Goal Lifecycles and Ontological Models for Intention Based Assistive Living within Smart Environments

Joseph Rafferty[1], Liming Chen[2], Chris Nugent[1] and Jun Liu[1]

[1] School of Computing and Mathematics, University of Ulster
[2]School Computer Science and Informatics, De Montfort University
Email: rafferty-j@email.ulster.ac.uk, liming.chen@dmu.ac.uk, {cd.nugent, j.liu} @ulster.ac.uk

Current ambient assistive living solutions have adopted a traditional sensor-centric approach, involving data analysis and activity recognition to provide assistance to individuals. The reliance on sensors and activity recognition in this approach introduces issues with scalability and ability to model activity variations. This study introduces a novel approach to assistive living which intends to address these issues via a paradigm shift from a sensor centric approach to a goal-oriented one. The goal-oriented approach focuses on identification of user goals in order to pro-actively offer assistance by either pre-defined or dynamically constructed instructions. This paper introduces the architecture of this goal-oriented approach and describes an ontological goal model to serve as its basis. The use of this approach is illustrated in a case study which focuses on assisting a user with activities of daily living.

Keywords: Ontology, Goal Modelling, Assistive Living, Goal Recognition, Activities of Daily Living, Smart Environments.

1 Introduction

The worldwide population is aging and as a result it is producing an uneven demographic composition [1], [2]. This is expected to reach a situation by 2050 where over 20% of the population will be aged 65 or over [1], [2]. This growth in aging population is expected to produce an increase in age related illness and will place additional burdens on healthcare provision [2]. In addition, the amount of informal support available will decrease due to a reduction in the global Potential Support Ratio (PSR). The PSR is the ratio of people that are the working age (15-64) to those older than 65 [1]. The PSR is expected to continue on a downward trend reaching a low of 4:1 by 2050. The PSR was previously 12:1 in 1950 and more recently 9:1 in 2009 [1].

Ambient Assisted Living (AAL) has been widely viewed as a promising approach to addressing the problems associated with ageing [3], [4]. Within this domain technology based solutions are used to support independent living and subsequently alleviate a portion of the aforementioned problems associated with ageing. Such an approach offers the potential of enhancing the quality of life of older people. Coupled with AAL is the notion of Smart Homes (SH). It is possible to create residential environments augmented with sensor technology and AAL type solutions. Typically SHs operate with the following ‘bottom-up’ process: sensors monitor an inhabitant’s activities/environment. Data from these sensors are then processed to identify Activities of Daily Living (ADL) for example bathing, preparing a meal, using the telephone. ADLs which are identified can be monitored to detect difficulties in task completion and to allow assistance to be offered through the SH environment when necessary [3]–[6]. As such, SHs allow older people to live longer independently, with a better quality of life, in their own homes.

The bottom-up approach, whist functional, has issues stemming from its sensor centric nature. Inhabitant privacy is potentially violated by recording activities which are then used as the basis for providing assistive services [3]–[6]. For efficient operation SHs require a large number of sensors to be placed in the environment which is realistically not feasible for widespread use due to scalability issues related to retrofitting a large number of homes with an appropriate suite of sensors. This retrofitting process presents itself with a substantial financial cost in addition to disturbance to inhabitants within their own homes. These sensor installations also require maintenance representing a potential further cost and disturbance. In addition, current SHs using this approach cannot flexibly handle variation in activity performance in a satisfactory way. Finally, reusability of some of these bottom-up SHs can be reduced as they rely on a record of events that occur only within their environment [3]–[6]. These problems represent a significant barrier to the uptake and adoption of SH technology.

To address these issues we propose a paradigm shift from a sensor centric approach to a 'top-down', goal driven approach to offer a solution, which can bring additional flexibility whilst simultaneously requiring fewer sensors. In a goal driven approach an inhabitant's goals are the focus of the assistive system in contrast to the processing of dense sensor recordings. By combining a goal recognition system with an action planning mechanism an assistant system will be produced which will allow flexible and proactive assessment of an intended inhabitant goal, thus facilitating assistance provision.

The remainder of the paper is organised as follows. Section 2 discusses related work. Section 3 proposes a top-down approach and characterizes SH inhabitant goals. Section 4 provides an overview and description of the ontological goal model which has been developed. Section 5 presents a use case to illustrate the use of goal models for assistive living and Section 6 concludes the paper.

2 Related work

Current work in the area of SHs largely focuses on the bottom-up approach. While the bottom-up approach follows a general process involving a number of key research areas, central to the approach is the process of activity recognition. The general 'bottom-up' approach is illustrated in Figure 1.

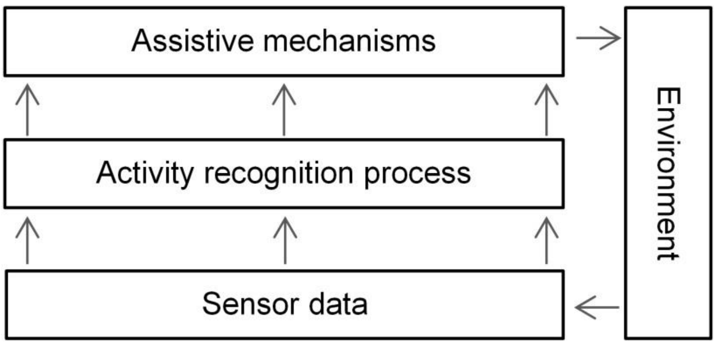


Figure 1 The 'bottom-up' approach for providing activity recognition within SHs.

