Chapter 2

A Possibilistic Approach for Activity Recognition in Smart Homes for Cognitive Assistance to Alzheimer's Patients

Patrice C. Roy [1], Sylvain Giroux [1], Bruno Bouchard [2], Abdenour Bouzouane [2], Clifton Phua [3], Andrei Tolstikov [4], and Jit Biswas [4]

[1] *DOMUS Lab., Université de Sherbrooke, J1K 2R1, Canada*
[2] *LIARA Lab., Université du Québec à Chicoutimi, G7H 2B1, Canada*
[3] *Data Mining Dep., I2R, 138632, Singapore*
[4] *Networking Protocols Dep., I2R, 138632, Singapore*

Corresponding author: patrice.c.roy@usherbrooke.ca

Abstract

Providing cognitive assistance to Alzheimer's patients in smart homes is a field of research that receives a lot of attention lately. The recognition of the patient's behavior when he carries out some activities in a smart home is primordial in order to give adequate assistance at the opportune moment. To address this challenging issue, we present a formal activity recognition framework based on possibility theory and description logics. We present initial results from an implementation of this recognition approach in a smart home laboratory.

2.1 Introduction

A major development in recent years is the importance given to research on ambient intelligence in the context of recognition of activities of daily living. Ambient intelligence, in opposition to traditional computing where the desktop computer is the archetype, consists of a new approach based on the capacities of mobility and integration of digital systems in the physical environment, in accordance with ubiquitous computing. This mobility and this fusion are made possible by the miniaturization and reduced power consumption of electronic components, the omnipresence of wireless networks and the fall of production costs. This allows us to glimpse the opportune composition of devices and services of all kinds on an infrastructure characterized by a granularity and variable geometry, endowed with faculties of capture, action, treatment, communication and interaction [1, 2].

One of these emerging infrastructures is the concept of smart home. To be considered as intelligent, the proposed home must inevitably include techniques of activity recognition, which can be considered as being the key to exploit ambient intelligence. Combining ambient assisted living with techniques from activity recognition greatly increases its acceptance and makes it more capable of providing a better quality of life in a non-intrusive way. Elderly people, with or without disabilities, could clearly benefit from this new technology [3].

Activity recognition, often referred as plan recognition, aims to recognize the actions and goals of one or more agents from observations on the environmental conditions. The plan recognition problem has been an active research topic in artificial intelligence [4] for a long time and still remains very challenging. The keyhole, adversarial or intended plan recognition problem [5] is usually based on a logic or probabilistic reasoning for the construction of hypotheses about the possible plans, and on a matching process linking the observations with some activity models (plans) related to the application domain. Prior work has been done to use sensors, like radio frequency identification (RFID) tags attached to household objects [6], to recognize the execution status of particular types of activities, such as hand washing [7], in order to provide assistive tasks like, for instance, reminders about the activities of daily living (ADL).

However, most of this research has focused on probabilistic models such as Markovian models and Bayesian networks. But there is some limitations with probability theory. Firstly, the belief degree concerning an event is determined by the belief degree in the contrary event (additivity axiom). Secondly, the classical probability theory (single distribution) cannot model (full or partial) ignorance in a natural way [8]. An uniform probability distribution on an event set better express randomness than ignorance, i.e. the equal chance of occurrence of events. Ignorance represents the fact that, for an agent, each possible event's occurrence is equally plausible, since there is no evidence that is available to support any of them by the lack of information. Hence, one of the solutions to this kind of problem is possibility theory [9], an uncertainty theory devoted to the handling of incomplete information.

Contrary as in probability theory, the belief degree of an event is only weakly linked to the belief degree of the contrary event. Also, the possibilistic encoding of knowledge can be purely qualitative, whereas the probabilistic encoding is numerical and relies on the additivity assumption. Thus, possibilistic reasoning, which is based on max and min operations, is computationally less difficult than probabilistic reasoning. Unlike probability theory, the estimation of an agent's belief about the occurrence of event is based on two set-functions. These functions are the possibility and necessity (or certainty) measures. Finally, instead of using historical sensors data like others probabilistic approaches, we use partial beliefs from human experts concerning the smart home occupant's behaviors, according to plausible environment's contexts. Since the recognition system can be deployed in different smart homes and that their environments are dynamics, it is more easier to obtain an approximation of the occupant's behaviors from human experts' beliefs than learning the behaviors in different smart home's settings. By using general descriptions of environmental contexts, it is possible to keep the same possibility distributions for different smart home's settings. Consequently, another advantage of possibility theory is that it is easier to capture partial belief concerning the activities' realizations from human experts, since this theory was initially meant to provide a graded semantics to natural language statements [10].

In the DOMUS [11] and LIARA research labs, we use possibility theory to address the problem of behavior recognition, where the observed behavior could be associated to cognitive errors. These recognition results are used to identify the various ways a smart home may help an Alzheimer's occupant at early-intermediate stages to carry out his ADLs. This context increases the recognition complexity in such a way that the presumption of the observed agent's coherency, usually supposed in the literature, cannot be reasonably maintained. We propose a formal framework for activity recognition based on description logic and possibility theory, which transforms the recognition problem into a possibilistic classification of activities. The possibility and necessity measures on behavior hypotheses allow us to capture the fact that, in some activities, erroneous behavior is as possible as normal behavior. Hence, in a complete ignorance setting, both behavior types are possible, although each type is not necessarily the one being carried out.

The chapter is organized as follows. Section 2.2 presents an overview of Alzheimer's disease. Section 2.3 presents an overview of some related approaches for activity recognition in smart homes. Section 2.4 presents the possibilistic activity recognition model that we propose. Section 2.5 presents the results of our implementation's experimentation based on real data from the AIHEC project at the Singapore's *Institute for Infocomm Research*. Furthermore, this section also presents a discussion of our results according to related recognition approaches. Finally, we conclude the paper, mentioning future perspectives of this work.

2.2 Overall Picture of Alzheimer's disease

Alzheimer's disease, or senile dementia of the Alzheimer's type (SDAT), is a disease of the brain characterized by progressive deterioration of intellectual abilities (cognitive skills and memory) of the carrier [12]. This disease evolves slowly over a period of seven to ten years. The capacity to carry out normal activities (reading, cooking, ...) decreases gradually, just like the capacity to produce judgments and answers that are suitable to everyday life problems. The cognitive decline of this dementia can be classified into seven degeneration stages, referring to the global scale of deterioration stages (GDS) of the primary cognitive functions of an individual [13]. The intermediate stages of the disease (3–5) constitute the longest portion of the degeneration process. The main symptoms of these stages are related to planning problems caused by sporadic memory losses, the weakening of the executive functions, and by concentration troubles that decreases attention to a particular task. A distraction (e.g., a phone call, an unfamiliar sound, ...) or a memory lapse can hinder the patient in accomplishing his activity, leading him to carry out the actions attached to his activity in the wrong order, to skip some steps of his activity, or to carry out actions that are not even related to his initial objectives [14]. However, the patient's capacity to perform a simple action (without many steps) remains relatively unaffected [13].

