A Smart Home Agent for Plan Recognition

Bruno Bouchard[1], Sylvain Giroux[1], and Abdenour Bouzouane[2]

[1] Université de sherbrooke, 2500, boul. de l'Université,
Sherbrooke, Québec, Canada J1K2R1
{Bruno.Bouchard, Sylvain.Giroux}@usherbrooke.ca
[2] Université du Québec à Chicoutimi, 555, boul. de l'Université,
Chicoutimi, Québec, Canada G7H2B1
abdenour_bouzouane@uqac.ca

Abstract. Assistance to people suffering from cognitive deficiencies in a smart home raises complex issues. Plan recognition is one of them. We propose a formal framework for the recognition process based on lattice theory and action description logic. The framework minimizes the uncertainty about the prediction of the observed agent's behaviour by dynamically generating new implicit extra-plans. This approach offers an effective solution to actual plan recognition problem in a smart home, in order to provide assistance to persons suffering from cognitive deficits.

1 Introduction

Recent developments in information technology and increasing problems in the health field, including population ageing and medical staff shortages, have opened the way to a whole set of new and promising research avenues, most notably, work on smart homes. A growing literature [3][6][8][11] has explored the process by which cognitive assistance, inside a smart home, is provided to occupants suffering from cognitive deficiencies such as Alzheimer's disease and schizophrenia, for the performance of their Activities of Daily Living (ADL). One of the major difficulties inherent to cognitive assistance is to identify the on-going inhabitant ADL from observed basic actions. This problem is known as *plan recognition* in the field of artificial intelligence [7].

The problem of plan recognition can be basically synthesized by the need "...to take as input a sequence of actions performed by an actor and to infer the goal pursued by the actor and also to organize the action sequence in terms of a plan structure" [15]. Thus, the main objective is to predict the behaviour of the observed agent. In the context of cognitive assistance, these predictions are used to identify the various ways a smart home (observer agent) may help its occupants (patients). An important assumption underlying this problem is that the observed agent is rational, i.e. that all his performed actions are coherent with his intentions. However, for patients suffering from cognitive deficiencies, rationality might indeed be a strong assumption. The purpose of this paper is then to initiate the development of a generic approach to plan recognition for a smart home, that could be applied to people with cognitive impairments.

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The literature related to plan recognition [1][3][7], in particular the logical approaches [10][17], share a significant limitation in that they do not take into account intra-dependencies between the possible plans in the recognition process. These intra-dependencies result from the fact that, even if possible plans might seem connected, the intentions concerning two distinct observations are not necessarily related. In fact, Kautz [10] has pointed out this problem in his work. Hence, taking into account of this intra-dependency factor should be a solution to the issue of completing the observer's plans library. Our approach addresses this problem and relies on lattice theory and action description logic [5]. We define algebraic tools allowing to formalize the inferential process of plan recognition in a model of reasoning by classification through a lattice structure. This interpretation model defines a recognition space. This space will not only serve to characterize the uncertainty in the prediction of a future action. It will also serve to determine the appropriate time when the assisting agent could be brought in to increase his autonomy in order to perform an assistance action in the habitat by taking over the ADL patient control.

The paper is organized as follows. Section 2 presents our model of plan recognition based on lattice theory. Section 3 shows how the model is implemented to address the ADL recognition problem that we encounter in the DOMUS project. Section 4 presents an overview of previous works in the field of plan recognition. Finally, Section 5 presents our conclusion and future work.

2 Recognition Space Model

For an observer agent, the process of plan recognition consists in finding a recognition space (model of interpretation), based on the set of possible plans. This space allows the observer to interpret the set of the observed actions, performed by a human or another observed agent in action, with the aim of predicting his future actions and thus the plausible plans that would enable us to explain his behaviour. Let $A = \{a, b, \ldots\}$ be the set of actions that an observed agent is able to perform and let $P = \{\alpha, \beta, \ldots\}$ be the set of known plans of the observer (his knowledge base). Let O be the set of observations such that $O = \{o \mid \exists a \in A \rightarrow a(o)\}$. The assertion $a(o)$ means that observation o corresponds to an a-type action. The definition of a possible plan α that would explain the observation o is expressed as follows:

Definition 1. A plan α is a possible plan for an action $a(o)$ if and only if $a \in \alpha$. The action $a(o)$ is a component of the sequence α.