Activity recognition processes are generally implemented using 2 main approaches: knowledge driven and data driven and are outline in the following Sections.

2.1 Data driven approaches

Data driven approaches use statistical and probabilistic methods to learn activity models from data sets in a supervised or unsupervised manner. In these approaches data sets are a compilation of sensor activations that have been generated from a SH. These data sets are then used to train activity models which map the relationship between events and activities. Activity models which have been learnt are then used to perform future recognition of the events recorded within the SH. The learning mechanisms are usually based on two general approaches, namely, generative and discriminative depending on the modelling strategy employed.

Generative approaches, such as those used in [7]–[12], attempt to produce a description of occurrences in a data set by fully mapping the relationship of sensor events and activities. These mappings identify the most likely activities that would occur given a set of observations. This classification of observations from a data set is achieved using probabilistic classification techniques such as a Hidden Markov Model or naïve Bayes classifiers. Generative approaches suffer from the requirement of a sufficient amount of data being available to produce the complete set of probabilistic representations in order to provide good functionality.

Discriminative approaches, such as those used in [13]–[18], can produce results using a less exhaustive data set compared to generative approaches. These approaches focus on matching input states (sensor data) to activity labels (classification). This approach may use techniques such as Nearest Neighbour modelling and artificial neural networks.

The general advantages of data driven approaches are that they allow the modelling of uncertainty and temporal parameters. Their disadvantages include the need to have a suitably large data set to learn from. Additionally, the reusability of these activity models is limited to the environment and scenarios that have produced the data set.

2.2 Knowledge driven approaches

Knowledge driven approaches to activity recognition use domain knowledge and *a priori* heuristics as the basis to create activity models. There are many general approaches used to realise knowledge driven approaches including mining, logical and ontological approaches, these are covered in this section.

Mining based approaches, such as those in [19]–[21], create activity models by mining representations of activities from publically available information. This approach mines instructive resources on the World Wide Web, such as how-to guides, to determine steps and objects required to achieve the task described. Similar to data-driven approaches this approach uses statistical and probabilistic activity modelling to produce representations of these activities [19]–[21].

Logical based approaches, such as those in [22], [23], encode representations of ADLs into logical structures using knowledge representation formalisms. These logical structures are combined with knowledge based inference to support activity recognition. Across the various logical approaches the knowledge formalisms used for activity modelling and recognition may vary, however, the overall process is common and is described as follows. Domain knowledge is gathered to define activities and their performance. Knowledge modelling approaches and formalisms are subsequently used to create logical representations of the activities, e.g. encoding plans into a lattice structure [23]. Reasoning mechanisms are applied to map changes in world state with a goal of determining what, if any, activities are occurring. Sensor and activity ontologies have been used in [24]–[29] as the basis for knowledge driven activity recognition and AAL applications. Ontological modelling [30], [31] allows explicit representation of a domain concept. This is achieved by structuring elements into a hierarchy of concepts and classes. These classes and concepts can have properties, relationships and restrictions.

The flexibility of ontologies has been leveraged to allow greater reuse of activity representations [24]. This particular implementation overcomes the flexibility issues that traditional logical approaches have encountered from their use of rigid activity representations. In this approach, common activity representations are used to provide generic representation of ADLs. On performance of an activity by an inhabitant, a relevant common representation is used to produce a personalised representation of a specific ADL.

Mining based approaches have an advantage over data driven approaches in that they don’t require large scale datasets. Nevertheless, this approach uses learning techniques and still has the disadvantages associated with data driven approaches. These include the issues affecting the reusability and flexibility of the activity representations that were previously learned.

Logic-based approaches do not require the production of a data set to provide training for the activity recognition mechanisms. This frees them from exclusive use with the environment and scenario that produced the data set [3]–[5], [24], [32], [33]. Additionally, this approach has clear operation as the mechanisms of activity recognition and encodings of ADL sets are explicitly defined. These approaches do have some negative aspects namely the difficulty representing uncertainty and the relatively rigid representations of ADL sets providing limited personalisation.

Ontological approaches add to the benefits of logical approaches through the addition of flexible models and allowing greater reusability inherent to ontological structures. Disadvantages include weakness in handling uncertainty and modelling, as with other current logical approaches.

A plethora of work relating to activity recognition and SHs currently exists with existing literature reviews [3]–[6], [32], [34], [35] providing further coverage of a large number of these works.

2.3 Goal driven approaches to SHs

In order to realise a goal driven approach to SHs, inhabitant's goals need to be suitably modelled for use by an assistive system. Goal modelling has previously been a focus in areas such as Intelligent Agents (IAs) [36], [37] and requirements analysis for software development [38], [39].

Initial work on formal goal modelling stemmed from research in goal oriented requirements engineering. This is a method of developing software requirements by examination of the goals and expectations of the product to be produced [40], [41]. Within the domain of goal oriented requirements engineering there are a number of approaches that exist such as i* [42], KAOS [43] and UML use case diagrams [44]. These initial approaches to goal modelling informed studies modelling goals within IAs

IAs are software entities which perceive their environments, plan and act towards achieving their goals [45]. In order to achieve these goals IAs can work in isolation or may cooperate with other entities which may be other IAs or humans.

