Possibilistic Behavior Recognition in Smart Homes for Cognitive Assistance

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Abstract

Providing cognitive assistance in smart homes is a field of research that receives a lot of attention lately. In order to give adequate assistance at the opportune moment, we need to recognize the observed behavior when the patient carries out some activities in a smart home. To address this challenging issue, we present a formal activity recognition framework based on possibility theory. We present initial results from an implementation of this possibilistic recognition approach in a smart home laboratory.

Introduction

A major development in recent years is the importance given to research on ambient intelligence in the context of recognition of the activities of daily living. Ambient intelligence 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 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 (Ramos, Augusto, and Shapiro 2008). 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 (Casas et al. 2008). Activity recognition, often referred as plan recognition (Geib 2007), 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 for a long time and still remains very challenging. It is usually based on a logic or probabilistic reasoning for the construction of hypotheses about the possible activities, and on a matching process linking the observations with some activity models (plans) related to the application domain. However, most of activity recognition research has focused on probabilistic models such as Markovian models and Bayesian networks. One limitation of probability theory and its extensions is its inability to simultaneously handle the lack of precision and the uncertainty of incomplete information. In fact, in the context of cognitive assistance, where the human agent is characterized by erratic behaviors, complete ignorance about the specific dependence between two actions cannot be represented by classical probability theory. Hence, one of the solutions to this kind of problem is possibility theory (Dubois and Prade 2007), devoted to formalizing ignorance about events. Moreover, 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 (Zadeh 1978).

At the Domus (Giroux et al. 2009) and LIARA labs, we use possibility theory to address this issue of recognizing behavior classified according 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 (Activities of Daily Living). 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, according to the observed actions, an erroneous behavior hypothesis is as possible as a normal behavior hypothesis when we want to explain the observed behavior of a patient when he carries out some activities. Hence, in a complete ignorance setting, both behavior types are possible, although each type is not necessarily the one being carried out. So, unlike probability theory, possibility theory is not additive. The paper is organized as follows. Firstly, we present our possibilistic activity recognition model. Thereafter, we present results of our implementation's experimentation based on real data from the AIHEC project at the Singapore's *Institute for Infocomm Research*. Finally, we conclude the paper, mentioning future perspectives of this work.

Possibilistic Activity Recognition Model

Our activity recognition model is based on possibility theory and on description logic (DL) (Baader et al. 2007). 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 is separated into two agents: the action recognition agent and the behavior recognition agent. This separation will allow us to change the action recognition model or the activity recognition model without modifying the other part in order, for instance, to try another approach. Action recognition refers to the recognition of the low–level action that was carried out in the smart home environment according to the changes observed in the environment's state. According to a possibilistic action formalization and to the set of environment contexts that could represent the observed environment 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. Behavior recognition refers to the recognition, according to the sequence of recognized actions, of the high–level behavior related to the accomplishment, in a erroneous or coherent way, of some activities. By using the sequence of observed actions and the activity plan ontology, the behavior recognition agent generates a set of hypotheses that could explain the observed coherent or erroneous behavior, and selects the most possible and necessary hypotheses in order to send them to an assistive agent, which will plan a helping task if needed.

Action Recognition

In our model, the observer agent has knowledge concerning the resident's environment, which is represented by using a formalism in description logic. By using the open world assumption, it allows us to represent the fact that the environment is partially observable. The family of DL $\mathcal{ALC}$ is used to represent the environment states. The observation of the environment's state with sensors allows us to obtain the low–level *context* C of the environment. Since the observation can be partial, this context can represent a subset of the environment's state space S, where states of this subset share some common environmental properties. More formally, a context C consists of a set of DL assertions where some states in S are entailed, so that $C^{\mathcal{I}} \subseteq S$ is not an empty state. $\cdot^{\mathcal{I}}$ is an interpretation function that assigns to a context C a subset of the interpretation domain $\Delta^{\mathcal{I}} = S$. For instance, the context where the patient is in the kitchen, the pantry door is open, and the pasta box is in the pantry can includes several possible states of the smart home environment. Also, a set of contexts can be seen as a partition of the environment's state space.