Consequently, the set of all possible plans for the observations O can be defined by $P_s^o = \{\alpha \in P \mid \exists (a, o) \in \alpha \times O \rightarrow a(o)\}$. Starting with this set of plans, we can deduce that the agent will at least perform one of them. However, its intentions can go beyond the set of possible plans. For instance, considering a well-known Kautz's example given in [10], we see that if we observe two actions *GetGun* and *GotoBank*, then we cannot automatically conclude that the observed agent wants to rob a bank, or deduce a disjunction of possible plans *Hunt* or *RobBank* as proposed by Kautz's theory. The fact is that his intentions can be to go on a hunting trip and to cash a check on the way, knowing that the initial set of possible plans were *RobBank* and *Hunt*. Therefore, the model that we designed formally structures the recognition process to take this reality into account. In order to algebraically define our recognition model, we need first to show an overview of the action model on which it is based. This action model is described in great detail in [5].

2.1 Action Model Overview

Our approach to the formalization of the actions follows the lines of Description Logic (DL) [2]. We draw on the state-transition action model to develop a theoretical model of the action [5]. An action a over a set of states of the world W is a binary relation $a(w) = \{e|(w,e) \in W \times W\}$ where w and e are respectively the current and next states. The actions operate on the conceptual and assertion formulas that are used to describe facts about a state of the world (the patient's environment). The set of states where an action a may be performed is given by the domain $Dom(a) = \{w \in W|\ w \models pre(a)\}$, where $pre(a)$ is the precondition of a, defined as a conjunction of assertion formulas concerning the conceptual objects as well as the roles that bind these objects. The co-domain is given by $CoDom(a) = \{e \in W|\ e \models pos(a)\}$, where $pos(a)$ expresses the effect of $a(w)$, defined by a set assertions formulas that change the interpretation of concepts and roles involved in an action $a(w)$. The following definition, described in [5], defines the subsumption relationship between action concepts:

Definition 2. Let a and b designate two actions. If $Dom(a) \subseteq Dom(b)$ and $CoDom(a) \subseteq CoDom(b)$, then b subsumes a and we denote $a \prec_p b$.

Based on our action model in DL, a plan structure α may be defined as a sequence of actions $a_1, \ldots, a_n$, denoted $\alpha(a_n \circ a_{n-1} \circ \cdots \circ a_1)$ where $\circ$ is a sequence operator and $\alpha(w_0) = a_n(a_{n-1}(\cdots(a_1(w_0))\cdots))$, allowing the transition from an initial state w_0 to a final state w_n. We now need to introduce a new concept of a variable plan to characterize the uncertainty in the predictions.

2.2 Variable Plan

Let $V = \{x, y, z, \ldots\}$ be the set of the action variables. An action variable x in a plan α corresponds to a variable for which we may substitute any sequence of actions included in its substitution domain $Sub(x) \subseteq 2^A$. A variable plan is then defined as a plan that contain at least one action variable in is sequence. This kind of plan corresponds to an intention schema, for which the instantiation allows to generate new implicit extra-plans that are not preestablished in the plans library. We define a substitution $\sigma : V \mapsto 2^A$ as a set of variable-actions pairs: $\sigma = \{x \leftarrow a_1, y \leftarrow a_2 \circ a_3, \ldots\}$, where $\sigma(\alpha) = (a_n, \ldots, \sigma(x), \ldots, \sigma(y), \ldots, a_1)$ corresponds to an instantiation of α, computed by substituting each action variable in α by the corresponding action sequence specified in σ. The only possible substitution for an action a is itself such that: $\forall a \in A$ then $\sigma(a) = a$.