IAs can exhibit a number of characteristics which vary depending on the goal of each specific implementation [45]. Such variations produce different goal models and representations [36], [37], [45], [46]. Of these approaches, IAs, which are based on the belief, desires and intention (BDI) [46] paradigm, have been based on human cognitive model and so provide a suitable basis for modelling the goals of a SH inhabitant.

IAs have been use previously to provide the basis for AAL applications [23], [32], [35], [47]–[52] but have not previously been used to model the goals of an inhabitant. These existing applications instead use IAs to implement traditional activity recognition based SH using one of two approaches as described below.

One approach models an entire SH as a single agent incorporating all the facilities needed to gather information, provide a decision making process and interface with hardware to perceive and affect the environment. For example, Bouchard et al. [37] used a single intelligent agent to create a SH to offer assistance to inhabitants. The agent operated within a SH which was equipped with location mechanisms, smart tags, sensors and identification systems. Signals from perception mechanisms are then used by a Low-level Activity Recognition (LAR) agent. The LAR transforms the low-level inputs into actions to be used by other software systems. A High-level Recognition Service (HRS) interprets the occupant behaviour to provide assistance to an inhabitant.

The alternative approach is to model SH systems as a set of complimentary and cooperative agents which are each specialised to deal with component tasks of the system. In one example, Roy et al. [52] used five agents to provide assistance to inhabitants with Alzheimer's disease. This system used a range of sensors and location systems to track interaction with objects in an environment. This sensor data was combined with an event manager and probabilistic model to recognise inhabitant actions and behaviour to provide assistance when required. These agents were each assigned tasks which were to; interpret sensor information, infer environmental context of action, recognise activity (using traditional approaches), hypothesise about inhabitant behaviour and offer assistance through actuators.

Traditionally goals in BDI IAs have been modelled implicitly, representing only actions required to achieve a goal. Recent works have added an explicit representation of a goal's objective to allow more flexible deliberation on goal pursuit [36], [37].

In [37] goals are modelled using two aspects: procedural and declarative. Declarative aspects are explicit goal statements, for example *Make coffee*. Procedural aspects are a stepwise instruction of activities which are engaged by an agent for example *(open cupboard) -> (get cup)*. Procedural aspects (action plans) can be combined with declarative aspects to allow advanced reasoning [46]. This combination provides a separation of goal representation and actions allowing deliberation on action plans to achieve a goal, as such this combination is needed to represent inhabitant goals.

Current goal models implicitly provide motivation for a software agent but are not suited for explicitly representing goals of a SH inhabitant. To model the goals of SH inhabitants, the goal modelling approach presented in this paper follows the work of Pokahr *et al*. [36] to model declarative and procedural aspects of goals that are pursued by SH inhabitants.

3 Goal driven top-down approach to assistive living

In order to realise a goal driven approach to assistive living, a number of aspects need to be considered. Firstly an overall architecture must be devised that clarifies the focus of goals and complementary components within an assistive living platform. The proposed architecture for this work is presented in Section 3.1. Inhabitant goals must be conceptualised and modelled in order to produce a suitable data structure. This data structure will then be used to inform the production of other components of the overall system in further works. This goal conceptualisation and modelling is presented in section 3.2

3.1 A generic architecture for goal driven top-down assistive living

A novel goal driven and top-down approach to assistive living within SHs is proposed, which is illustrated in Figure 2. The architecture of the approach consists of a number of components, namely a goal repository, a goal recognition component, a specific goal generation mechanism, an activity planning component and an assistance provisioning component.

A goal repository is used to store goals, which have been defined by domain knowledge, in an expressive manner. The goal recognition component [53] interprets sensor activations within the SH to recognise which goal in the repository is most likely being pursued by the SH inhabitant.

Recognised goals are then passed to the specific goal generation process to be deliberated on and, if required, nominate for assistance. Activity planning determines an action plan to be performed to achieve a nominated goal. An assistive provisioning component uses such action plans to provide stepwise assistance to an inhabitant, e.g. an audio instruction. In order to realise this goal driven paradigm an explicit and expressive goal model is required which is the focus of the remainder of this paper.

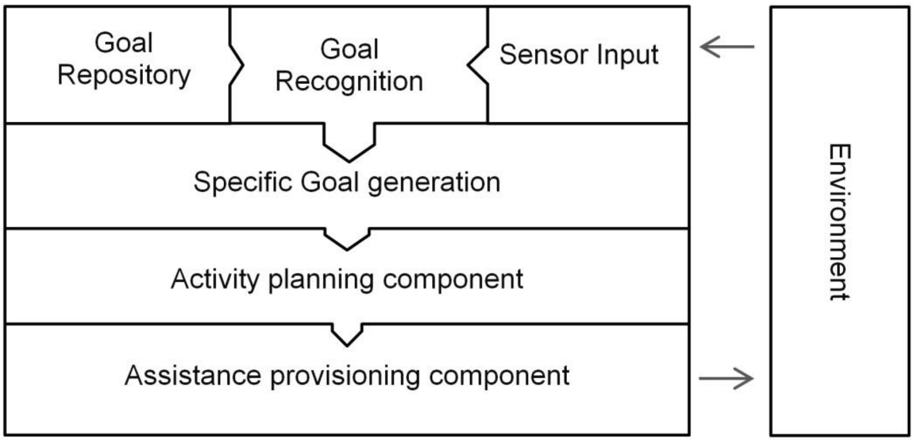


Figure 2 The proposed generic approach to a goal driven assistive solution.