In these intermediate stages, patients suffering from Alzheimer's disease do not need to be totally taken in charge. They need a supervision and a specific intervention on the part of an assistant. When continuous support is provided to Alzheimer's patients in the form of cognitive assistance, the degeneration process of the disease is slowed down, making it possible for a patient to remain at home longer [15]. Hence, the development of an artificial agent able to assist Alzheimer's patients at an intermediate stage, when the situation require it, would make it possible to decrease the workload carried by natural and professional caregivers. This type of technology has the potential to delay the fateful moment of institutionalization of patients by alleviating some caregiver duties and by giving a partial autonomy to patients. In the longer term, it will also constitute an economically viable solution to the increasing cost of home care services. Consequently, the research in this field will have important social and economic impacts in the future.

When an Alzheimer's patient performs a task requiring cognitive skills, it is possible that inconsistencies become present in his behavior [16]. In the plan recognition problem, the presence of these inconsistencies results in erroneous execution of activities (erroneous plans), according to certain types of particular errors. In a real context, the people without such impairment can also act in an inconsistent manner, but on a level less important and

regular than that of an Alzheimer's patient. The main difference is that a healthy person is usually able to recognize his behavioral errors and corrects them in order to achieve his initial goals. In contrast, an Alzheimer's patient will act incoherently, even while performing familiar tasks, and his behavior will become more inconsistent as the disease evolves. Also, we must consider that hypotheses concerning the behavior of the observed patient can fall into the scope of reactive recognition [17]. More precisely, a patient at an early stage is not necessarily making errors; he can simply temporarily stop the execution of an activity plan to begin another one in the middle of an activity realization. This way, the patient deviates from the activity originally planned by carrying out multiple *interleaved* activities, in order to react to the dynamic of his environment [13]. This is coherent behavior.
Starting from this point, if one wishes to establish an effective recognition model capable of predicting any type of correct or incorrect behavior, the confrontation of these two investigations, erroneous versus interleaved, constitutes a necessity that is in conformity with reality, but which is also paradoxical. The detection of a new observed action, different from the expected one, cannot be directly interpreted as an interruption of the plan in progress, in the objective of pursuing a new goal. In fact, this action can be the result of an error on the part of a mentally impaired patient, or a healthy but fallible human operator. However, this unexpected action is not inevitably an error, even in the most extreme case where the patient is at an advanced stage of his disease. This context raises a recognition dilemma that is primarily due to the problem of completing the activity plan library, which of course cannot be complete in any domain. This dilemma is important in a context of cognitive deficiency such as Alzheimer's disease. A person suffering from Alzheimer's disease will tend to produce more errors, induced by his cognitive deficit, than a healthy person when he carries out his activities of daily living. Like healthy people, Alzheimer's patients carry out activities in an interleaved way. Consequently, the consideration of interleaved and erroneous realizations that could explain the current behavior of an Alzheimer's patient is important.

2.3 Related Work

In the last two decades, the AI community produced much fundamental work addressing the activities recognition issue. This work can be divided into three major trends of research. The first one comprises works based on logical approaches [18], which consist of developing a theory, using first order logic, for formalizing the recognition activity into a deduction or an abduction process. The second trend of literature is related to probabilistic models [19, 20], which define activity recognition in terms of probabilistic reasoning, based primarily on some Markovian models or on Bayesian networks. The third trend covers emerging hybrid approaches [21–23] that try to combine the two previous avenues of research. It considers activity recognition as the result of a probabilistic quantification on the hypotheses obtained from a symbolic (qualitative) algorithm. A significant amount of the fundamental work of these three trends was concerned with applicative contexts different from AmI, supposing most of the time that the observed entity always acts in a coherent way, avoiding many important issues such as recognizing erroneous behavior associated with some activities' realization. Currently, there are many research groups working on assistive technologies that try to exploit and enhance those activity recognition models in order to concretely address the activities recognition problem in a AmI context for cognitive assistance in a smart environment. The remainder of this section presents a non-exhaustive list of applications, exploiting activity recognition, related to this context of cognitive assistance in a smart environment.

The MavHome (Managing an Adaptive Versatile Home) project [24] is a smart home based on a multi-agents architecture, where each agent perceives its state through sensors and acts, in a rational way, on the smart home environment, in order to maximize the inhabitants' comfort and productivity. For instance, we can have devices that are automatically controlled according to the behavior prediction and the routine and repetitive task patterns (data mining) of the inhabitant. The location prediction uses the *Active Lezi* algorithm, which is based on the LZ78 compression algorithm. It uses information theory's principles to process historical information sequences and thereby learn the inhabitant's likely future positions. This algorithm has been tested on synthetic and real data, with an accuracy of 64 % and 55 % respectively. By adding temporal rules, based on Allen's temporal logic, to this algorithm, the synthetic data set and real data set prediction accuracies increase to 69 % and 56 % respectively [25]. The inhabitant action prediction is based on the SHIP (Smart Home Inhabitant Prediction) algorithm, which considers the most recent sequence of actions (commands to devices issued by the inhabitants) with those in the inhabitant's history, in order to predict the inhabitant interactions (commands to devices) with the smart home. The SHIP algorithm prediction accuracy on real data set is 53.4 %. The ED (Episode Discovery) algorithm, based on data mining techniques, is used to identify significant episodes (set of related device events that can be partially/totally ordered or not) that are present in the inhabitant history. Those episodic patterns allow them to minimize the length of the input stream by using the minimum description length principle (MDL), where each instance of a pattern is replaced with a pointer to the pattern definition. By combining the Active Lezi and the ED algorithms, the prediction accuracy on the real data set is improved by 14 %. These results indicate the effectiveness of these algorithms in predicting the inhabitant's activities. Nevertheless, an algorithmic analysis in terms of response time is indispensable, before more conclusions can be drawn.

The Gator Tech Smart House developed by the University of Florida's Mobile and Pervasive Computing Laboratory [26] has been used to conduct several cutting-edge research works aiming to create the technology, framework and systems that will make happen the concept of assistive environments benefiting the growing elderly and disabled population around the world. That research includes personal assistant, sensors, recognition systems, localization and tracking technology, robotic technology, ... One of their recent projects, closely related to our research on activity recognition, is on a health platform that monitors the activity, diet and exercise compliance of diabetes patients [27]. The activity recognition is based on Hidden Markov Models (HMM), one for each task to recognize. By using the sensor data, the activity recognition is able to quantitatively evaluate the completion status of an activity and qualitatively evaluate the steps that are missing. By using real data from the CASAS smart apartment at Washington State University [28], five tasks' HMMs, trained on those data, were able to achieve a recognition accuracy of 98 % on this real data set. Concerning erroneous behavior, the tasks' HMMs were able to detect errors (missing or wrongly carried out steps) of 19 participants.

