\{sugar\}) * m(\{sugar\} \to \{Making\ hot\ drink, \neg Making\ hot\ drink\}) \\
& \qquad + m_{sugar}(\{\neg sugar\}) * m(\{\neg sugar\} \to \{Making\ hot\ drink, \neg Making\ hot\ drink\}) \\
& \qquad + m_{sugar}(\{sugar, \neg sugar\}) * m(\{sugar, \neg sugar\} \to \{Making\ hot\ drink, \neg Making\ hot\ drink\}) \\
& \quad = 0 \times 0.6 + 0.95 \times 1 + 0.05 \times 1 = 1.0.
\end{aligned}$$

Step 7 — *Combining mass functions on an activity node*. Mass function $m1$, $m2$ and $m3$ on activity node "Making hot drink" calculated in the last step are from three different independent evidence sources, i.e. the sensor "sfri", the group of sensors "scup", "swat", "sket", "stea" and "scof", and the sensor "ssug", they are combined by Dempster's combination rule to achieve the consensus.

$$\begin{aligned}
& m_{Making\ hot\ drink}(\{Making\ hot\ drink\}) = m1_{Making\ hot\ drink} \oplus m2_{Making\ hot\ drink} \\
& \qquad \oplus m3_{Making\ hot\ drink}(\{Making\ hot\ drink\}) = 0.258, \\
& m_{Making\ hot\ drink}(\{\neg Making\ hot\ drink\}) = m1_{Making\ hot\ drink} \oplus m2_{Making\ hot\ drink} \\
& \qquad \oplus m3_{Making\ hot\ drink}(\{\neg Making\ hot\ drink\}) = 0.609, \\
& m_{Making\ hot\ drink}(\{Making\ hot\ drink, \neg Making\ hot\ drink\}) = m1_{Making\ hot\ drink} \oplus m2_{Making\ hot\ drink} \\
& \qquad \oplus m3_{Making\ hot\ drink}(\{Making\ hot\ drink, \neg Making\ hot\ drink\}) = 0.133.
\end{aligned}$$

Calculating Bel and Pls: From mass function on "Making cold drink" and on "Making hot drink", we can calculate the beliefs over the claim "Making cold drink" and "Making hot drink" as follows.

$$\begin{aligned}
& Bel(\{Making\ cold\ drink\}) = m(\{Making\ cold\ drink\}) = 0.903, \\
& Pls(\{Making\ cold\ drink\}) = m(\{Making\ cold\ drink\}) \\
& \qquad + m(\{Making\ cold\ drink, \neg Making\ cold\ drink\}) = 0.903 + 0.097 = 1.0; \\
& Bel(\{Making\ hot\ drink\}) = m(\{Making\ hot\ drink\}) = 0.258, \\
& Pls(\{Making\ hot\ drink\}) = m(\{Making\ hot\ drink\}) \\
& \qquad + m(\{Making\ hot\ drink, \neg Making\ hot\ drink\}) = 0.258 + 0.133 = 0.391.
\end{aligned}$$

Bel on "Making cold drink" is 0.903 with a value of 0.645 greater than that on "Making hot drink", and (*Pls*–*Bel*) is smaller on "Making cold drink" than "Making hot drink". These results indicate that with a high confidence we can identify that the activity "Making cold drink" has been performed in the kitchen.

In an evidential network of activities–activity, belief distribution on the node at top-most layer is calculated along the network from belief distributions on nodes at the bottom layer. For the first type of activities–activity networks, the belief of an activity is the maximum of beliefs over its sub-activities at the next layer below. With the second type of activities–activity networks, it is the equally weighted sum of sub-activities one layer down the network.