3.2 Goal characterisation and conceptual modelling

ADLs are tasks related to daily living, such as, preparing drinks, preparing a meal and grooming. An ADL is usually composed of a sequence of sub-actions. For example, preparing a cup of tea involves fetching the teapot, a cup, hot water, milk and sugar.

In the presented goal driven top-down approach to assistive living within SHs, goals represent the inhabitant's intention and are realised by performing actions, similar to the realisation of ADLs. Nevertheless, goals are a more abstract representation of activity and so a goal can range from representing many ADLs, one ADL or a simple subset of an activity required to partly achieve an ADL. For example a goal of *GetCup* may be incorporated into a *MakeTea* goal which in turn could be one of multiple goals involved with a *DailyNourishment* goal. Based on how an ADL is performed we can characterise inhabitant's goals in terms of the following dimensions: *types*, *activation conditions* and *state*.

ADLs have different characteristics affecting their recurrence [54], these need to be considered when creating generic types of inhabitant goals. A subset of ADLs achieve something with no set recurrence characteristics, an example of such an IADL is making a cup of tea. Others have set recurrence conditions.

This realisation allows us to characterise inhabitant goals in two categories, namely *Achieve* goals and *Maintain* goals. *Achieve* goals are pursued by inhabitants and are goals that have no set recurrence conditions, e.g. making a cup of coffee. *Maintain* goals represent conditions that an inhabitant must maintain, for example monitoring and controlling blood pressure.

During the performance of an ADL different stages of its completion are encountered. These stages are mapped to the lifecycle of a goal through activation conditions. As such, Activation conditions make it possible to model how inhabitants adopt, manage and pursue goals as their attitude to a goal is reflected by its stage in the overall process lifecycle. Examples of these are presented in Table 1. Both goal types have specific conditions to uniquely cater for their use cases.

The stage of a goal lifecycle is determined by which activation conditions have been encountered. For example, a goal is *adopted* when its precondition becomes true; when it is being pursued by an inhabitant.

Adopted goals can be in one of three states, as reflected by the activation conditions which are encountered: *active*, *suspended* or *assist.* An *active* state represents that the goal is actively pursued by an inhabitant; this is the initial state of an *adopted* goal. *Suspended* state represents that goals are not actively being pursued and *Assist* state represents the condition that goals are in need of assistance.

Achieve goals have an additional achievement condition to determine if a goal has been a success. *Maintain* goals add both an additional *maintain* state and a regular check for a *trigger* condition. In *maintain* goals, the *trigger* condition is used to determine if goal maintenance should occur; at this point the goal is in the *maintain* state. When a goal is in a *maintain* state the *assist* condition is eligible and will determine if assistance would be offered. Unlike *Achieve* goals, *Maintain* goals do not reach an achieved state; however, they remain active when their precondition is valid. The lifecycle of an Achieve goal is presented in Figure 3 and the lifecycle of a maintain goal is presented in Figure 4. In the overall goal-driven approach to a SH these lifecycles are leveraged by the goal recognition and specific goal generation components.

Using this goal representation and lifecycle it becomes possible to offer assistance for an inhabitant when necessary. This assistance would be realised by the use of associated actions plans. These plans are used to determine the current state of goal progress and guide an inhabitant towards goal completion.

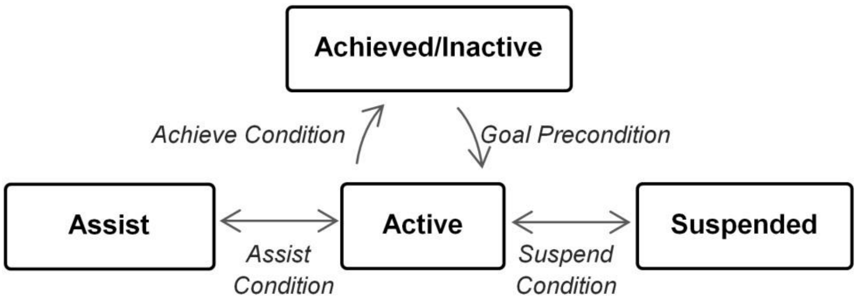


Figure 3 The lifecycle of an achieve goal.

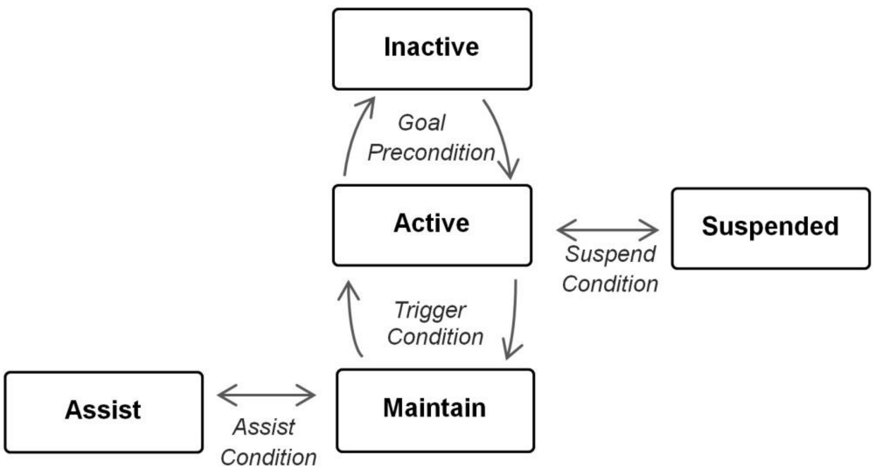


Figure 4 The lifecycle of a maintain goal.