The Smart Environments Research Group at Ulster University [29] works on different aspects of cognitive assistance in smart homes. In one recent project [30], they proposed a solution to model and reason with uncertain sensor data with the aim of predicting the activities of the monitored person. Their recognition approach is based on the Dempster-Shafer (DS) theory of evidence [31], an alternative theory for uncertainty that bridges fuzzy logic and probabilistic reasoning and uses belief functions. The use of DS allows them to fuse uncertain information detected from sensors for activities of daily living (ADL), which are monitored within a smart home, by using an ordinal conditional function and merging approaches to handle inconsistencies within knowledge from different sources. It allows them to combine evidence from various sources and arrive at a degree of belief (represented by a belief function) that takes into account all the available evidences. They use background knowledge (such as a caregiver's diary) to resolve any inconsistencies between the predicted (recognized) action and the actual activities. The strength of this recognition method is that it allows one to capture the fact that sensors provide only imprecise data and that some informations or sources are, a priori, more reliable than others. However, the weakness of approaches based on DS theory is that the complexity of combining evidences is related to the number of focal elements used by the belief functions, which can be high in a real smart home context. Also, we can note that even if validation based on simulation is planned by the team, this approach has never been tested yet on real data.

The research team led by Mihailidis [32] has developed COACH (Cognitive Orthosis for Assisting aCtivities in the Home), which is a prototype aiming to actively monitor an Alzheimer's patient attempting a specific task, like the hand washing activity, and to offer assistance in the form of guidance (prompts or reminders) when it is most appropriate. The system uses a camera to obtain as observations a set of state variables, such as the location of patient's hands, in order to determine the completion status of the task according to a handcrafted model of the activity. If a problem occurs, such as an error being made or the patient being confused, the system computes the most appropriate solution to finish the task, using a probabilistic approach based on Partially Observable Markov Decision Processes (POMDP) [33], and then guides the person in the completion of his activity. Experiments and clinical trials with the COACH system, including Alzheimer's patients and therapists, have shown very promising results in monitoring a single pre-established activity (Hand Washing) and in providing adequate assistance at the right moment [15]. However, a major limitation of the prototype is presuming that the system already knows which activity is in progress, and thus supposing that it can only have one on-going task at a time.

The Barista system [34] is a fine-grained ADL recognition system that uses object IDs to determine which activities are currently carried out. It uses Radio Frequency Identification (RFID) tags on objects and two RFID gloves that the user wears in order to recognize activities in a smart home. With object interactions detected with the gloves, a probabilistic engine infers activities according to the probabilistic models of activities, which were created from, for instance, written recipes. The activities are represented as sequences of activity stages. Each stage is composed of the objects involved, the probability of their involvement, and, optionally, a time to completion modelled as a Gaussian probability distribution. The activities are converted into Dynamic Bayesian Networks (DBN) by the probabilistic engine. By using the current sub-activity as a hidden variable and the set of objects seen and time elapsed as observed variables, the engine is able to probabilistically estimate the activities from sensor data. The engine was also tested with hidden Markov models (HMM) in order to evaluate the accuracy precision of activity recognition [20].

These models were trained with a set of examples where an user performs a set of interleaved activities. However, some HMM models perform poorly, and the DBN model was able to identify the specific on-going activity with a recognition accuracy higher than 80 %. This approach is able to identify the currently carried out ADL in a context where activities can be interleaved. However, this approach does not take into account the erroneous realization of activities, because the result of the activity recognition is the most plausible on-going ADLs.

2.4 Possibilistic Activity Recognition Model

Our activity recognition model is based on possibility theory and on description logics (DL) [35]. DL is a family of knowledge representation formalisms that may be viewed as a subset of first-order logic, and its expressive power goes beyond propositional logic, although reasoning is still decidable. In our model, the activity recognition process can be separated into three agents: the environment representation agent, the action recognition agent, and the behavior recognition agent. The environment recognition agent infers the plausible contexts that could explain the current observed environment's state resulting from an action realization. This observed state, which can be partial, is obtained from information retrieved from the smart home's sensor events. Our approach assumes that there is an event manager agent that collects sensor events and evaluates if an action was carried out by the smart home's occupant.

The action recognition agent infers the most plausible low-level action that was carried out in the smart home according the change observed in the environment's state. In accordance with a possibilistic action formalization and to the set of plausible environment contexts that could represent the observed environment's state resulting from an action realization, the action recognition agent selects in the action ontology the most possible and necessary recognized action that could explain the environment changes.

The behavior recognition agent infers hypotheses about the plausible high-level occupant's behavior related to the accomplishment, in an erroneous or coherent way, of some intended activities. When the smart home's occupant performs some activities, its behavior, which could be coherent or erroneous, is observed as a sequence of actions. According to the plausible sequence of observed actions and to a possibilistic activity formalization, the behavior recognition agent infers a behavior hypothesis set and evaluates the most possible and necessary hypotheses in order to send them to an assistive agent. Our approach assumes that there is a smart home's assistive agent that uses information from different agents, including the behavior recognition agent, in order to plan, if needed, a helping task, through some smart home's effectors, towards the smart home's occupant.

2.4.1 *Environment Representation and Context*

In our model, knowledge concerning the resident's environment is represented by using a formalism in DL. By using the open world assumption, it allows us to represent the fact that knowledge about the smart home environment's state is incomplete (partially observable). Smart home environment's states are described with terminological (concepts and roles) and assertional (concepts' instances and relations between them) axioms. DL assertions describing the environment's state resulting from an action realization are retrieved from information sent by an event manager, which is responsible to collect sensor events and to infer if an action was carried out. In order to reduce the size of plausible states to consider for action and activity formalizations, our approach use low-level environment's *contexts*.

A context c is defined as a set of environmental properties that are shared by some states s in the environment's state space S. More formally, a context c can be interpreted as a subset of the environment's state space ($c^{\mathscr{I}} \subseteq S$) [1], where states of this subset share some common environmental properties described by the context assertions. For instance, the context where the occupant is in the kitchen, the pantry door is open, and the pasta box is in the pantry can matches several possible states of the smart home environment. It is possible to partition the environment's state space with a set of contexts. Since the observation of the current state is partial, it is possible to have multiple contexts that could explain the current observed state. Thus, our approach must infer, by using a reasoning system, the plausible contexts that can be satisfied by the current observed state's assertions.

2.4.2 *Action Recognition*

In order to infer hypotheses about the observed behavior of the occupant when he carries out some activities in the smart home environment, we need to recognize the sequence of observed actions that were performed in order to achieve the activities' goals. In our model, we formalize action according to a context-transition model where transitions between contexts resulting from an action realization are quantified with a possibility value.