On the evidential network of "Making drink" in Fig. 3a, "Making cold drink" and "Making hot drink" are the two alternative sub-activities of "Making drink" activity. With the beliefs on "Making cold drink" and "Making hot drink" calculated above, the belief about that the inhabitant is making drink is calculated by the maximization operator as follows.

$$\begin{aligned}
Bel(Making\ drink) &= \max(Bel(Making\ cold\ drink),\ Bel(Making\ hot\ drink)) \\
&= \max(0.903,\ 0.258) = 0.903, \\
Pls(Making\ drink) &= \max(Pls(Making\ cold\ drink),\ Pls(Making\ hot\ drink)) \\
&= \max(1.0,\ 0.391) = 1.0.
\end{aligned}$$

We are confident that "Making cold drink" has been performed, consequently at the abstract level we strongly believe that the inhabitant has performed "Making drink" in the kitchen.

5.3. Sensor deployment

Some sensors are used for recognising a single activity whereas others can contribute to several activities. For example, in the case study in the previous section, sensor *swat*, *sket*, *stea*, *scof* and *ssug* are used by "Making hot drink". However,

Table 5
Bels on "Making cold drink" and "Making hot drink" when one sensor was active

Name	*Bel(Making cold drink)*	*Bel(Making hot drink)*	*Bel(Making hot drink) − Bel(Making cold drink)*
sket	0	0.175	+0.175
swat	0	0.213	+0.213
scup	0.475	0.238	−0.238
stea	0	0.238	+0.238
scof	0	0.238	+0.238
sfri	0.428	0.067	−0.361
ssug	0	0.380	+0.380

Table 6
Bels on "Making cold drink" and "Making hot drink" when two sensors were active

Name	*Bel(Making cold drink)*	*Bel(Making hot drink)*	*Bel(Making hot drink) − Bel(Making cold drink)*
scup-stea	0.475	0.475	+0
sfri-ssug	0.428	0.421	−0.006
scup-swat	0.475	0.450	−0.025
scup-ssug	0.475	0.527	+0.052
scup-sket	0.475	0.413	−0.063
sfri-sket	0.190	0.504	+0.314
sfri-swat	0.190	0.527	+0.337
sfri-stea	0.190	0.540	+0.352
swat-sket	0	0.388	+0.388
sket-stea	0	0.413	+0.413
swat-stea	0	0.450	+0.450
sket-ssug	0	0.489	+0.489
swat-ssug	0	0.512	+0.512
stea-ssug	0	0.527	+0.527
scup-sfri	0.903	0.257	−0.645

Table 7
Bels on "Making cold drink" and "Making hot drink" when three Sensors including *stea* and *ssug* were active

Name	*Bel(Making cold drink)*	*Bel(Making hot drink)*	*Bel(Making hot drink) − Bel(Making cold drink)*
sket-scup-ssug	0	0.636	+0.636
swat-stea-ssug	0	0.659	+0.659
scup-stea-ssug	0.475	0.675	+0.200
sfri-stea-ssug	0.190	0.716	+0.526

Table 8
Bels on "Making hot drink" along with the different reliability discount rates of sensor *sket*

Reliability discount rate r	0.3	0.4	0.5	0.6	0.7	0.8
Bel(Making hot drink)	0.896	0.899	0.900	0.902	0.904	0.905

sensor *scup* and *sfri* are used by both activities "Making cold drink" and "Making hot drink". As such sensor activations can have a significant impact on recognizing and distinguishing between these two activities.

Table 5 gives belief values of performing an activity when only one single sensor is working. All belief values are less than 0.5 and the differences of belief values between two activities are even smaller. This result indicates that neither of the activities can be recognized with a high degree of confidence by only using a single sensor.

Table 6 presents beliefs related to different combinations of two sensors. From the table, we can see *Bel(Making cold drink)* is 0.903 (very close to 1) with a value of 0.645 greater than *Bel(Making hot drink)* when deploying sensor *scup* and *sfri*. With these two sensors "Making cold drink" can be identified. For "Making hot drink" it is not possible with any combinations of two sensors to provide a reasonable degree of belief. However, the combination of *stea* and *ssug* does favour "Making hot drink" more than "Making cold drink". These simulations provide an indication on the operational bounds of the model and can be used from a reverse engineering perspective to set the threshold of the minimum number of sensors required before the environment should be deemed non-functional.