In order to infer hypotheses about the observed behavior of the patient 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 carry out the activities. 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 1. A *possibilistic action* a is a tuple (C_{pre_a}, C_{post_a}, π_{init_a}, π_{trans_a}), where 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 $\mathcal{A}$, which contains the set of possible actions that can be carried out by the patient, is represented by an action ontology, where each action is partially ordered according to an action subsumption relation $\sqsubseteq_{\mathcal{A}}$, which can be seen as an extension of the concept subsumption relation $\sqsubseteq$ of DL (Baader et al. 2007). This 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.

Proposition 2. Let a, $b \in \mathcal{A}$ be two action tuples (C_{pre_a}, C_{post_a}, π_{init_a}, π_{trans_a}) and (C_{pre_b}, C_{post_b}, π_{init_b}, π_{trans_b}). If a subsumes b, denoted by $b \sqsubseteq_{\mathcal{A}} a$, then we have: (**i**) for each context d in C_{pre_b}, there exists a context c in C_{pre_a} where $d \sqsubseteq c$ and $\pi_{init_b}(d) \leqslant \pi_{init_a}(c)$, (**ii**) and for each context e in C_{post_b}, there exists a context f in C_{post_a} where $e \sqsubseteq f$ and $\pi_{trans_b}(d, e) \leqslant \pi_{trans_a}(c, f)$.

In other words, 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 $OpenDoorPantry$. With this action subsumption relation, we can define an *action ontology*, which represents all the possible actions that an observed patient can carry out in the smart home environment. This action ontology is represented by an ordered set ($\mathcal{A}$, $\sqsubseteq_{\mathcal{A}}$), where $\mathcal{A}$ is a set of actions and $\sqsubseteq_{\mathcal{A}}$ is the action subsumption relation (order relation). For instance, for the action set $\{All$, $OpenDoor$, $OpenPantryDoor$, $OpenFridgeDoor\}$, we have the partial order ($OpenFridgeDoor \sqsubseteq_{\mathcal{A}} OpenDoor$, $OpenPantryDoor \sqsubseteq_{\mathcal{A}} OpenDoor$, $OpenDoor \sqsubseteq_{\mathcal{A}} All$).

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 patient. 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, we need to use the *observation* of the current environment state. An observation at a time t, denoted by obs_t, consists of a set of DL assertions, according to the environment terminology, that represent the state of the environment resulting from an action realization at a time t. This observed state can be partial or complete according to the information that can be retrieved from the environment's sensors. An observation *timestamp* $t \in \mathcal{T}_s$ is associated with a time value $t_i \in \mathcal{T}$ 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 the action ontology $\mathcal{A}$ indicates the possibility, denoted by $\pi_{pre_t}(a)$, that a particular action $a \in \mathcal{A}$ could be the next one to be carried out by the observed patient according to the environment state observed by obs_t. Thus, π_{pre_t} is obtained by selecting, for each action, 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 observation ($obs_t \models c_i$).

The action recognition possibility distribution π_{rec_t} on $\mathcal{A}$ indicates the possibility, denoted by $\pi_{rec_t}(a)$, that a particular action $a \in \mathcal{A}$ was carried out by the observed patient, according to the environment states observed by obs_{t-1} and obs_t. Thereby, π_{rec_t} is obtained by selecting, for each action, the maximum value among the transition possibilities $\pi_{trans_a}(c_i, c_j)$ for the transitions (c_i, c_j) between the pre–action contexts $c_i \in C_{pre_a}$ entailed by the previous observation ($obs_{t-1} \models c_i$) and the post-action contexts $c_j \in C_{post_a}$ entailed by the current observation ($obs_t \models c_j$).