Proposition 2.1. *A* possibilistic action *a is a tuple* $(C_{pre_a},\ C_{post_a},\ \pi_{init_a},\ \pi_{trans_a})$, *where*

[1] $\cdot^{\mathscr{I}}$ is an interpretation function that assigns to a context C a subset of the interpretation domain $\Delta^{\mathscr{I}} = S$ (the interpretation of c corresponds to a nonempty set of states).

C_{pre_a} and C_{post_a} are context sets and π_{init_a} and π_{trans_a} are possibility distributions on those context sets.

C_{pre_a} is the set of possible contexts before the action occurs (pre-action contexts), C_{post_a} is the set of possible contexts after the action occurs (post-action contexts), π_{init_a} is the possibility distribution on C_{pre_a} that an environment's state in a particular context $c_i \in C_{pre_a}$ allows the action to occur, and π_{trans_a} is the transition possibility distribution on $C_{pre_a} \times C_{post_a}$ if the action does occur.

The action library, which contains the set of possible actions $\mathscr{A}$ that can be carried out by the occupant, is represented with an action ontology $(\mathscr{A}, \sqsubseteq_{\mathscr{A}})$, where each action is partially ordered according to an action subsumption relation $\sqsubseteq_{\mathscr{A}}$, which can be seen as an extension of the concept subsumption relation $\sqsubseteq$ of DL [35]. This order relation, which is transitive, allows us to indicate that a concept is more general than (subsumes) another concept. In other words, a subsumed concept is a subset of the subsumer concept. According to the action subsumption relation $\sqsubseteq_{\mathscr{A}}$, if an action subsumes another one, its possibility values are at least as possible as the action subsumed. For instance, since $OpenDoor$ subsumes $OpenDoorPantry$, then the $OpenDoor$ possibility is greater or equal than the $OpenDoorPantry$ possibility, since $OpenDoor$ is more general than $OpenDoorPantry$.

This action ontology is used when we need to evaluate the most possible action that could explain the changes observed in the smart home environment resulting from an action realization by an observed occupant. At the same time, we evaluate the next most possible action that can be carried out according to the current state of the smart home environment. In order to evaluate the recognition and prediction possibilities on the action ontology at a time t, which is associated to a time value that indicates the elapsed time since the start of the recognition process, we need to use the *observation* obs_t of the current environment state, represented by a set of DL assertions. This observed state can be partial or complete according to the information that can be retrieved from the environment's sensors. Furthermore, each observation timestamp $t \in \mathscr{T}_s$ is associated with a time value $t_i \in \mathscr{T}$ that indicates the elapsed time (in minutes, seconds, ...) since the start of the recognition process.

From this observation obs_t, we need to evaluate the set of contexts c_i that are entailed by this observation ($obs_t \models c_i$). Since the environment can be partially observable, multiple entailed contexts are possible. Those entailed contexts are then used to evaluate the possibility distributions for the prediction and recognition of actions. The action prediction possibility distribution π_{pre_t} on $\mathscr{A}$ indicates, for each action, the possibility that the action could be the next one carried out according to the current state observed by obs_t. Thus, for each action $a \in \mathscr{A}$, the prediction possibility $\pi_{pre_t}(a)$ is obtained by selecting the maximum value among the initiation possibilities $\pi_{init_a}(c_i)$ for the pre-action contexts $c_i \in C_{pre_a}$ that are entailed by the current observation ($obs_t \models c_i$). The action recognition possibility distribution π_{rec_t} on $\mathscr{A}$ indicates, for each action, the possibility that the action was carried out according to the previous and currents states observed by obs_{t-1} and obs_t. Thus, for each action $a \in \mathscr{A}$, the recognition possibility $\pi_{rec_t}(a)$ is obtained selecting the maximum value among the transition possibilities $\pi_{trans_a}(c_i, c_j)$ for the pre-action contexts $c_i \in C_{pre_a}$ and post-action contexts $c_j \in C_{post_a}$ that are entailed by the previous and current observations ($obs_{t-1} \models c_i$ and $obs_t \models c_j$).

With this action recognition possibility distribution π_{rec_t}, we can evaluate the possibility and necessity measures that an action was observed at a time t. The possibility that an action in $Act \subseteq \mathscr{A}$ was observed by obs_t, denoted by $\Pi_{rec_t}(Act)$, is given by selecting the maximum possibility among the actions in Act ($\pi_{rec_t}(a)$, $a \in Act$). The necessity that an action in $Act \subseteq \mathscr{A}$ was observed by obs_t, denoted by $N_{rec_t}(Act)$, is given by selecting the maximum value in π_{rec_t} and to subtract the maximum possibility among the actions not in Act ($\pi_{rec_t}(a)$, $a \notin Act$). According to those possibility and necessity measures (Π_{rec_t} and N_{rec_t}), the most plausible action a that could explain the changes observed in the environment state described by obs_t, is selected in $\mathscr{A}$. If more than one action is plausible, the selected observed action is the most specific action among the actions that commonly subsume the most specific actions among theses plausible actions, according to the action subsumption relation $\sqsubseteq_{\mathscr{A}}$. For instance, if the most plausible actions are All, $OpenTap$, $OpenColdTap$ and $OpenHotTap$, then $OpenTap$ is selected since it is the most specific common subsumer of $OpenColdTap$ and $OpenHotTap$, which are the most specific actions in the plausible action set.

This new observed action (a,t) is sent to the behavior recognition agent, which uses the sequence of observed actions to infer behavior hypotheses concerning the realization of the occupant's activities. This sequence of actions represents the *observed plan* P_{obs_t}, and consists to a set of observed actions (a_i, t_j) totally ordered by the sequence relation $\prec_{\mathscr{T}}$. For instance, let obs_0 and obs_1 be two observations where the time values associated to the timestamps 0 and 1 are 3 minutes and 4 minutes, respectively. Then the observed plan $(OpenDoor, 0) \prec_{\mathscr{T}} (EnterKitchen, 1)$ indicates that $OpenDoor$ was observed, according to obs_0, 3 minutes after the start of the recognition process and that $EnterKitchen$ was then observed, according to obs_1, 1 minute later. This observed plan will be used by the behavior recognition agent to generate a set of hypotheses concerning the occupant's observed behavior when he carries out some activities.

2.4.3 *Behavior Recognition*

In order to have hypotheses about the behavior associated with the performance of some activities, we need to formalize activities as plan structures by using the action ontology $\mathscr{A}$. An activity plan consists of a partially ordered sequence of actions that must be carried out in order to achieve the activity's goals.

