POSSIBILISTIC ACTIVITY RECOGNITION

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Abstract: The development towards ambient computing will stimulate research in many fields of artificial intelligence, such as activity recognition. To address this challenging issue, we present a formal activity recognition framework based on possibility theory, which is largely different from the majority of all recognition approaches proposed that are usually based on probability theory. To validate this novel alternative, we are developing an ambient agent for the cognitive assistance of an Alzheimer's patient within a smart home, in order to identify the various ways of supporting him in carrying out his activities of daily living.

1 INTRODUCTION

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 aims to recognize the actions and goals of one or more agents from a series of observations on the environmental conditions. Due to its many-faceted nature, research addressing the recognition problem in smart environments refer to activity recognition as plan recognition, which relates behaviours to the performer's goals. The plan recognition problem has been an active research topic (Augusto and Nugent, 2006) for a long time and still remains very challenging. The keyhole, adversarial or intended plan recognition problem (Geib, 2007) is usually based on a probabilistic-logical inference for the construction of hypotheses about the possible plans, and on a matching process linking the observations with some activity models (plans) related to the application domain.

Prior works have been done to use sensors, like radio frequency identification (RFID) tags attached to household objects (Philipose et al., 2004), to recognize the execution status of particular types of activities, such as hand washing (Mihailidis et al., 2007), in order to provide assistive tasks like, for instance, reminders about the activities of daily living (ADL) (Pollack, 2005). However, most of these researches has largely focused on probabilistic models. One limitation of probability theory is that it is insufficient to handling imperfect information, which is impressed of uncertainty and imprecision. In the context of cognitive assistance, where the human agent is characterized by erratic behaviours, complete ignorance about the specific dependence between two actions cannot be represented with the classical probability theory. The possibility theory (Dubois and Prade, 1988), an alternative to probability theory, is an uncertainty theory devoted to the handling of incomplete information. By using a pair of dual set-functions (possibility and necessity measures) instead of one, this theory allows us to capture partial ignorance, so that it is possible to represent partial belief about events. Also, it is more easier to capture partial belief concerning the activities realization from human experts, since this theory was initially meant to provide a graded semantics to natural language statements (Zadeh, 1978).

At the Domus and LIAPA labs, we investigate possibility theory to address this issue of recognizing behaviours 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. 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

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propose a formal framework for activities 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 behaviour hypotheses allow us to capture the fact that, in some case, erroneous behaviours concerning the realization of activities can be equally possible than normal behaviours. Hence, in a complete ignorance setting, both behaviour types are fully possible, where 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. Section 2 presents our new possibilistic recognition model. Section 3 presents an overview of related work. Finally, we conclude the paper by outlining future plans with this work.

2 POSSIBILISTIC ACTIVITY RECOGNITION MODEL

In our model, the observer agent has knowledge concerning the resident's environment, which is represented by using a formalism in 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. By using the open world assumption, it allows us to represent the fact that the environment is partially observable. 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 ($C \subseteq S$), where states of this subset share some common environmental properties. For instance, the context where the patient is in the kitchen, the pantry door is open, and the pasta box is in the pantry includes several possible states. Also, a set of contexts can be a partition of the environment's state space.

In order to infer behavioural hypotheses about the realization of activities by an observed patient, the notion of possibilistic actions must be formalized, since activities are carried out by performing a sequence of actions that affect the environment's state. A *possibilistic action* on the set of environment's states S is a nondeterministic action where the transitions between states are quantified with a possibility distribution.

Definition 2.1 (Possibilistic Action)**.** A possibilistic action a is a tuple $(C_{pre_a}, C_{pos_a}, \pi_{init_a}, \pi_{trans_a})$, where C_{pre_a} and C_{pos_a} are context sets and π_{init_a} and π_{trans_a} are possibility distributions.

C_{pre_a} is the set of possible contexts before the action occurs (pre–action contexts), C_{pos_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 allows the action to occur, and π_{trans_a} is the transition possibility distribution between contexts in C_{pre_a} and C_{pos_a} if the action does occur.

The action library is represented with an ontology, where the set of possible actions $\mathcal{A}$ is partially ordered with the 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).