π_{rec_t} allows us to evaluate the possibility and necessity $\Pi_{rec_t}(Act)$ and $N_{rec_t}(Act)$ that an action $a \in Act \subseteq \mathcal{A}$ was observed at a time t. $\Pi_{rec_t}(Act)$ is obtained by taking the maximum $\pi_{rec_t}(a)$ among the actions $a \in Act$. $N_{rec_t}(Act)$ is obtained by taking the maximum $\pi_{rec_t}(b)$ among the actions $b \in \mathcal{A}$ and subtracting the maximum $\pi_{rec_t}(a)$ among the actions $a \in \overline{Act}$, where $\overline{Act} = \mathcal{A} \setminus Act$ is the complement of Act. The possibility and necessity measures Π_{rec_t} and N_{rec_t} are then used to select the most possible action that could explain the changes observed in the environment state described by the current obs_t.

An *observed action* at time t, denoted by $(a,\ t)$, is obtained by selecting the most possible (and necessary) action $a \in \mathcal{A}$ according to the $\Pi_{obs_t}(a)$ and $N_{obs_t}(a)$ values. If there is more than one most possible action, then a is selected among those most possible actions by using the action subsumption relation: (**i**) takes the most specific actions among those most possible actions, (**ii**) gets the common subsumer actions on those specific actions, (**iii**) and selects the most specific action among those subsumer actions. For instance, if the most possible 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 most possible 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 accomplishment of the patient's activities. This sequence, which is the *observed plan* P_{obs_t}, consists of a totally ordered set $(\mathcal{A}_t, \prec_\mathcal{T})$, where $(a_i, t_j) \in \mathcal{A}_t$ denotes that a_i is the most plausible observed action at the time t_j, and $\prec_\mathcal{T} \subseteq \mathcal{A}_t \times \mathcal{A}_t$ is a total order (sequence) relation. 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 $(OpenDoor, 0) \prec_\mathcal{T} (EnterKitchen, 1)$ 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. It should be noted that not only the observed plan is sent to the behavior recognition agent, but also the possibility distributions on the action set. This gives more flexibility to the architecture, since it is possible that the behavior recognition approach could be substituted with another approach.

Behavior Recognition

The hypotheses about the behavior, which is associated with the performance of some activities, are made according to an activity formalization in a plan structure. 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 3. An activity α is a tuple $(\mathcal{A}_\alpha,\ \prec_\alpha,\ C_{real_\alpha},\ \pi_{real_\alpha},\ \pi_{err_\alpha})$ where $\mathcal{A}_\alpha \subseteq \mathcal{A}$ is the activity's set of actions, which is partially ordered by a temporal relation $\prec_\alpha \subseteq \mathcal{A}_\alpha \times \mathcal{A}_\alpha \times \pi_{time_\alpha}$ where π_{time_α} represents a set of temporal possibility distributions $\pi_{time_{\alpha,k}}$, C_{real_α} is the set of possible contexts related to the activity realization, π_{real_α} is the possibility distribution on C_{real_α} that a context is related to a coherent realization of the activity, and π_{err_α} is the possibility distribution on C_{real_α} that a context is related to an erroneous realization of the activity.

Each relation $(a_i, a_j, \pi_{time_{\alpha,k}}) \in \prec_\alpha$ allows us to describe the possible delays, according to the temporal distribution $\pi_{time_{\alpha,k}}$, between the carrying out of a_i and a_j. The temporal distribution $\pi_{time_{\alpha,k}}$ on $\mathcal{T}$, which is a set of time values, indicates for each time value $t_l \in \mathcal{T}$, the possibility $\pi_{time_{\alpha,k}}(t_l)$ that t_l represents a coherent delay between the realization of a_i and a_j. For instance, the activity $WatchTv$ can have an activity plan composed of the actions $SitOnCouch$, $TurnOnTv$ and $TurnOffTv$ and the temporal relations $(SitOnCouch, TurnOnTv, \pi_{time_0})$ and $(TurnOnTv,\ TurnOffTv,\ \pi_{time_1})$, where π_{time_0} and π_{time_1} indicates possible delays between the realization of the actions, according to Figure 1.