Proposition 2.2. *An activity α is a tuple $(\mathscr{A}_\alpha, \circ_\alpha, C_{real_\alpha}, \pi_{real_\alpha})$, where $\mathscr{A}_\alpha \subseteq \mathscr{A}$ is the activity's set of actions, which is partially ordered by a temporal relation $\circ_\alpha \subseteq \mathscr{A}_\alpha \times \mathscr{A}_\alpha \times \mathscr{T} \times \mathscr{T}$, where $\mathscr{T}$ represents a set of time values, C_{real_α} is the set of possible contexts related to the activity realization, and π_{real_α} is the possibility distribution that a context is related to the realization of the activity.*

The use of time values allows us to describe the minimum and maximum delays between the carrying out of two actions. So, the $\circ_\alpha$ relation, which is transitive, can be seen as an ordering relationship with temporal constraints between two actions in the activity plan. For instance, the activity $WatchTv$ can have an activity plan composed of the actions $SitOnCouch$, $TurnOnTv$ and $TurnOffTv$ and the sequence relations $(SitOnCouch, TurnOnTv, 0, 5)$ and $(TurnOnTv, TurnOffTv, 5, 480)$, where the time values are in minutes.

The activity plan library, which contains the set of possible activity plans $\mathscr{P}$ that can be carried out by the occupant in the smart home environment, is represented with an activity plan ontology $(\mathscr{P}, \sqsubseteq_{\mathscr{P}})$, where each activity plan is partially ordered according to an activity subsumption relation $\sqsubseteq_{\mathscr{P}}$. In other words, if an activity subsumes another one, its possibility values are at least as possible than the activity subsumed. For instance, since $CookFood$ subsumes $CookPastaDish$, then the $CookFood$ possibility is greater or equal than the $CookPastaDish$ possibility, since $CookFood$ is more general than $CookPastaDish$. For each observation obs_t, the activity realization possibility distribution π_{real_t} is evaluated. The activity realization possibility distribution π_{real_t} on $\mathscr{P}$ indicates, for each activity, the possibility that the environment's state observed by obs_t is related to the activity realization. Thus, for each activity $\alpha \in \mathscr{P}$, the realization possibility $\pi_{real_t}(\alpha)$ is obtained by selecting the maximum value among the context possibilities $\pi_{real_\alpha}(c_i)$ for the contexts $c_i \in C_{real_\alpha}$ that are entailed by the current observation $(obs_t \models c_i)$.

By using the activity plan ontology and the observed plan, the behavior recognition agent can generate hypotheses concerning the actual behavior of the observed occupant when he carries out some activities. Since multiple activity realizations can explain the observed plan, we need to evaluate partial activity realization paths, which represent partial/complete realizations of activities. A *partial activity realization path* $path_j \in Path$ consists to a subset of the observed plan P_{obs_t}, where the selected observed actions represent a coherent partial/complete realization of a particular activity plan, according to the sequence and temporal constraints defined in the activity plan and the action subsumption relation. For instance, given the observation plan $(SitOnCouch, 0) \prec_{\mathscr{T}} (TurnOnElectricalAppliance, 1)$ and the $WatchTv$ activity plan, we can have as partial path the associations $((SitOnCouch, 0)$, $SitOnCouch)$ and $((TurnOnElectricalAppliance, 1)$, $TurnOnTv)$ (since $TurnOnTv$ is subsumed by $TurnOnElectricalAppliance$).

Since the set of partial paths $Path$ depends on the observed plan P_{obs_t}, we must update $Path$ for each new observed action by extending, removing, or adding new partial paths according to the temporal constraints defined in the activities' plans. With this partial activity realization path set $Path$, we need to evaluate the possibility that a particular partial path is associated with a coherent behavior or an erroneous behavior. The coherent partial path distribution $\pi_{Path_{C,t}}$ on $Path$ indicates, for each partial path $path_j \in Path$, the possibility that the partial path is associated to a coherent behavior according to the observed plan P_{obs_t}. Thus, for each partial path $path_j \in Path$, the possibility is obtained by selecting the maximum value between the minimum prediction possibility π_{pre_t} among the next possible actions in the activity plan and the minimum value among the recognition possibilities π_{rec_t} for the partial path's observed actions and the activity realization possibilities π_{real_α} for the partial path's activity for each observation time t in the partial path. The erroneous partial path distribution $\pi_{Path_{E,t}}$ on $Path$ denotes, for each partial path $path_j \in Path$, the possibility that the partial path is associated to an erroneous behavior according to the observed plan P_{obs_t}. So, for each $path_j \in Path$, the possibility is obtained by selecting the minimum value among the recognition possibilities π_{rec_t} for the observed action not in the partial path and the activity realization possibilities π_{real_α} for the partial path's activity for each observation time t not in the partial path.

By considering the set of possible activities $\mathscr{P}_{poss} \subseteq \mathscr{P}$ that are in the partial path set $Path$, we can generate hypotheses concerning the observed behavior of a occupant when he carries out some activities in the smart home environment. A behavior hypothesis $h_i \in \mathscr{H}_t$ consists to a subset of $\mathscr{P}_{poss}$, where each activity in the hypothesis is not subsumed by another activity in the hypothesis. Two interpretations can be given to each hypothesis h_i. A hypothesis h_i can be interpreted as a *coherent behavior* where the occupant carries out, in a coherent way, the activities in the hypothesis. Those activities can, at the current observation time, be partially realized. Also, a hypothesis h_i can be interpreted as an *erroneous behavior* where the occupant carries out some activities in an erroneous way, while the activities in the hypothesis, if any, are carried out in a coherent way. According to these two interpretations, we evaluate the coherent behavior and erroneous behavior possibility distributions, $\pi_{Bev_{C,t}}$ and $\pi_{Bev_{E,t}}$, on the behavior hypothesis set $\mathscr{H}_t$. The coherent possibility distribution $\pi_{Bev_{C,t}}$ indicates, for each $h_i \in \mathscr{H}_t$, the possibility that a behavior hypothesis denotes coherent behavior according to the observed plan P_{obs_t} and the partial paths associated to the activities in the hypothesis. If there is no activity in the hypothesis or that some observed actions in P_{obs_t} are not associated to at least one partial path, the possibility is zero. Otherwise, for each behavior hypothesis $h_i \in \mathscr{H}_t$, the possibility $\pi_{Bev_{C,t}}(h_i)$ is obtained by selecting the maximum value among the activities' minimal coherent partial path possibilities. The erroneous possibility distribution $\pi_{Bev_{E,t}}$ indicates, for each $h_i \in \mathscr{H}_t$, the possibility that a behavior hypothesis denotes erroneous behavior according to the observed plan P_{obs_t} and the partial paths associated to the activities in the hypothesis. If there is no activity in the hypothesis, the possibility is obtained by selecting the minimal action recognition possibility among the actions in the observed plan P_{obs_t}. Else, for each behavior hypothesis, the possibility $\pi_{Bev_{E,t}}(h_i)$ is obtained by selecting the maximum value among the activities' minimal erroneous partial path possibilities.