Definition 3. $\alpha(a_n \circ \cdots \circ x \circ \cdots \circ a_1)$ is a variable plan if and only if there exists a substitution $\sigma(x) \in 2^A$ such that $\alpha(a_n \circ \cdots \circ \sigma(x) \circ \cdots \circ a_1)$ is a consistent plan.

We note that the consistency properties will be defined in the next section. An action variable will be introduced inside a new plan, resulting from the computation of the lower bound between a pair of incomparable possible plans. Incomparable plans mean that both contain at some i-*th* position of their sequence two actions that cannot both be subsumed by any common action. In such a case, an action variable whose substitution domain is equal to the composition of these two incompatible actions will be introduced. For instance, we can refer to Kautz's example and suppose that we have two incomparable possible plans $RobBank(GotoBank \circ GetGun)$ and $Hunt(GotoWood \circ GetGun)$. The actions $GotoBank$ and $GotoWood$ are incomparable and a variable plan $(x \circ GetGun)$ will result from the computation of the lower bound of these two plans. The substitution domain of the variable x would then be $Sub(x) = \{GotoBank \circ GotoWood, GotoWood \circ GotoBank\}$. From there, we can define the subsumption relationship that organizes plans into a taxonomy.

Proposition 1. Let α, β be two plans. We have $\alpha \prec_p \beta$ if there is a substitution $\sigma = \{x \leftarrow a_i, y \leftarrow b_j, \ldots\}$ such that $\forall i \in [1, |\beta|], (a_i, b_i) \in \alpha \times \beta$ then $\sigma(a_i) \prec_p \sigma(b_i)$, where $|\beta|$ is the cardinality of plan.

Proof 1. The proof directly follows from that of Definition 2 and the definition of plans subsumption. Let $Dom(\sigma(a_i)) = \{w \in W |\ w \models pre(\sigma(a_i))\}$. If $Dom(\sigma(a_i)) \subseteq Dom(\sigma(b_i))$, then $\forall (w, e) \in Dom(\sigma(a_i)) \times CoDom(\sigma(a_i))$, we have $(w, e) \in Dom(\sigma(b_i)) \times CoDom(\sigma(b_i))$. Therefore $w \models pre(\sigma(b_i))$ *and* $e \models pos(\sigma(b_i))$. If action $b_i \in \beta$ may be performed in every state where action $a_i \in \alpha$ is executable, then action b_i subsumes action a_i. Therefore, $\alpha \prec_p \beta$. $\diamond$

With these basic formal elements, the issue then is how to adequately refine the set of possible plans partially ordered by this subsumption relation. The solution we propose is to organize them into a taxonomy and make explicit the extra-plans that are implicit (induced by the existing intra-dependencies) by applying the composition and the disunification operation on each pair of incomparable possible plans.

2.3 Plans Composition

Let $\alpha, \beta \in P_s^o \times P_s^o$ be two possible plans interpreting a sequence of observed actions O at a specific time t. By composition, one seeks to determine all consistent combinations between the future actions succeeding the observations in the possible plans. The result of the composition of plans α and β, denoted $\alpha \oplus \beta$, is a set of extra-plans satisfying the following consistency properties:

1. Stability: each extra-plan in $\alpha \oplus \beta$ is formed by: (i) a set of partial plans included in the knowledge base P of the observer, (ii) at least one action common to plan α and to plan β, and (iii) a composition of actions that are component of α or component of β. There is no possibility of introducing other external actions.
2. Closure: each extra-plan in $\alpha \oplus \beta$ must admit an upper bound $\alpha \nabla \beta$ and a lower bound $\alpha \varDelta \beta$. Hence, the extra-plans must be included in the interval $[\alpha \varDelta \beta, \alpha \nabla \beta]$.