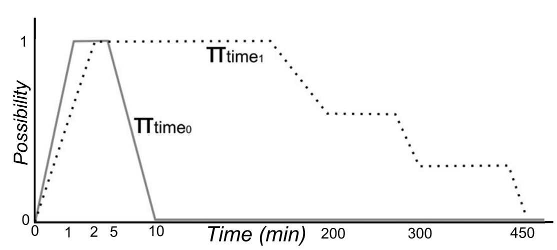

Figure 1: Temporal distributions for $WatchTv$.

This activity formalization allows us to recognize different kinds of behavior, such as, for instance, interleaved behaviors (normal realization of multiple activities where their actions are interleaved in the observed behavior), temporal errors (normal sequence of the activity's actions but the time constraints are not respected), sequence errors (some activity's actions are badly ordered), realization errors (irrelevant actions added to the activity's actions), and completion errors (unable to complete the activity).

The set $\mathcal{P}$ of possible activity plans that can be carried out by the patient in a smart home is partially ordered according to an activity subsumption relation $\sqsubseteq_{\mathcal{P}}$.

Proposition 4. Let α, $\beta \in \mathcal{P}$ be two activity tuples ($\mathcal{A}_\alpha$, $\prec_\alpha$, C_{real_α}, π_{real_α}, π_{err_α}) and ($\mathcal{A}_\beta$, $\prec_\beta$, C_{real_β}, π_{real_β}, π_{err_β}). If α subsumes β, denoted by $\beta \sqsubseteq_{\mathcal{P}} \alpha$, then we have: for each context d in C_{real_β}, there exists a context c in C_{real_α} where $d \sqsubseteq c$, $\pi_{real_\beta}(d) \leqslant \pi_{real_\alpha}(c)$, and $\pi_{err_\beta}(d) \leqslant \pi_{err_\alpha}(c)$.

In other words, if an activity subsumes another one, its possibility values are at least as possible than the activity subsumed. For instance, if $CookFood$ subsumes $Cook\text{-}PastaDish$, then the $CookFood$ possibility will be greater or equal than the $CookPastaDish$ possibility, considering that $CookFood$ constitutes a more general activity and considering that $CookPastaDish$ implies $CookFood$. With this activity subsumption relation $\sqsubseteq_{\mathcal{P}}$, we can define an activity plan ontology ($\mathcal{P}$, $\sqsubseteq_{\mathcal{P}}$) where the set of all possible activity plans $\mathcal{P}$ that can be carried out in the smart home environment is partially ordered according to $\sqsubseteq_{\mathcal{P}}$.

After each observation obs_t, we need to evaluate the possibility distributions π_{real_t} and π_{err_t} on the activity plan ontology $\mathcal{P}$, which indicates the possibility that the environment's state observed by obs_t is related, respectively, to an coherent realization and erroneous realization of the activity. The coherent activity realization possibility distribution π_{real_t} on $\mathcal{P}$ indicates the possibility, denoted by $\pi_{real_t}(\alpha)$ that the environment's state observed by obs_t is related to a coherent realization of the activity plan $\alpha \in \mathcal{P}$. Hence, π_{real_t} is obtained by selecting, for each activity plan $\alpha \in \mathcal{P}$, 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 observation ($obs_t \models c_i$).