With those two possibility distributions, we can evaluate, in the same manner as the action recognition, the possibility and necessity measures that each hypothesis represents coherent or erroneous behavior that could explain the observed actions P_{obs_t}. The possibility and necessity measures that a hypothesis in $B \subseteq \mathscr{H}_t$ represents coherent behavior that could explain the observed plan P_{obs_t}, is given by $\Pi_{Bev_{C,t}}(B)$ and $N_{Bev_{C,t}}(B)$, which are obtained from the $\pi_{Bev_{C,t}}$ possibility distribution. The possibility and necessity measures that a hypothesis in $B \subseteq \mathscr{H}_t$ represents erroneous behavior that could explain the observed plan P_{obs_t}, is given by $\Pi_{Bev_{E,t}}(B)$ and $N_{Bev_{E,t}}(B)$, which are obtained from the $\pi_{Bev_{E,t}}$ possibility distribution. The most possible and necessary hypotheses are then selected according to the $\Pi_{Bev_{C,t}}$, $N_{Bev_{C,t}}$, $\Pi_{Bev_{E,t}}$ and $N_{Bev_{E,t}}$ measures on the hypothesis set $\mathscr{H}_t$. The result of the behavior recognition is then sent to an assistive agent, which will use it to plan a helping task if needed.

2.4.4 *Overview of the activity recognition process*

Let us illustrate the recognition process of our possibilistic model inside a smart home environment with a small example, where the possible activities are *DishWashing*, *DrinkCupWater*, and *WatchTv*. Suppose that the environment's sensor events indicate a context where a kitchen tap is open. According to the set of entailed contexts and the possibilistic formalization of the actions in the action ontology $\mathscr{A}$, the system evaluates the action prediction and recognition possibility distributions for the current observation. By using the possibility and necessity measure obtained from the recognition possibility distribution, the system finds three plausible actions that could explain the environment changes: *OpenHotWaterKitchen*, *OpenColdWaterKitchen*, and *OpenTapKitchen*. According to the action subsumption relation defined in the action ontology, the recognized action that will be appended to the observed plan is *OpenTapKitchen*, since it is the most specific common subsumer for *OpenHotWaterKitchen* and *OpenColdWaterKitchen* (the most specific actions). Let suppose that we observe the action *TurnOnTv* 1 minute later, which is associated to the activity *WatchTv*. Then, the observed plan used for the behavior recognition will be: $(OpenTapKitchen, 0) \prec_{\mathscr{T}} (TurnOnTv, 1)$. According to the possible activities and their partial paths, some behavior hypotheses $h_i \in \mathscr{H}_t$ are generated and the system evaluates the coherent behavior and erroneous behavior possibility distributions on these hypotheses. According to the possibility and necessity measures obtained from these possibility distributions, the system selects the most plausible behavior hypotheses and sends them to an assistive system that will plan a helping task if needed. For instance, a plausible hypothesis can denotes a coherent behavior where the observed occupant carries out, in a interleaved way, the *WatchTv* and *DishWashing* activities. If the temporal constraints associated with the next action of *DishWashing* are not satisfied later in the recognition process, this previous hypothesis will be rejected.

2.5 Smart Home Validation

In this section, we present results from our possibilistic model implementation in the *Ambient Intelligence for Home based Elderly Care* (AIHEC) project's infrastructure at Singapore's *Institute for Infocomm Research* (I^2R) [36]. This infrastructure consists of a simulated smart home environment, which contains stations that represent smart home rooms (pantry, dining, ...). The behavior of the observed person is monitored by using pressure sensors (to detect sitting on a chair), RFID antennas (to detect cup and plate on the table and in the cupboard), PIR sensors (to detect movement in the pantry and dining areas), reed switch sensors (to detect opening and closing of the cupboard), accelerometer sensors (to detect occupant's hand movements), and video sensors (mainly to annotate and audit the observed occupant's behavior). The event manager, which collect the dining and pantry sensor events, is based on a Dynamic Bayes Network (DBN) [37]. It should be noted that other approaches could be used instead of DBN in the event manager. Also, the lab environment uses a wireless sensor network.

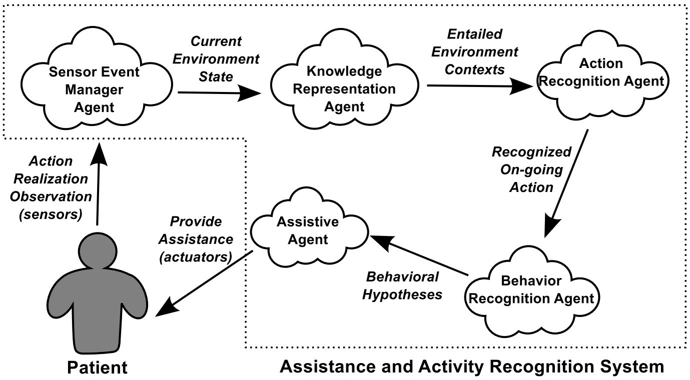

Fig. 2.1 Simplified Smart Home Assistance System

Our possibilistic behavior recognition model is implemented according to the simplified smart home system architecture (Figure 2.1), and is subdivided into three agents: environment representation agent, action recognition agent, and behavior recognition agent. The system architecture works as follows. Basic events related to an action realization by the smart home's occupant are generated by the sensors and are sent to a sensor event manager agent. The sensor event manager agent, which is based on a DBN in this case, infers that an action was carried out and sends the current smart home environment's state, which could be partially observable, to the environment representation agent. The environment representation agent, which has a virtual representation of the smart home environment encoded in a *Pellet* description logic system [38], infers which contexts are entailed by the current (partial) environment state. Those entailed contexts are then sent to an action recognition agent, which will use a possibilistic action formalization and the action ontology to select the most plausible action that could explain the observed changes in the environment. This recognized action is sent to a behavior recognition agent, which will use the sequence of observed actions (observed plan) and the activity plan ontology to generate possibilistic hypotheses about the behavior of the observed occupant. These hypotheses, with information from other agents, will be used by an assistive agent, which will plan a helping task, if needed, towards the smart home's occupant by using the smart home's actuators.

2.5.1 *Results*

A previous trial was carried out in this simulated smart home environment, where 6 actors simulated a meal-time scenario several times (coherent and erroneous behavior) on 4 occasions. This meal-time scenario, which is an eating ADL (activity of daily living), contains several sub-activities: getting the utensils (plate), getting the food (biscuit), getting drink (water bottle) from the cupboard in the pantry to the table, eating and drinking while sitting on the chair, and putting back the utensils, food, and drink in the cupboard. These activities can be interleaved. For instance, the actor can bring the utensils, food and drink at the same time to the table, where some actions are shared between these activities (e.g. open the cupboard). Some erroneous realizations for this scenario were carried out and are mainly associated with realization errors (forget an activity step, add irrelevant actions, break the temporal constrain between two activity's actions), where some of them can also be considered as an initiation error (do not start an activity), or a completion error (forget to finish the activity). By using the sensor databases for each observed behavior, a set of observed sequences of smart home events was recognized, constituting a set of behavioral realizations. Among those observed behaviors, we select 40 (10 coherent/30 erroneous) scenario realizations that are the most representative, since some of them are similar. The selected coherent scenario realizations represent a coherent behavior of the activities, in an interleaved way, in the meal-time scenario. The selected erroneous scenario realizations represent an erroneous behavior of the meal-time scenario, with or without some coherent partial activity realizations. In those erroneous realizations, there is usually more than one error type that occurs (realization, initiation and completion errors). Each selected scenario realization was simulated in our model implementation by inputting the smart home events related to each realization and to use the sensor event manager, in order to recognize the sequence of observed actions and to generate hypotheses concerning the observed behavior, according to the environment, action and activity ontologies. The main goal of our implementation experimentation is to evaluate the high-level recognition accuracy about the observed behavior associated with the realization of the meal-time scenario. Since our recognition approach is based on the knowledge about the observed smart home environment's state, problems related to sensors (e.g. noise) are managed by a sensor event manager, in this case a DBN. This sensor event manager sends the observed environment's state to our environment manager agent, which infers the plausible contexts that could explain the current observed state.