4 Ontological goal modelling

Ontological modelling [30] allows explicit representation of knowledge by structuring it into a hierarchy of concepts and classes which have properties, relationships and restrictions. Ontologies use data properties and object properties to describe a concept. Data properties model the attributes of a concept such as a goal name using primitive data types, e.g. a string. Object properties model interrelationships between concepts, e.g. a goal can be achieved by an action plan, thus an object property AchievedBy can link a Goal concept with an ActionPlan concept.

Ontologies have been previously used in [24] to overcome the limitations of knowledge driven activity recognition. Notably the use of ontologies allowed flexibility in modelling user activities by introducing a method to model variation in user activities by providing a base representation of common ADLs that can be used as the basis for personalisation.

In this goal driven approach, ontologies represent inhabitant goals and so provide the basis for the goal repository component.

4.1 Ontological representation of inhabitant goals

The goals characterised in Section 3.2 have been conceptualised and encoded within an ontology by using the Protégé ontology engineering tool [55]. Goals have two aspects to be represented; declarative and procedural. The properties of these two aspects need to be considered when modelling inhabitant goals in order to encode them in the ontology.

Declarative aspects represent a meta-level representation of a goal; in essence this represents a high level summary of the goal. Providing declarative aspects allows expressive representation of a goal and provides an avenue for flexible deliberation of inhabitant goals. Table 1 presents the properties of the declarative aspect of inhabitant goals.

Table 1. The properties of declarative aspects of a goal.

Term	Description	Example
	Base goal	
Name	The name of the Goal.	"MakeCoffee"
Description	A description of the Goal (optional).	"An inhabitant goal for making coffee."
Precondition	A property showing when a goal is likely to be considered by an inhabitant and so will be deliberated on.	The representation that the goal recognition has determined an inhabitant is wishing to make coffee; (*Intent.IdentifiedGoal == MakeCoffee && Intent.IdentifiedGoal == KichenGoal).*
SuspendCondition	This represents conditions where a goal is considered to be suspended.	A representation showing an inhabitant is pursuing an incompatible goal which suspends pursuit of this one. An example of such is, an inhabitant pursuing any goal which inherits a core bathroom activity goal (which is inherited by all bathroom goals); *Intent.IdentifiedGoal == BathroomGoal.*
AssistCondition	This represents a condition where a goal is in need of assistance.	Goal progression is occurring in a confused manner; *Intent.Sys.UnknownGoal == True.*
OperationalState	The current state of the goal. Typically this will be 1 of 4 eligible states;	"Active"

	["Inactive" | "Active" | "Assist"| "Suspended"].	
PreviousEventTimestamp	Time stamp of a previous goal action as represented by Unix time.	511582260
	Achieve Goal	
AchievementCondition	This condition under which a goal is considered to be achieved.	All the actions to complete the goal have been performed; *Intent.IdentifiedGoal == MakeCoffee && Intent.IdentifiedGoal.hasCompleteActionPlan().*
	Maintain Goal	
TargetCondition	The target condition to be maintained by the goal.	An ambient temperature of 19^{o} Celcius; *Home.Environment.AmbientTemp == 19C*.
TriggerCondition	The condition specifying when the target maintains condition should be pursued.	Ambient temperature is not below 18^{o} or over 20^{o}Celsius; *18C> Home.Environment.AmbientTemp < 20C*.
MaintenanceCheckFrequency	The frequency which the maintain goal is checked (in seconds).	300 (s)

Procedural aspects of goals, also known as action plans, need to be considered. These procedural aspects provide a representation of steps of how to complete a goal. The properties of this aspect are presented in Table 2.

Table 2. The properties of an action plan and atomic actions.

Term	Description	Example
	Action Plan	
Name	The name of the Action plan.	"MakeCoffee_Latte"
Description	The description of the plan (optional).	"Making a latte with an espresso machine"
	Atomic Action	
Name	The name of the atomic action	"Place coffee in hopper"
Precondition	A precondition needed for this action to be eligible. This will generally be the action status of the effect of an atomic action. At times where there is no precondition required this can be left empty.	*this.CoffeeHopperCleared.ActionStatus == True.*
Effect	The effect when an atomic action is completed.	CoffeeInHopper
Action status	The status of this particular action, showing if it has been completed or not; typically this is True or False.	True

Two graphical representations of this ontology are presented below. Figure 5 presents the ontology as a hierarchy of concepts whilst Figure 6 presents the classes and properties of the ontology as depicted in the Protégé ontology modelling tool.

In the presented ontology, the general class of a Goal has a hasGoalprofile object property linking to a GoalProfile. The GoalProfile entity contains all the common properties for a base goal type. The goal class contains two sub classes to cater for the needs of achieve and maintain goal types. These sub classes contain individual data properties for their goal types. The goal concept is linked by a hasActionPlan object property to the ActionPlan concept. The ActionPlan in turn has a hasAction object link which is used to link to the component AtomicAction concept.

The use of this hasActionPlan object property allows a goal to have multiple action plans which can be followed to complete the goal. For example, the MakeCoffee goal presented in Table 1 has one associated action plan as shown in Table 2. The action plan shown in Table 2 is a representation of making a latte coffee with an espresso maker. Alternative coffee preferences and production methods can be catered for by linking their differing ActionPlan concepts to this goal by using the hasActionPlan concept.