We note that the composition of a plan α with itself gives the same plan α. Now, let us reconsider Kautz's example where *GetGun* is the observed action. The set of possible plans according to this observation is $P_s^{GetGun} = \{RobBank(GotoBank \circ GetGun), Hunt(GotoWood \circ GetGun)\}$. The composition of the plans *RobBank* and *Hunt* is $(RobBank \oplus Hunt) = \{(GotoBank \circ GotoWood \circ GetGun), (GotoWood \circ GotoBank \circ GetGun)\}$. These new extra-plans are dynamically computed according to the observed action *GetGun*. One can ask a question regarding the computational complexity of this composition operation. The answer is that the combination of the incomparable possible plans is not done blindly. First, we only consider the consistent possible plans, which satisfy the stability and closure criteria (first filter). Second, the possible plans that we consider are those which are in the lattice structure bounded by the upper and lower bounds (second filter). Finally, for each pair of incomparable plausible plans, we combine them by using the disunification operation (third filter), which will be defined in the next section. These filters allow us to reduce and control the computational complexity of the composition operation.

2.4 Disunification for Recognition Space Lattices

We define the set of plausible plans P_l^o as the union of the composition pairs of possible plans, according to the set of observed actions O, such that:

$$P_l^o = \bigcup_{\alpha, \beta \,\in\, P_s^o} \alpha \oplus \beta$$

We consider P_l^o as an interpretation model for O if P_l^o forms a lattice structure ordered by the subsumption relation of plans and if each couple of incomparable possible plans admits an upper bound ∇ and a lower bound $\varDelta$.

Proposition 2. The set of plausible plans P_l^o ordered by the subsumption relation $\prec_p$, forms a lattice[1] structure, denoted $\Re_o =< P_l^o, \prec_p, \varDelta, \nabla >$.

This recognition space is the interpretation model of the observed agent behaviour, where the infinimum of the lattice corresponds to the schema of minimal intention. It is defined as a plan that can contain action variables serving to characterize not only the uncertainty in the prediction of a future action but also

[1] The proof is available in *http://www.brunobouchard.com/proposition2_proof.pdf*

the appropriate moment where the observer assisting agent could be brought to increase its autonomy to perform an assistance action in the habitat.

Definition 4. Let $\alpha(a_n \circ \cdots \circ a_1), \beta(b_m \circ \cdots \circ b_1) \in P_l^o$ interpret the observed actions O, where $|O| = k$. The upper bound $\alpha \nabla \beta$ is the least common partial plan subsumer $\pi(c_r \circ \cdots \circ c_1)$, such that $\forall i \in [1, r]$, with $k \leq r \leq min(n, m), \forall o_{j\ \in [1,k]}, \forall (a_i, b_i) \in \alpha \times \beta$, then $c_j(o_j), o_j \in O, a_i \prec_p c_i$ and $b_i \prec_p c_i$.

The symbol π represents the result of the upper bound computation between two plans α and β, including the observations. Consequently, the upper bound cannot be empty as it is minimally composed of the observations. According to the previous example, the least common partial subsuming plan between the possible plans *RobBank* and *Hunt* is $(RobBank \nabla Hunt) = (GetGun(o_1))$, where $o_1 \in O$ is the only observation corresponding to the action type *GetGun*. The lower bound of two incomparable possible plans consists of the observed actions, followed by the predictions related to the future actions which are represented by action variables. The interest on computing this lower bound is to find a new intention schema by disunifying the possible plans using the first-order logic disunification operation *DisU* [9]. Thereafter, this intention schema is used to reunify the possible plans through the composition operation previously defined to generate new implicit extra-plans.