Concerning behavior recognition accuracy, when we look if a particular scenario realization is among the most possible and necessary behavior hypotheses (subsets with only one hypothesis), our model was able to recognize 56.7 % of the erroneous behaviors and 80 % of the coherent behavior (overall 62.5 %)(first part of Figure 2.2). When we look if a particular scenario realization is in a hypothesis set among the most possible and necessary subsets of the behavior hypothesis set (second part of Figure 2.2), our model was able to recognize 63.3 % of the erroneous behavior (overall 67.5 %). In this case, a most possible and necessary hypothesis subset consists to a set of hypotheses where their possibility values maximize the necessity measure according to a certain threshold (fixed value or a ratio of the possibility measure). When we consider the erroneous realizations as generic erroneous behavior (erroneous realizations without coherent activities partially carried out), our model was able to recognize 100 % of them (95 % overall) (third part of Figure 2.2). One of the main reasons that some behavior realizations (coherent and erroneous) are not recognized is related to the rigidity of the action temporal relation, where the only time constraint is a time interval between actions. In this case, some erroneous or coherent realizations are instead considered as generic erroneous realizations, since the coherent partial activities' realizations are not recognized. Furthermore, in some cases, the sensor configuration changes a little bit (mainly the PIR sensor), and that influences the accuracy of the event manager system. For instance, a change in the PIR sensor localization can produce a lot of perturbations: zones detected by the PIR sensors become overlapped, while the training on the event recognizer is made on non-overlapping zones. It should be noted that all possibility distributions and temporal constraints are obtained from one's belief instead of historical data.

Figure 2.3 plots, for each scenario realization, the system runtime for each observed action that was recognized by our possibilistic model implementation. The runtime includes the interactions with the description logic reasoning system, the action recognition and the behavior recognition. Since the focus of the experimentation is the performance of our behavior recognition implementation, the runtime prior to the smart home event recognition is not considered. For this simulation, the runtime is generally between 100 and 200 milliseconds for each action observed. We observe bell shaped curves, which are an effect that results from a diminution of the partial activity realization path set's size. This size

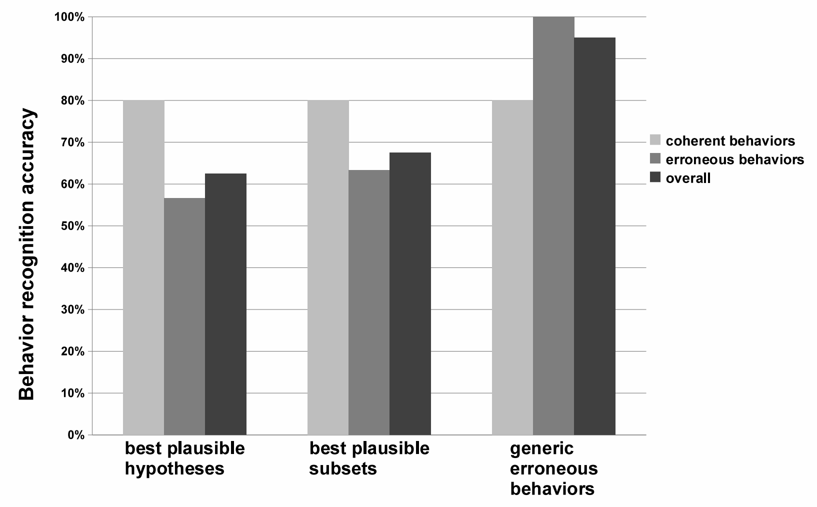

Fig. 2.2 Recognition Accuracy of Behavior Recognition: Best Plausible Hypothesis, Best Plausible Subset, and Generic Erroneous Behaviors

diminution results from the fact that some temporal constraints between actions described in the activity plans are no longer satisfied, so that subsets of the partial path set must be removed. It should be noted that the number of actions carried out and the time between them for each scenario realization are different from those of another scenario realization, since each scenario realization represents a specific behavior.

2.5.2 *Discussion*

Several previous related work, such as that of Cook [24] (MavHome project), Mihailidis [7] (Coach project), Helal [26] (Gator Tech Smart House) and Patterson [34] (Barista system), have conducted the same kind of experiments that we did, using synthetic and real data on comparable problems of similar size. Comparing our experimental results with these previous one is not a simple task. One of the main reasons is the rather different nature of the used recognition approaches and algorithms. In our case, we experimented with a hybrid (logical and possibilistic) approach aiming to recognize precisely the occupant's correct and incorrect behavior. The output of our recognition algorithm, which takes the form of a set of behavior hypotheses with a possibility distribution that partially order these hypotheses according to the possibility and necessity measures obtained from the possibility distribution, is difficult to compare with other probabilistic approaches, since they do not capture the same facets of uncertainty. Thus, probability theory offers a quantitative model

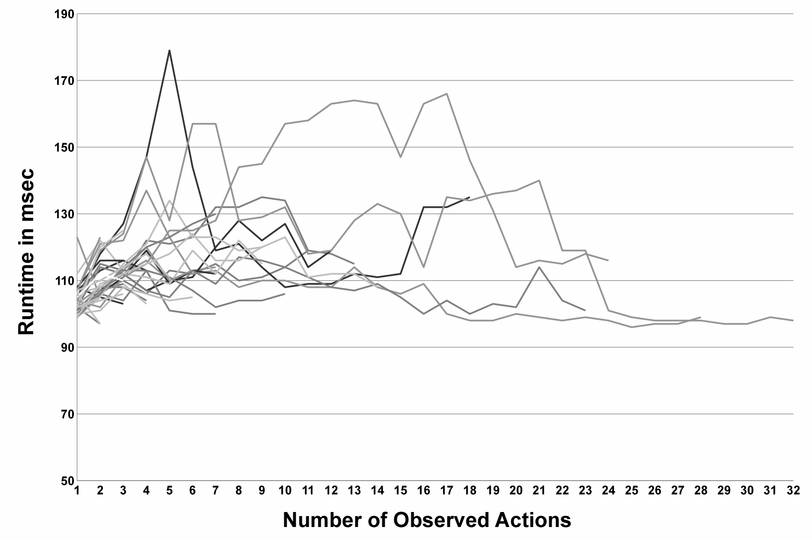

Fig. 2.3 Activity Recognition Runtime per Observed Action for the Scenario Realizations

for randomness and indecisiveness, while possibility theory offers a qualitative model of incomplete knowledge [39].