The erroneous activity realization possibility distribution π_{err_t} on $\mathcal{P}$ indicates the possibility, denoted by $\pi_{err_t}(\alpha)$ that the environment's state observed by obs_t is related to an erroneous realization of the activity plan $\alpha \in \mathcal{P}$. Thus, π_{err_t} is obtained by selecting, for each activity plan $\alpha \in \mathcal{P}$, the maximum value among the context possibilities $\pi_{err_\alpha}(c_i)$ for the contexts $c_i \in C_{real_\alpha}$ that are entailed by the 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 patient 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* $path_j$ is a tuple $(\alpha_j, P_{obs_t}, R_{path_j})$, where $\alpha_j \in \mathcal{P}$ is the activity that is partially carried out, P_{obs_t} is the observed plan, and $R_{path_j} \subseteq \mathcal{A}_t \times \mathcal{A}_{\alpha_j}$ is a set of observed actions $(a_i, t_k) \in \mathcal{A}_t$ from the observed plan P_{obs_t} that are associated with actions $a_l \in \mathcal{A}_{\alpha_j}$ in the activity plan α_j, so that $((a_i, t_k), a_l) \in R_{path_j}$. The observed actions in R_{path_j} must represent a coherent partial realization of the activity α_j, according to the sequence and temporal constraints defined in the activity plan α_j. It should be noted that if an observed action (a_i, t_k) is associated with an activity action a_l, denoted by $((a_i, t_k), a_l) \in R_{path_j}$, then the observed action must subsume the activity action ($a_l \sqsubseteq_{\mathcal{A}} a_i$). For instance, given the observed plan $(SitOnCouch, 0) \prec_{\mathcal{T}} (TurnOnElectricalAppliance, 1)$ and the $WatchTv$ activity plan, we can have as partial path the associations $((SitOnCouch, 0),\ SitOnCouch)$ and $((TurnOn\text{-}ElectricalAppliance, 1),\ TurnOnTv)$ (since $TurnOn\text{-}Tv$ 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: (**i**) a partial path $path_j \in Path$ is extended if the new observed action subsumes one of the next possible actions in the activity plan and if the extended partial path respects the constraints in the activity plan. Also, we must keep a copy of the original partial path, since it is possible that the new observed action is not associated to the partial path's activity, (**ii**) a partial path $path_j \in Path$ is removed if the maximum delays for the next possible action in the activity plan are exceeded, (**iii**) a partial path $path_j$ is added in $Path$ if the new observed action subsumes one of the activity's actions that can be directly carried out.

With this partial activity realization path set $Path$, we need to evaluate the possibility distributions $\pi_{Path_{C,t}}$ and $\pi_{Path_{E,t}}$ on $Path$, which indicates the possibility that a particular partial path is associated, respectively, to a coherent behavior or an erroneous behavior. The coherent partial path realization possibility distribution $\pi_{Path_{C,t}}$ on $Path$ indicates the possibility, denoted by $\pi_{Path_{C,t}}(path_j)$, that a particular partial path $path_j \in Path$ is associated with a coherent behavior according to an observed plan P_{obs_t}. Thus, $\pi_{Path_{C,t}}$ is obtained by considering, for each $path_j \in Path$, the action prediction possibility for each action in the activity plan that could be the next one to be carried out, the action prediction and recognition possibilities for the actions that are in the partial path, the coherent activity realization possibility for the activity associated to the partial path, and the time possibilities for the action transitions in the partial path.

The erroneous partial path realization possibility distribution $\pi_{Path_{E,t}}$ on $Path$ indicates the possibility, denoted by $\pi_{Path_{E,t}}(path_j)$, that a particular partial path $path_j \in Path$ is associated with an erroneous behavior according to an observed plan P_{obs_t}. Thereby, $\pi_{Path_{E,t}}$ is obtained by considering, for each $path_j \in Path$, the action prediction and recognition possibilities for the observed actions not in the partial path, and the erroneous activity realization possibilities for the activity associated to the partial path.

By considering the set of possible activity plans $\mathcal{P}_{poss} \subseteq \mathcal{P}$ that could be partially carried out, which are the activity plans associated to partial paths in $Path$, we can generate hypotheses concerning the observed behavior of a patient when he carries out some activities in the smart home environment.

Proposition 5. A behavior hypothesis h_i consists of a subset of $\mathcal{P}_{poss}$ where $\forall \alpha_j \in h_i, \nexists \alpha_k \in h_i, \alpha_i \neq \alpha_k \wedge \alpha_i \sqsubseteq_{\mathcal{P}} \alpha_k$.