Definition 5. Let $\alpha(a_n \circ \cdots \circ a_1), \beta(b_m \circ \cdots \circ b_1) \in P_l^o$ interpret the observed actions O, with $|O| = k$. The lower bound $\alpha \varDelta \beta$ is the most common partial plan subsumed, given as follows:

$$\alpha \varDelta \beta = \begin{cases} b_m \circ \ldots \circ b_{n+1} \circ DisU(a_n, b_n) \circ \ldots \circ DisU(a_{k+1}, b_{k+1}) \circ o_k \circ \ldots \circ o_1, & if\ n \leq m \\ b_n \circ \ldots \circ b_{m+1} \circ DisU(a_m, b_m) \circ \ldots \circ DisU(a_{k+1}, b_{k+1}) \circ o_k \circ \ldots \circ o_1, & if\ m \leq n \end{cases}$$

where *DisU* is a disunification operation defined as an injective application: $A \cup V \times A \mapsto A \cup V$, on the set of incomparable actions of plans α, β:

$$DisU(a, b) = \begin{cases} c \quad iff \quad \exists c \in A\ :\ c \prec_p a\ and\ c \prec_p b \\ x \quad elsewhere,\ with\ Sub(x) = \{a \circ b, b \circ a\} \end{cases}$$

To summarize, the recognition process consists in finding a recognition space $\Re_o$, which is a minimal model of interpretation of the observations O that admits a supremum ∇_{sup}, corresponding to the most specific common subsumer of all possible plans, and that admits an infinimum $\varDelta_{inf}$, corresponding to the minimal intention schema predicting the future behaviour of the observed agent. This space $\Re_o = \{\delta \in P_l^o | \varDelta_{inf} \prec_p \delta \prec_p \nabla_{sup}\}$ constitutes a very interesting tool to characterize and to control the recognition process. Of course, it is assumed that all the observed actions are related. Consequently, we build a lattice structure starting from the first observation that will be refined when new observations will be detected. This refinement will be computed by extracting a sub-lattice (a new refined recognition space) from the initial lattice structure, and so on.

3 Recognition of Activities in a Smart Home

The DOMUS [2] lab consists of a standard apartment with a kitchen, living room, dining room, bedroom, and bathroom that are equipped with sensors, smart tags (RFID), location and identification systems for objects and people, audio and video devices, etc. This smart home is used to explore ways to provide pervasive cognitive assistance to people suffering from cognitive deficiencies such as Alzheimer's disease, head traumas, and schizophrenia [11]. As we can see on Figure 1, the current infrastructure allows the connection of sensors (movement detectors, lighting system, pressure mats, etc.) to services that generate low-level information (for instance, basic actions and localization) [16]. In the current implementation, most of devices (sensors and effectors) are monitored and controlled through a Crestron-based infrastructure. Basic events are generated by sensors and are directly sent to the agents. Consequently, our low-level activity recognition (LAR) agent can register as an event listener, though a Java interface, in order to get the inputs sent by the sensors. This agent transforms low-level inputs into low-level actions that can be analyzed by higher level-agents. These inputs will then be used as a starting point from high-level recognition process.

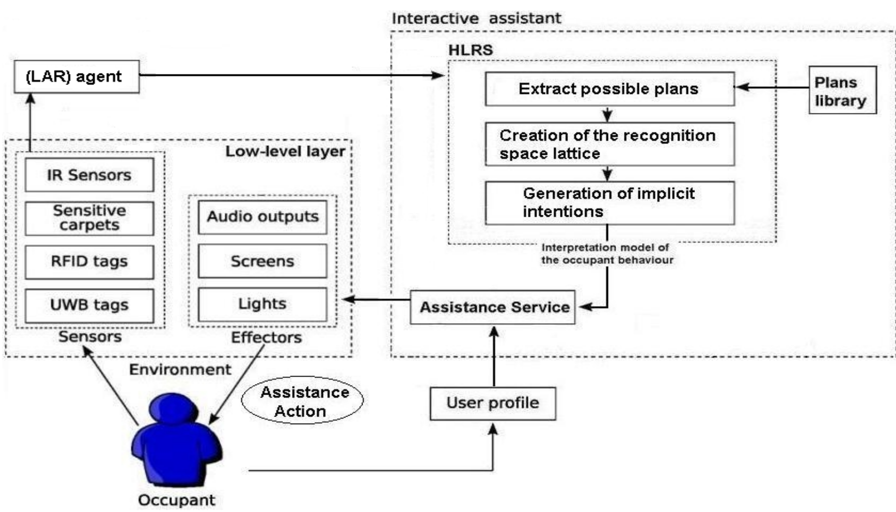

Fig. 1. Achitecture of the system

The LAR agent owns a virtual representation of the habitats environment encoded in a description logic knowledge base described with the PowerLoom system [13]. This terminological base is composed of a set of conceptual and assertional objects that synthesize the elements of the environments. In other