Proposition 2.2 (Action subsumption)**.** Let $a, b \in \mathcal{A}$ be two action tuples $(C_{pre_a},\ C_{pos_a},\ \pi_{init_a},\ \pi_{trans_a})$ and $(C_{pre_b},\ C_{pos_b},\ \pi_{init_b},\ \pi_{trans_b})$. If an action b is subsumed by an action a, denoted by $b \sqsubseteq_{\mathcal{A}} a$, then for all context d in C_{pre_b}, there exists a context c in C_{pre_a} where $d \sqsubseteq c$, $\pi_{init_b}(d) \leqslant \pi_{init_a}(c)$, and for each context e in C_{pos_b}, there exists a context f in C_{pos_a} where $e \sqsubseteq f$ and $\pi_{trans_b}(e|d) \leqslant \pi_{trans_a}(f|c)$.

For instance, the *OpenDoor* action subsumes the *OpenPantryDoor* action, where the *OpenDoor* is at least as possible than *OpenPantryDoor* in contexts where *OpenPantryDoor* can be carried out or observed.

With this action library, the recognition agent evaluates the most possible action that can explain the changes observed in the environment. An *observation* at a time t, denoted by obs_t, consists to a set of DL assertions describing, according to the sensors, the environment's state resulting from an action realization. Since the observation obs_t can be partial, multiple contexts c_i can be entailed by this observation ($obs_t \models c_i$), which influences the possibility and necessity measures of observation for each action.

To determine such possibility and necessity measures of action observation, a possibility distribution on the action library concerning the possibility that a particular action was observed according to the previous action prediction possibilities (possibility that an action will be the next one carried out) and the current action recognition possibilities (possibility that an action is the one that was carried out) must be evaluated. The *action prediction possibility distribution* at a time t, π_{pre_t}, is obtained by selecting, for each action $a \in \mathcal{A}$, the maximum possibility value among the action initiation possibilities $\pi_{init_a}(c_i)$ for the pre–action contexts $c_i \in C_{pre_a}$ entailed by the observation obs_t. The *action recognition possibility distribution* at a time t, π_{rec_t}, is obtained by selecting, for each action $a \in \mathcal{A}$, the maximum possibility value among the action transition possibilities $\pi_{trans_a}(c_i, c_j)$ for the pre–contexts $c_i \in C_{pre_a}$ entailed by the previous observation obs_{t-1} and the post–contexts $c_j \in C_{pos_a}$ entailed by the current observation obs_t. Since the prediction possibilities must be taken into account when evaluating the action observation possibilities, the *observation addition operator* $\oplus_{obs}$ is used on the previous prediction possibility distribution $\pi_{pre_{t-1}}$ and the current recognition possibility distribution π_{rec_t} to compute the current action observation possibility distribution π_{obs_t}. The $\oplus_{obs}$ operator selects, for each action $a \in \mathcal{A}$, the maximum possibility value between the prediction possibility $\pi_{pre_{t-1}}(a)$ and the recognition possibility $\pi_{rec_t}(a)$, in order to obtain the observation possibility $\pi_{obs_t}(a)$.

So, for each observation obs_t, we evaluate the *action observation possibility distribution* π_{obs_t}, which allows us to select the most possible observed action at the time t, according to the possibility and necessity measures of action observation, Π_{obs_t} and N_{obs_t}. Those measures, which allow us to indicate the possibility $\Pi_{obs_t}(Act)$ and necessity $N_{obs_t}(Act)$ that an action a in a subset $Act \subseteq \mathcal{A}$ ($\{a\}$ is also a subset) was observed by the observer agent, according to the environment's state described obs_t, are given by:

$$\Pi_{obs_t}(Act) = \max_{a \in Act} \left(\pi_{obs_t}(a)\right), \tag{1}$$

$$N_{obs_t}(Act) = \max_{\{b \in \mathcal{A}\}} \left(\pi_{obs_t}(b)\right) - \Pi_{obs_t}(\overline{Act}), \tag{2}$$

$$= \min_{a \notin Act} \left(\max_{\{b \in \mathcal{A}\}} \left(\pi_{obs_t}(b)\right) - \pi_{obs_t}(a) \right) . \tag{3}$$

$\Pi_{obs_t}(Act)$ is obtained by taking the maximum value among the observation possibilities $\pi_{obs_t}(a)$ of the actions a in Act. $N_{obs_t}(Act)$ is obtained by taking the minimum possibility value among the values resulting from the subtraction of the maximum value in the distribution (since it can be not normalized, i.e. at least one value at 1) with the observation possibilities $\pi_{obs_t}(a)$ of the actions a not in Act ($a \in \overline{Act}$).