In Table 7, we investigate the impact of deploying a third sensor in conjunction with sensors *stea* and *ssug*. The aim was to investigate if adding another sensor will strengthen the belief of "Making hot drink". The results presented in the table shows that indeed the belief is increased with the inclusion of the additional sensor.

In addition to considering the number of sensors which are required to make a reliable assessment of the context it is also possible to consider the impact of reliability of a given sensor on the overall decision making process. Suppose all sensors except *sket* are active. The sensor *sket* is a tilt sensor. Its reliability very much depends on what angle has it been held when pouring water into the cup. Table 8 shows the different reliability discount rates of sensor *sket* and the subsequent changes to the belief value of "Making hot drink". Although these values are high it is apparent that as its reliability discount rate increases, the overall Belief values of the final decision increase. The correlation reveals the inactive state of the sensor *sket* has been discounted most as a result of the impact on the belief over "Making hot drink" while the reliability decreases resulting in the increased belief on the activity.

6. Related work

Over the last several years, research conducted within the area of activity monitoring has become very active due to the demands for smart environment technology to offer support and improve the quality of life for individuals with disabilities and those wishing to age in place [18]. A large number of research projects have studied the use of various sensor based technologies to facilitate an assisted living environment. For example, MavHome [19–21] is a project motivated to support the automation of the intelligent environment. Within this project motion sensors are deployed to determine the location of the inhabitant. This location based information is subsequently considered with other sensory based information such as temperature, atmospheric moisture measurements etc. All of this information can then be used to make an inference about the environment and the status of the inhabitant within the environment. As a direct result the surrounding environment itself can then support the automatic control of devices with the goal of reducing the inhabitant's interaction with the environment itself. The Adaptive Home [22] is another research example which uses sensors to determine ideal settings for lights and fans within the home. Lately simple low-cost state-change sensors, typically common to home security systems, have been considered to be suitable solutions to be used in smart home environments due to their perceived low levels of invasiveness.

A limited number of research studies have been presented which may be considered to be similar to the work presented in the current paper in relation to the management of sensor uncertainty in smart home environments. In [4], radio-frequency-identification (RFID)tags are placed on objects of interest to detect object interactions. This work has shown the promise which 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 elderly or disabled people in terms of their perceived desire to use such a solution. Tapia et al. [5] report the use of a set of simple sensors to recognise activities performed by an inhabitant. Their technique is based on the identification of patterns in terms of how the inhabitant move things. In [2], simultaneous tracking and activity recognition (STAR) was developed for room-level tracking and activity recognition. Although this work has similarities with the work presented in the current study, the system is limited to whether or not an inhabitant is moving. Other research efforts have demonstrated some achievements in terms of recognising activities. The majority of them have at their core a probabilistic reasoning method to, in the first instance learn behaviour patterns and follow this to use the method to recognise activities. A potential drawback of such an approach is the fact studies of behavioural patterns require large amounts of activity historical data. Although there have been reports addressing the sequential issue of object interactions involved in performing an activity for identifying individuals, there has been little exploration focused towards the uncertainty of sensor information and how to cope with. It is therefore possible to present that in comparison with previous studies our current framework has introduced an innovative concepts through deploying Evidence Theory for reasoning uncertainty within the context of smart environments. The novelty of our approach is that it can model uncertainty at a low sensor level and also has the ability of managing the reliability of the system and therefore ensuring safety of the environment. In addition, it addresses the trust that is a less explored but important issue within the realms of sensor management for smart homes promoting the notion of 'aging in place'.