Moreover, the objectives of our respective experiments are also somewhat different. In our case, the focus of our experiment was to know if our method is able to correctly identify the observed occupant's correct behavior, which could be related to the realization of multiple interleaved activities and to erroneous deviations from the occupant. In contrast, the experiment of Mihailidis [7], as an example, focused only on the identification of the person's current activity step, while assuming to know the current on-going activity. These two objectives and methods are quite different and lead to some difficulties in comparing them.

Despite the heterogeneous nature of previous works experiments, we can draw some useful comparisons and conclusions from the evaluation of their experimental results. First, most of the previous work exploited a form of probabilistic model (Markovian or Bayesian based). These approaches seem to give better results in recognizing an on-going activity and the current activity step with a small plan library. For instance, the results presented by Helal *et al.* [27] with a Hidden Markov Model give a recognition accuracy of 98 % in identifying the correct activity among five candidates. Also, this approach was able to detect, in a qualitative way, the omitted steps of those activities. The approach of Patterson [34], based on Dynamic Bayesian Networks, was able to identify the specific on-going activity with a recognition accuracy higher than 80 %. The Markovian model proposed by Mihailidis [7] also has shown amazing results in recognition accuracy. However, this last approach only focused on monitoring a single activity.

In the light of these experimental results, we can draw some comparisons. First, despite their good results, these previous probabilistic models seem to be adapted to small recognition contexts with only a few activities. It seems much more difficult to use them on a large scale, knowing that each activity must be handcrafted and included in a stochastic model, while conserving the probability distribution. Also, the propagation of probabilities following an observation can be quite laborious while dealing with a large activity library. One of the main probabilistic approaches, the Hidden Markov Model, requires an exponential number of parameters (according to the number of elements that describe the observed state) to specify the transition and observation models, which means that we need a lot of data to learn the model, and the inference is exponential [40]. Moreover, a lot of these approaches assume that the sensors are not changing and the recognition is then based on the sensor events and on historical sensors data. This is a limitation, since the smart home environment is dynamic (sensors can be removed, added, moved) and the recognition system could be deployed in different smart homes. For high-level recognition, it is more easier to work with environment's contexts, which are common in different smart homes, if more general concepts are used to describe the contexts. Also, most previous models simply do not take into account the possibility of recognizing coherent behavior composed of a few activities with their steps interleaved. They also tend to only identify certain precise types of errors (ex. missing steps), while avoiding the others. Finally, we believe that the biggest problem of using a purely probabilistic theory is the inability of handle together the imprecision and the uncertainty of the incomplete information in a natural way. One way to deal with this difficulty is to use a probabilistic interval, which means that there are two probability distributions (one for the minimum values and one for the maximum values). Our approach based on possibility theory, seems to have more flexibility and potential, and to be more advantageous regarding these issues. For instance, by using only one possibility distribution, we can obtain possibility and necessity measures (the interval) on the hypotheses. It allows us to capture partial belief concerning the activities' execution from human experts, since this theory was initially meant to provide a graded semantics to natural language statements. It also allows us to manage a large quantity of activities, to take into account multiple interleaved plans, and to recognize most types of correct and incorrect behavior. Furthermore, applications based on possibility theory are usually computationally tractable [41].

2.5.3 *Summary of Our Contribution*

By looking at the previous approaches, we can note that most applications are based on a probabilistic reasoning method for recognizing the observed behavior. They mainly learn the activities' patterns by using real sensor data collected in the smart home. A potential drawback of such an approach is that, in order to have an adequate probabilistic model, the required amounts of historical data on activity realization can be quite large. Also, since the inhabitant profile influences the activities' realization, the probabilistic model should be tailored to the inhabitant in order to properly recognize the observed behavior. Furthermore, if we want to deploy an assistive system in existing homes, where each home configuration can be quite different from another, the learning process will need to be carried out again. Some approaches propose learning erroneous patterns of some activities, but since there exist many ways to carry out activities having errors associated with their realizations, the erroneous pattern library will be always incomplete. Moreover, the patient's habits may change from time to time, according to new experiences, the hour of the day, his physical and psychological condition, etc. Therefore, the patient's routines must be constantly re-learned, and an adaptation period is required by the system.

Our possibilistic activity recognition model can be seen as a hybrid between logical and *probabilistic* approaches. By using knowledge concerning the environment state, the action ontology, the activity ontology, and uncertainty and imprecision associated with each level of the recognition process, our model evaluates a set of behavioral hypotheses, which is ranked according to the erroneous and coherent behavior possibility distributions. Since learning the patient profile from the sensors is a long term process, the use of possibility theory in our recognition model allows us to capture partial belief from human experts, from its origin as a graded semantics to natural language statements [10]. The knowledge of these human experts concerning the patient profile is incomplete and imperfect, and therefore difficult to represent by probability theory. Our approach takes into account the recognition of coherent (interleaved or not) and erroneous behavior, where both behavior types are valid hypotheses to explain the observed realization of some activities, instead of choosing one behavior type by default. For instance, if some events are not in the learned activity pattern, instead of considering only erroneous behavior or interleaved coherent behavior, both behavior types must be considered in the hypotheses that could explain the observed behavior. In other words, erroneous and coherent (interleaved or not) behaviors are both valid explanations for the patient's observed behavior when he carries out some activities.

2.6 Conclusion

Despite the important progress made in the activity recognition field for the last 30 years, many problems still occupy a significant place at a basic level of the discipline and its applications. This paper has presented a formal framework of activity recognition based on possibility theory and description logics as the semantic model of the agent's behavior. It should be emphasized that the initial framework and our preliminary results are not meant to bring exhaustive or definitive answers to the multiple issues raised by activity recognition. However, it can be considered as a first step toward a more expressive ambient agent recognizer, which will facilitate the support of imprecise and uncertain constraints inherent to smart home environments. This approach was implemented and tested on a real data set, showing that it can provide, inside a smart home, a viable solution for the recognition of the observed occupant's behavior, by helping the system to identify opportunities for assistance. An interesting perspective for the enrichment of this model consists of using a possibilistic description logic to represent the environment's observed state, thus taking into account the uncertainty, imprecision and fuzziness related to the information obtained from the sensors and to the description (concepts, roles, assertions) of the environment. Finally, we clearly believe that considerable future work and large scale experimentation will be necessary, in a more advanced stage of our work, to help evaluate the effectiveness of this model in the field.

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