Thus, a behavior hypothesis h_i is an element of the power set of $\mathcal{P}_{poss}$ where each activity plan in the hypothesis is not subsumed by another activity plan in the hypothesis. Two interpretations can be given to a particular hypothesis h_i: coherent behavior and erroneous behavior. h_i can be interpreted as *coherent behavior* where the patient carries out the activities $\alpha_j \in h_i$. Those activities can, at the current observation time, be partially realized. h_i can be interpreted as *erroneous behavior* where the patient carries out some activities in an erroneous way, while the activities $\alpha_j \in h_i$ are carried out in a coherent way. Since h_i can be empty, we cover also the case where the patient accomplishes some activities in an erroneous way without some coherent activity realizations. Concerning the erroneous behaviors, multiple error types are possibles (sequence, realization, judgment, initiation, completion, and organization), but the behavior recognition is unable to disambiguate the observed error type. Furthermore, multiple error types can happen at the same time in the observed behavior.

Since each hypothesis h_i in the behavior hypothesis set $\mathcal{H}_t$ for the current observed plan P_{obs_t} can be interpreted in two ways, we need to evaluate two possibility distributions on $\mathcal{H}_t$: the coherent behavior possibility distribution $\pi_{Bev_{C,t}}$ and the erroneous behavior possibility distribution $\pi_{Bev_{E,t}}$. The coherent behavior possibility distribution $\pi_{Bev_{C,t}}$ on $\mathcal{H}_t$ indicates the possibility, denoted by $\pi_{Bev_{C,t}}(h_i)$, that a particular hypothesis $h_i \in \mathcal{H}_t$ represents a coherent behavior according to the observed plan P_{obs_t}. Thus, $\pi_{Bev_{C,t}}$ is obtained by selecting, for each $h_i \in \mathcal{H}_t$, the maximum value among the minimal coherent partial path possibilities for each activity in h_i. If some actions in the observed plan are not in the partial paths of the activities in h_i, then $\pi_{Bev_{C,t}}(h_i)$ is 0.

The erroneous behavior possibility distribution $\pi_{Bev_{E,t}}$ on $\mathcal{H}_t$ indicates the possibility, denoted by $\pi_{Bev_{E,t}}(h_i)$, that a particular hypothesis $h_i \in \mathcal{H}_t$ represents an erroneous behavior according to the observed plan P_{obs_t}. Thereby, $\pi_{Bev_{E,t}}$ is obtained by selecting, for each $h_i \in \mathcal{H}_t$, the maximum value among the minimal erroneous partial path possibilities for each activity in h_i. If h_i is empty, then $\pi_{Bev_{E,t}}(h_i)$ is obtained according to the action recognition possibilities for the actions in the observed plan.

With those two possibility distributions, we can evaluate the possibility and necessity that each hypothesis represents a coherent or an erroneous behavior which could explain the observed actions P_{obs_t}. The possibility and necessity measures that a hypothesis $b_i \in B \subseteq \mathcal{H}_t$ 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 $\pi_{Bev_{C,t}}$. The possibility and necessity measures that a hypothesis $b_i \in B \subseteq \mathcal{H}_t$ 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 $\pi_{Bev_{E,t}}$.

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 $\mathcal{H}_t$. The results of the behavior recognition are then sent to an assistive agent, which will use it to plan a helping task if needed.