[2] The DOMUS lab is sponsored by the Natural Sciences and Engineering Research Council of Canada (NSERC) and by the Canadian Foundation for Innovation (CFI).

words, this knowledge base serves to define the current state of the environment. When new inputs are received from hardware sensors, the LAR agent updates the state of the world and creates an action structure, representing the changes that happened to the environment, according to our model of action described in [5]. This action structure is then classified according to a taxonomy of low-level actions to identify its conceptual type. Thereafter, the LAR agent notifies the cognitive assistant that a new low-level action is detected and it sends the actions type. Actually, we suppose that the low-level sensors give us correct inputs. Another DOMUS team is working on detection and isolation of sensors failure, in order to relax this strong assumption and to minimize low-level uncertainty.

3.1 High-Level Recognition Service

The assistant agent is equipped with a high-level recognition service (HLRS), which provides an interpretation model of the occupant behaviour as input to assistance service. We now discuss a simple assistance example that illustrates the principles of our high-level plan recognition process. Let us assume the case of Peter, a person with Alzheimer's disease at level 3 (mild cognitive decline) by referring to the global scale of the deterioration stages of the primary cognitive functions of an individual [14]. In the morning, Peter gets out of bed and moves towards the kitchen. The pressure mat located at the base of Peter's bed has detected his awakening and has activated the recognition system. The movement detector located at the kitchen entrance indicates that Peter has entered that room. The low-level action recognition system receives the sensors inputs, given by the Crestron infrastructure, and then conceptualizes the changes that have just occurred in the environment in an action structure that it classifies through its taxonomy to identify the observed action $GoToKitchen$. While referring to the knowledge base of the smart home, the observed action may be performed for several purposes, that is, to prepare a cup of tea in the kitchen or to wash a dish. To be able to plan a future assistance task, the agent must initially understand Peter's intentions by building a minimal interpretation model describing the plausible plans that can explain his behaviour at this specific moment. This model takes the form of a lattice built following our recognition model, as shown in Figure 2. On the left of the figure, one may see the description of low-level actions (top left) and the high-level activities (bottom left) that has been recognized by the system. On the top right, one can see a graphical tool built in SVG[3] (here showing the kitchen) that allows us to simulate the activation of the various environment sensors by clicking on the corresponding graphical objects. On the bottom right, one can see the recognition space lattice resulting from the high-level recognition.

The set $P = \{$ *WashDish(StartWashing* $\circ$ *GoToKichen), PrepareTea(GetWater* $\circ$ *GoToKitchen), WatchTv(TurnOnTv* $\circ$ *GoToLivingRoom), Drink(GetWater)*$\}$ constitutes the knowledge base of the assistant agent and includes all the

[3] Scalable Vector Graphics. Language for describing two-dimensional graphics in XML. See SVG web page http://www.w3.org/Graphics/SVG/