In order to flexibly model complex user goals, goal inheritance should be catered for. Goal inheritance provides a mechanism for user goals to incorporate properties from other goals thus reducing the overhead required to model inhabitant goals. This inheritance is catered for by the inheritsGoal object property. The flexibility offered by goal inheritance is presented in Section 4.2.

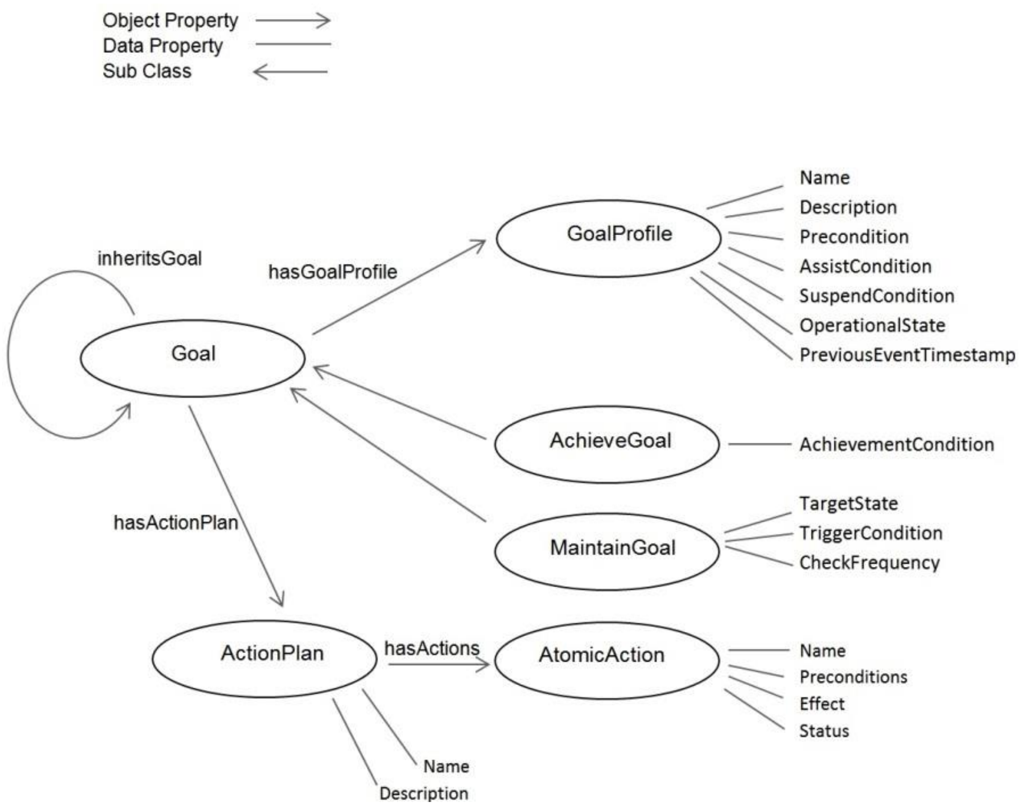


Figure 5 The classes, object properties and data properties of the proposed goal ontology.

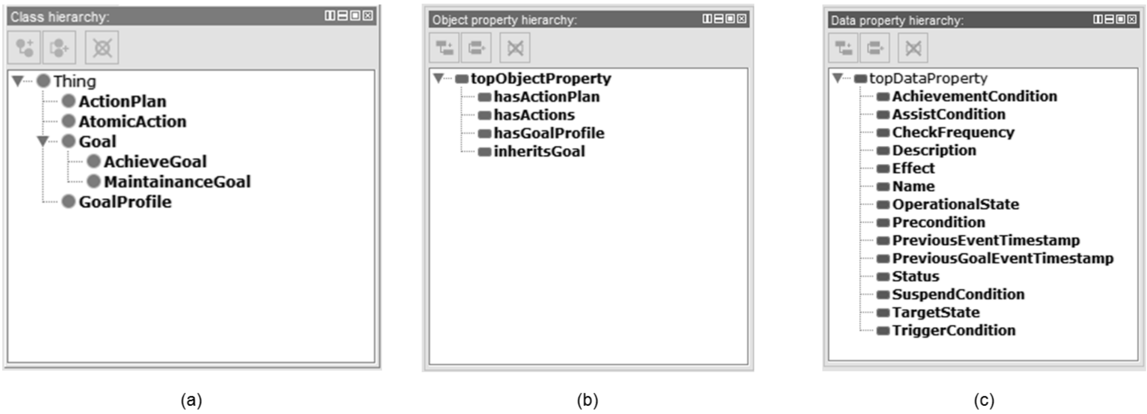


Figure 6 The classes (a), object properties (b) and data properties (c) of the goal ontology. (As shown in the protégé ontology engineering tool.)

4.2 Goal inheritance

Inhabitant goals can share a number of common tasks or contexts that can be efficiently modelled by using goal inheritance. Goal inheritance allows non-identifying and non-instance properties of goals, such as preconditions and action plans, to be incorporated into other goals. Identifying properties are those such as a goal's name or its description, instance properties are those such as OperationalState and PreviousEventTimestamp.