7. Summary and future work

In this paper we have introduced a framework within which information management within Smart Homes can be processed to support the decision making process of activity recognition. Within our work we have shown how unreliable sensor information can be accommodated for through the use of a number of information management tools for example the Dempster–Shafer theory of evidence and the equally weighted sum operator. We have proposed evidential networks to represent the hierarchy of inferring context-aware activities based on sensor data. Six evidential operations have been formalised for activity inference on evidential networks which can accommodate the fusion of different types and sources of information. Within the paper we demonstrated the concepts of this work through a worked example and consider that this may be useful in terms of a tutorial type exercise for the tools we have proposed. We have also shown that the numbers of sensors and the reliability of each sensor have a significant impact on the overall result in terms of the decision making process. This is a useful result and can be used to support two key features within information management for Smart Homes. On the one hand it is possible to provide a degree of confidence in the result the automatic processing proposes. Information from other sources can be used to support the overall end result hence reducing the impact of a specific sensor failure. On the other hand, the framework can be used to identify thresholds of the minimum numbers of sensors which should be deployed within the environment at design time to provide sufficient information to discriminate between a number of activities.

Currently we are developing simulations of activities of daily living in a smart home which have been used to validate our evidential approach of activity inference. This is appreciated to be a limitation, in terms of not validating with real data, however plans are currently in place to test the framework within a real smart home environment.

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Xin Hong holds a B.Sc. honours degree from Fudan University in China and a Ph.D. in Artificial Intelligence from the University of Ulster in the UK. She is currently a research associate in the School of Computing and Mathematics at the University of Ulster. Her research interests include reasoning under uncertainty, intelligent diagnosis, pattern recognition, information fusion. Her recent research activities focus on technology development and applications for improving quality of life in independent living for elderly.

Chris Nugent received a Bachelor of Engineering in Electronic Systems and D.Phil. in Biomedical Engineering both from the University of Ulster. His current research within biomedical engineering addresses the themes of Technologies to Support Independent Living, Medical Decision Support Systems specifically in the domain of computerised electrocardiology, the development of Internet based healthcare models and wearable healthcare systems.

Dr. Maurice Mulvenna is a Senior Lecturer in the School of Computing and Mathematics at the University of Ulster. He has over 120 publications in artificial intelligence and pervasive computing. He is Editorial Review Board member for the International Journal of Ad Hoc and Ubiquitous Computing and the International Journal of Advanced Intelligence Paradigms, winner of 2001 European IST Grand Prize and grant holder on research and innovation projects worth around $50M. He is a member of IEEE, senior member of ACM, and a chartered member of the BCS.

Sally McClean is currently Professor of Mathematics in the School of Computing and Information Engineering at the University of Ulster. She took her first degree in Mathematics at Oxford University, then a M.Sc. at Cardiff University in Mathematical Statistics and Operational Research followed by a Ph.D. at the University of Ulster. Her research interests are in mathematical modelling, applied probability, multivariate statistical analysis and applications of mathematical and statistical methods to computer science, particularly database technology. She has published and edited five books and has over 200 research papers in these subject areas. She is a Fellow of the Royal Statistical Society, a member of the IEEE Computer Society, a member of the Operational Research Society, and an Associate Fellow of the Institute of Mathematics and its Applications.

Bryan Scotney received a BSc in Mathematics from the University of Durham, UK in 1980, and a Ph.D. in Mathematics from the University of Reading, UK in 1985. He is Professor of Informatics and currently Director of the Computer Science Research Institute at the University of Ulster. He has over 150 publications in total, spanning Statistical Databases, Image Processing, and Mathematical Computation. He has published widely in the area of Knowledge Discovery and Data Mining, focusing on solving the problems of integration of heterogeneous data from distributed sources, particularly where the information available is imprecise and / or uncertain. Much of this work has been supported by funding from four EU FP5 projects (with McClean) to address issues of harmonisation of Official Statistics. Most recently, he is Co-Investigator on EPSRC award EP/F030118/1. His early research interest in computational mathematics is now focussed onto the area of digital image processing; this work is concerned mainly with methodological development, but also has application to machine vision and medical imaging. He is currently President of the Irish Pattern Recognition and Classification Society.