Behavior Recognition Scenario

Let us illustrate the recognition process of our possibilistic model inside a smart home's kitchen. Suppose that the environment's sensor events indicate that a kitchen door was open. According to the action ontology $\mathcal{A}$, the entailed contexts, and the action prediction and recognition possibility distributions, there are three most possible and necessary actions that could explain the environment changes: $OpenKitchenDoor$, $OpenPantryDoor$ and $OpenFridgeDoor$. According to the action subsumption relation, the observed action that will be sent to the behavior recognition is $OpenKitchenDoor$. Let suppose that we observe the action $TurnOnFoodHeatingAppliance$, which subsumes $TurnOnMicrowave$ and $TurnOnStove$, 1 minute later. Thereby, the observed plan is $(OpenKitchenDoor, 0) \prec_{\mathcal{T}} (TurnOnFoodHeatingAppliance, 1)$. According to this observed plan and the activity plan ontology $\mathcal{P}$, the possible activities that could be partially carried out are $CookFrozenDish$ and $CookPasta$. Then, we have some behavioral hypotheses: (1) erroneous behavior without coherent activity realization, (2) erroneous behavior with coherent realization of the $CookPasta$ or $CookFrozenDish$ activities, and (3) coherent behavior with coherent realization of the $CookPasta$ or $CookFrozenDish$ activities. If the system does not observed the action $CloseFridgeDoor$ within the specified delays according to the temporal constraints defined in the $CookFrozenDish$ activity (time possibility distribution), the partial paths associated to $CookFrozenDish$ will be removed in $Path$. Even if the system observes $CloseFridgeDoor$ within the specified delays, the possibility of a coherent behavior with the $CookFrozenDish$ activity will decrease if the elapsed time between $OpenFridgeDoor$ and $CloseFridgeDoor$ has a low possibility according to the time possibility distribution between the two actions in $CookFrozenDish$. If the system observes the action $OpenColdTap$, which is associated to the $DrinkWater$ activity, then we can consider, among the hypotheses, the interleaved realization of $DrinkWater$ with $CookFrozenDish$ or $CookPasta$.

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* ($\mathrm{I^2R}$) (Phua et al. 2009). The AIHEC 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 a cupboard nearby), 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 patient's hand movements), and video sensors (mainly to annotate and audit the observed patient's behavior). Dining and pantry events were obtained by using a Dynamic Bayesian Network (DBN) for eating activity recognition (Tolstikov et al. 2008). Also, the lab environment uses a wireless sensor network.

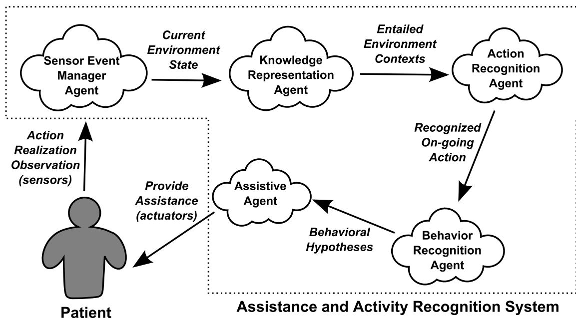

Figure 2: Simplified Assistance and Activity Recognition System

Our possibilistic activity recognition model is implemented according to the simplified smart home system architecture (Figure 2). The system architecture works as follows. Basic events related to an action realization are generated by sensors and are sent to a sensor event manager agent, which will send the current environment's state, according to the sensor events, to a knowledge representation agent. The knowledge representation agent, which has a virtual representation of the environment encoded in a *Pellet* description logic system (Sirin et al. 2007), infers which contexts are entailed by the current 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 possible 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 patient.

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 consists of getting utensils (plate), food (biscuit) and drink (water bottle) from the cupboard in the pantry, sitting on the chair to eat and drink, and putting back the utensils/food/drink in 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), 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 realizations represent a coherent realization, in an interleaved way, of the activities in the meal–time scenario. The selected erroneous realizations represent an erroneous realization 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, 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 recognition accuracy about the observed behavior associated with the realization of the meal–time scenario.