For example, a number of goals could be pursued in a kitchen context which may have common preconditions and actions. In order to reduce the effort required to model these goals, a base kitchen goal could be specified which these goals can inherit using the inheritsGoal object property. This base kitchen goal would contain preconditions to represent goals that would take place in a kitchen environment and may not necessarily have an associated action plan.

A more complex scenario showing inheritance is depicted in Figure 7. In this scenario, the 3 top level beverage goals (Black Coffee, White Coffee and Milkshake) share common elements (e.g. conditions) and actions. Common elements and actions include obtaining a Mug or Cup for the beverage, boiling and pouring water into a vessel and adding milk to the Mug or Cup. These common preconditions and actions are inherited by these 3 top level goals from the Mug/Cup goal, Hot Drink Goal and Milky Drink Goal.

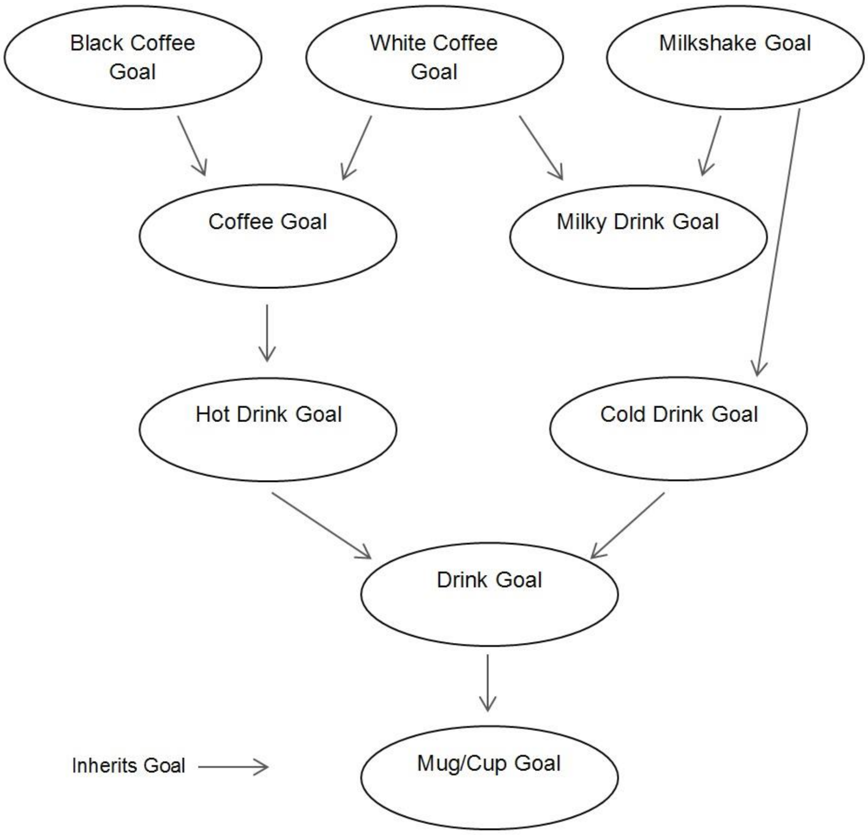
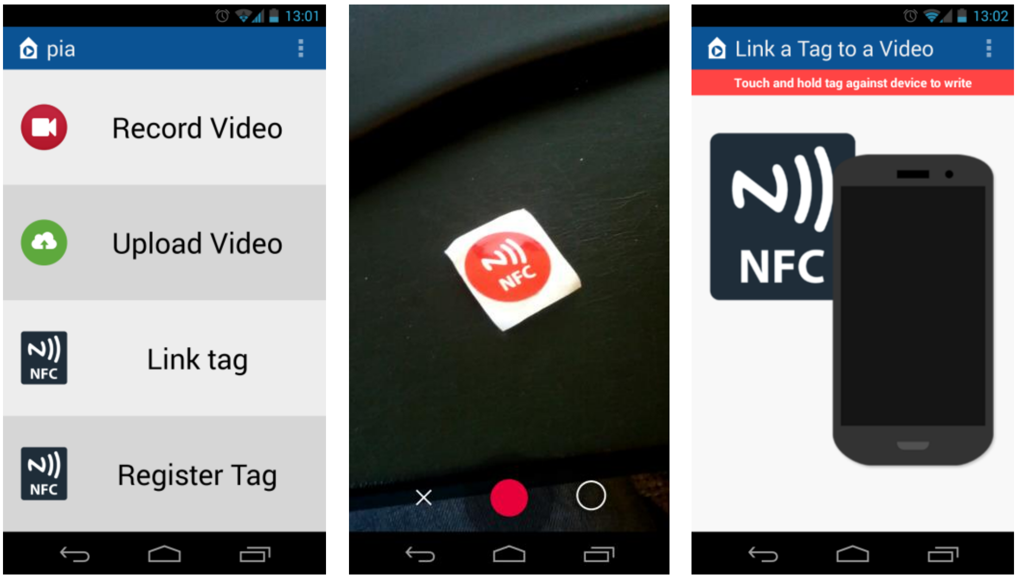


Figure 7 The use of goal inheritance to model a number of goals which may be pursued in a kitchen environment.