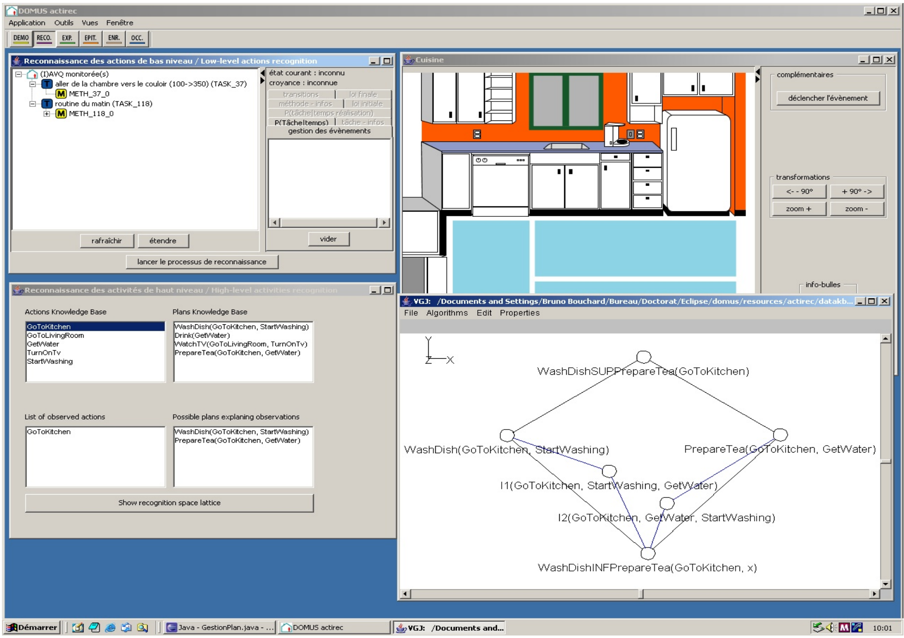

Fig. 2. DOMUS application of activities recognition

plans (ADL) of the occupant. The set O contains all the observed actions o_1 detected by the system, in this case, only one action of the $GoToKitchen$ type, such as $O = \{GoToKitchen(o_1)\}$. The set P_s^o contains all the known plans including, in their decomposition, the observed action that is the plans $PrepareTea$ and $WashDish$. The lattice supremum corresponds to the smallest common subsumer of the set of possible plans P_s^o which is the partial plan made up solely by the observation. The lattice infinimum corresponds to the minimal intention schema of the occupant, as shown on the bottom left of Figure 2. The action variable x, obtained by the disunification operation, characterizes uncertainty in the prediction of the next action. The substitution domain of this variable is $Sub(x) = \{StartWashing \circ GetWater, GetWater \circ StartWashing\}$. The minimal intention schema enables us to generate, by the substitution process of the action variables, two new coherent extra-plans that did not exist beforehand in P, that is I_1 and I_2, as shown in Figure 2. These extra-plans are the result of the disunification and the composition of the possible incomparable plans according to their intra-dependencies. Extra-plans I_1 and I_2 are consistent, according to the consistency criteria defined in Section 2.3, as there is a decomposition of partial plans where each one subsumes a known plan included in P . The recognition space $\Re_o$ is composed of all the plans that can be classified between the lattice infinimum and supremum, such as $\Re_o = \{$ *WashDish, PrepareTea, WashDish* ∇ *PrepareTea, WashDish* Δ *PrepareTea,* I_1, $I_2\}$. These set constitute the whole plausible plans that can explain the behaviour of the occupant. Now, let us suppose that a second observation $GetWater(o_2)$ was detected. The new interpretation model would then be the sub-lattice upper bounded by $PrepareTea$ and lower bounded by $WashDish \Delta PrepareTea$, as shown in Figure 2. Let us now suppose that the assistant agent has detected that the inhabitant remains still for a certain period of time. In such a case, the assistant agent will have to increase his autonomy level by taking control of the home using the intention schema of the inhabitant, defined by the infinimum $\Delta_{inf} = (x \circ GoToKitchen)$ of the lattice, to predict what the person wanted to do. In our example, the occupant wishes to prepare tea or pursues two distinct goals represented by the extra-plan I_1, that is $WashDish$ and $DrinkWater$. In this context, the smart home would be authorized to perform an action of assistance, like reminding the occupant of the procedure to achieve his inferred goals in the event of a memory lapse (i.e. Alzheimer's disease).