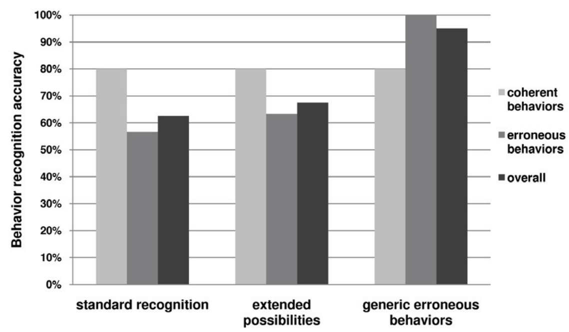

Figure 3: Recognition Accuracy of Behavior Recognition: Standard Recognition, Recognition with Extended Possibilities, Recognition by Considering Generic Erroneous Behaviors

Concerning behavior recognition accuracy, our model was able to recognize 56.7% of the erroneous behaviors and 80% of the coherent behavior (overall 62.5%) when we only consider the most possible behavior hypotheses according to the possibility distributions (first part of Figure 3). By expending the possibility range for the most possible behavior hypotheses (second part of Figure 3), our model was able to recognize 63.3% of the erroneous behavior (overall 67.5%). 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 that erroneous behavior (95% overall) (third part of Figure 3). 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 possibilistic 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. Also, in some cases, the sensor configuration changes a little bit (mainly the PIR sensor), and that influences the accuracy of the event recognition 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.

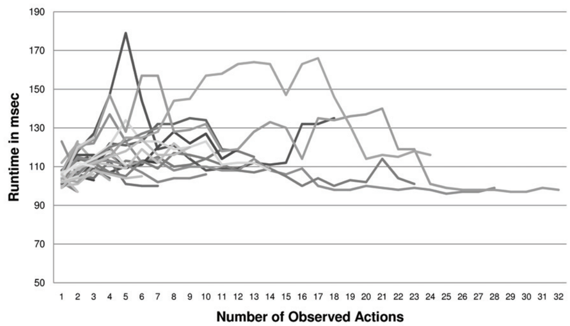

Figure 4: Activity Recognition Runtime per Observed Action for the Scenario Realizations

Figure 4 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 reasonably normal distributions, which is an effect that results from a diminution of the partial activity realization path set's size. This size 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.

Our possibilistic recognition model is more efficient than our previous recognition model based on lattice theory and probabilistic description logic (Roy et al. 2009). In this previous model, the action formalization is more restrictive and the hypothesis generation takes more resources, since it generates specific behavior plans instead of considering more generic behavior. Because of that, some behavior is not recognized. For instance, if the first action observed is not the first one in an activity, the specific hypothesis is not generated. Also, the previous model does not have temporal constraints; this limits the recognition of temporal errors. For instance, a temporal erroneous behavior, where time constraints between actions are not respected, will be recognized as a coherent realization of some activities, since the observed actions respect the sequence constraints in the activity plans.

Several previous related work, such as that of Cook (Cook, Youngblood, and Das 2006) (MavHome project), Mihailidis (Mihailidis et al. 2007) (Coach project), Helal (Helal et al. 2005) (Gator Tech Smart House) and Patterson (Patterson et al. 2007) (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. Some assumptions about the activity recognition are different, such as the activity granularity (events, actions, tasks, activities, ADL, . . .), the occupant's cognitive disorder (observed behavior categories), the modularity of the system (activity recognition with assistive task at the same time), the activity recognition category (keyhole, intended, adversarial), and the scope of the recognition (only the actions, only the activities, the behavior as a whole). For instance, the experiment of Mihailidis (Mihailidis et al. 2007), 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. Some adaptations must be made in order to compare with the previous approaches on a common ground such, for instance, the recognition accuracy.

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 in (Helal, Cook, and Schmalz 2009) 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 et al. 2007), 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 (Mihailidis et al. 2007) 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. Moreover, another important limitation of these probabilistic models is the difficulty of simultaneously handling multiple interleaved activities and erroneous behavior. 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. 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 (Dubois and Prade 2007).

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 possibilistic DL 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 patient's behavior, by helping the system to identify opportunities for assistance. An interesting perspective for the enrichment of this model consists in conducting an extension of this framework in order to simultaneously deal with the vagueness of an activity's duration and the noises of the sensors. The measurements of necessity and possibility of the activities will depend on the correlation between these constraints, allowing us to further refine the explanation of the activities. 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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