5 Use scenarios for assistive living

In the following Section we use the EU AAL funded PIA Project[1] as the basis of a scenario to illustrate the suitability of the developed goal model in a top-down, goal-driven SH setting. PIA aims to provide a system capable of assisting SH inhabitants by reminding them of the steps required to perform an ADL. PIA provides assistance by affixing NFC[2] tags to items associated with ADLs, for example, tags attached to a medication container or coffee maker. Caregivers record relevant instructional videos, upload them to the PIA system and associate them with these tags. Inhabitants use devices such as smartphones to interact with these tags. On interaction with a tag the device reads identifiers and references an associated ADL in a database to obtain and display video clips to illustrate to the user how to perform the task. The interface of the PIA application is shown in Figure 8. Further information about the PIA project is available in [56].

[1] PIA AAL Funded Research Project available at: http://www.pia-project.org/
[2] Near Field Communication – A short range contactless communication technology



(a) (b) (c)

Figure 8 Screen shots of the menu (a), video recording (b) and tag linking (c) interface of the implemented PIA app.

In this case study, the PIA solution is extended by employing the top-down approach to create a more capable system with less inhabitant interaction and awareness.

In this scenario[3], a number of inhabitant goals are modelled and stored in the goal driven assistive system. These inhabitant goals are stored within the goal ontology allowing reuse, the ability to extend goals and use of semantic technologies to provide scalable operation. These goals involved include those shown in the hierarchy presented in Figure 7, in addition to a *BrushTeeth* achieve goal and inherited *BathroomActivity* and *KitchenActivity* goals.

A goal recognition component monitors sensor activity, in conjunction with the activation conditions present in each goal, to determine the goal most likely pursued by an inhabitant. The specific approach used by this goal recognition mechanism can vary [53] and is beyond the scope of this scenario.

During the course of a day, the inhabitant enters a kitchen environment. This is a precondition for the *KitchenActivity goal* which is inherited as a number of goals including the *Mug/Cup goal*. This *KitchenActivity goal* has a suspend condition which factors in the inhabitant pursing goals which inherit other context based goals, such as a *BathroomActivity goal* or a *BedroomActivity goal*. At this stage all goals which inherit the *KitchenActivity goal* are considered as being potentially pursued by the goal recognition mechanism. The inhabitant acts further and engages in reaching for a mug or cup; this leads the goal recognition mechanism to add weight to the probability that the inhabitant's goal involves the *Mug/Cup goal* or one of the many goals which inherit it. Further actions are performed by the inhabitant, indicating goals based on the *Hot Drink goal* are most likely to be pursued by the inhabitant.

At this point, the inhabitant may become confused and not pursue their goal. The *Hot Drink goal* incorporates an assist condition that will trigger if the inhabitant has not moved towards the goal within a reasonable timeframe. When this inactivity is shown the assist stage of the lifecycle is encountered and assistance is rendered. Using action plans associated with the goal, the assistive system determines the atomic actions that have been enacted and constructs some illustrative guidance that

[3] This use scenario assumes a fully implemented goal driven assistive system that uses a small number of contact sensors affixed to objects within a residence and has a method of providing illustrative guidance based on video.

will show the inhabitant the remaining steps required to complete the task. To provide this instruction, the video repository of the PIA project can be used in a process of dynamically matching appropriate video sequences or potentially producing an appropriate instructional video from multiple clips. This assistance can then be delivered to multiple screens within the inhabitant's environment, including personal smart devices (e.g. a tablet or mobile phone) and smart TVs.

Once reminded how to achieve the goal the inhabitant continues to act towards the next inherited goal which is a *Coffee goal.* This goal has an assist condition which also reflects that the inhabitant has not acted towards their goal within a reasonable time; this condition overrides the assist condition of the *Hot Drink goal*.

At this stage the inhabitant wishes to brush their teeth and moves to the bathroom to engage in the *BrushTeeth goal* which inherits the *BathroomActivity*. Although the inhabitant is not acting towards the *Coffee goal,* this deviation does not contribute towards the assist condition to be encountered due to the suspend condition factoring in pursuit of the *BathroomActivity* goal. Once the inhabitant returns to the kitchen the *Coffee goal* is no longer suspended and may be used to provide assistance if the assist condition is encountered. In this particular case the inhabitant successfully pursues the *BlackCoffee goal* and so encounters its *AchieveCondition* which retires the goal for consideration by the goal recognition mechanism.

This scenario extends the PIA solution by leveraging its video repository and infrastructure while changing its paradigm from that of an on-demand delivery mechanism for instructive guidance to that of a goal driven assistive system. This paradigm change enables the PIA project to provide automated assistance instead of requiring an inhabitant to have the mental capacity to use the manual on-demand solution.

6 Conclusion

This paper introduced a top-down, goal driven approach to realising a SH in order to address the shortcomings of the current widespread sensor-focused paradigm.

We have proposed an architecture which can be used to realise this goal driven approach. In the first step towards realising this architecture, we have characterised and developed a conceptual model for the goals of SH inhabitants. This model has been represented in an ontology which has been described. To illustrate the suitability of the developed ontological goal model for this approach and general goal driven approach to assistive living, we presented a use scenario extended from the PIA project to show the use of such a system in assistive living.

This approach conceptually shows a novel method of producing an assistive living system. While testing and evaluation await further implementation of this system, the proposed approach and underlying mechanisms have never been used to produce such an assistive system.

Future work will produce and integrate all components required for this approach. Once the overall system is produced, the performance and suitability of such an approach will be evaluated. During evaluation, the suitability of goal modelling, the capability of goal recognition and the flexibility of illustrative guidance will be considered.

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