4 Related Works

Several approaches have been explored to seek solutions to plan recognition, such as the probabilistic approaches [1][6][7], the learning approaches [3][12] and the logical approaches [10][17]. The probabilistic methods, primarily based on the on the Markovian model [6], Bayesian networks [1] and on the Dempster-Shafer theory [7], use a set of probabilistic rules which enable to update the probability attributed to each plausible hypothesis following an observation. The conclusion drawn from the recognition process by the system is simply the hypothesis having the highest probability. For instance, Boger *et al.* [6] used such approach in the development of the COACH system; a cognitive aide for patients with dementia based on a partially observable Markov decision process (POMDP). This system aims to monitor a cognitively impaired user attempting a handwashing task, and to offer assistance in the form of task guidance (e.g. prompts or reminders). The weakness of the probabilistic approaches stems from the heuristic methods used to compute the probability of each competing hypothesis, which are highly dependent on the context [7]. The learning techniques seek to identify patterns from the observed actions in order to build a probabilistic predictive model of the observed agent behaviour. They have been used by [12] in order to develop the *Activity Compass* system; a cognitive assistant for early-stage Alzheimer's patients. It is based on a Bayesian learning model of a patient moving through a transportation network. The main limitation of this kind of approaches is due to the fact that the generalization learned rule might lead to infer inconsistent behaviour and also to a very large amount of training data. Moreover, these techniques cannot make useful predictions when novel events occur. The logical approaches of Kautz [10] and Wobke [17] are closer to our work. In these two theories, the observer agent starts with a plan library expressed with first-order axioms forming an abstraction/decomposition hierarchy. Kautz proposes a set of hypotheses (exhaustiveness, disjointedness, component/use, minimum cardinality), based on McCarthy's circumscription theory, that serves to extract a minimal covering model of interpretation from the hierarchy, based on a set of observed actions. The weakness of Kautz's approach is that all plans inferred as possible through the covering model are considered equiprobable. Wobke has proposed a solution to this limitation using situation theory [4]. His proposal, based on Kautz's work, consists in defining a partial order relation organizing hierarchy's elements by level of plausibility. A significant limitation of Wobke's work is created by the situation semantics (a particular case of possible worlds semantics), which is too complex to make operational in a real context. Finally, these previously explored approaches assume that the observer have a complete knowledge of the domain and thus, they cannot recognize plans that are not included in the plans library.

In contrast, our approach defines algebraic tools that allow to exploit the existing relations between possible plans in order to dynamically generate new plausible extra-plans that were not preestablished in the knowledge base. Consequently, our work partially addresses the problem of completing the plans library, which indeed cannot be complete in any domain. Another promising improvement of our model would be to organize the result of the recognition process into a structured interpretation model, which takes the form of a lattice, rather than a simple disjunction of possible plans without any classification. Therefore, our approach minimizes the uncertainty related to observed patient's behaviour by bounding the plausible recognition plans set. Moreover, we notice that the computational complexity of our recognition process is decreasing as the number of observations increases. This performance is due to the refinement process, which, instead of creating a whole new lattice, extracts a refined sub-lattice from the first one created.

5 Conclusion

In this paper, we proposed a non-quantitative approach, based on lattice theory and action description logic, for re-examining the main issues surrounding the problem of formalizing plan recognition. This approach provides a viable solution to plan recognition problems by minimizing uncertainty about the prediction of the observed agent's behaviour. This is achieved by dynamically generating implicit extra-plans resulting from intra-dependencies existing between possible plans. It should be emphasized that this initial framework is not meant to bring exhaustive answers to the issues raised by the multiple problems related to plan recognition. However, it can be considered as a first step towards developing a complete formal plan recognition theory, based on the classification paradigm. It should bring effective solutions to concrete problems such as plan recognition in a smart home. For further work, we plan to extend our logical model by attributing a probability to each plausible plan according to contextual information, such as the time of the day, and according to the inhabitant's specific profile, such as the learned patient's habits. Such hybrid approach will address the equiprobability problem of the possible plans characteristics to logical recognition models and thus, it will offer a means to favour one explanation over another in the lattice recognition space.

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