By obtaining the possibility and necessity measures for each action, we can then select the most possible observed action a_t that can explain the changes in the environment's state, described by the observation obs_t, resulting from the realization of an action at time 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, the least common subsumer action, according to the action subsumption relation, of this action subset is selected as the observed action a_t. For instance, if the most possible actions are $OpenTap$, $OpenColdTap$ and $OpenHotTap$, then the $OpenTap$ action is selected since it subsumes both $OpenColdTap$ and $OpenHotTap$. The new observed action a_t is sent to the behaviour recognition agent, which uses the sequence of observed actions to infer behaviour hypotheses concerning the realization of the patient's activities.

Such activities are defined as plan structures, which consist of a planned sequence of actions that allows to accomplish the activity's goals.

Definition 2.3 (Activity)**.** An activity α is a tuple $(Act_\alpha, \circ_\alpha, C_{rel_\alpha}, \pi_{rel_\alpha})$, where $Act_\alpha \subseteq \mathcal{A}$ is the activity's set of actions, which is partially ordered by a sequence relation $\circ_\alpha \in Act_\alpha \times Act_\alpha \times \mathcal{T} \times \mathcal{T}$, where $\mathcal{T}$ represents a set of time values, C_{rel_α} is the set of possible contexts related to the activity realization, and π_{rel_α} is the possibility distribution that a context is related to the execution of the activity.

The use of time values allow us to describe the minimum and maximum delays between the realization of two actions. So, the $\circ$ relation, which is transitive, can be seen as an ordering relationship with temporal constraints between two actions in the activity plan. For instance, the activity $WatchTv$ can have an activity plan composed of the actions $SitOnCouch$, $OpenTv$ and $CloseTv$ and the sequence relations $(SitOnCouch, OpenTv, 0, 5)$ and $(OpenTv, CloseTv, 5, 480)$ (do not watch tv for more than 8 hours) , where the time values are in minutes.

By using the observation obs_t, we evaluate, for each activity plan α in the plan library $\mathcal{P}$, the possibility value that the current observed environment's state is related to the realization of an activity α. The activity realization possibility distribution is obtained by taking, for each activity plan $\alpha \in \mathcal{P}$, the maximum possibility value among the context possibilities $\pi_{rel_\alpha}(c_i)$ for the contexts $c_i \in C_{rel_\alpha}$ entailed by the observation obs_t.

As previously mentioned, the most possible action a_t that could explain the changes in the environment's state according to the observation obs_t resulting from an action realization is sent to the behaviour recognition agent, which uses the sequences of observed actions to generate hypotheses concerning the behaviour of the patient when he performs some activities. This sequence of observed actions forms an *observed plan* P_{obs_t}, which consists to a totally ordered set $(a_1, \ldots, a_i, \ldots, a_t)$, where each a_i is the most possible and necessary observed action for the observation obs_i. For instance, the observed plan $((OpenDoor, t = 0, 3), (EnterKitchen, t = 1, 4))$ indicates that for obs_0, the $OpenDoor$ action was observed at a timestamp of 3 minutes after the start of the recognition process, and for obs_1, the $EnterKitchen$ action was observed one minute later (timestamp of 4 minutes).

Since the current observed behaviour can contain partial or complete coherent realizations of some activity plans, we must define the notion of *partial ex-*

ecution path. A partial execution path $Path_{Exe_j}$ for an activity plan α is a subset of the observed plan P_{obs_t}, where each observed action in the partial path is associated to an action in the activity plan α. Also, the observed actions in the partial path $Path_{Exe_j}$ must represent a coherent realization of a part of the activity plan, where the sequence and temporal constraints defined in the activity plan must be respected according to the observed actions in the partial path. For instance, for the observation plan $((SitOnCouch, t = 0,4),\ (OpenElectricalAppliance, t = 1,5))$, possible partial paths for the $WatchTv$ activity plan could be the $SitOnCouch$ action only or the $SitOnCouch$ action followed by the $OpenElectricalAppliance$ action (since $OpenElectricalAppliance$ subsumes $OpenTv$).

At each new observed action a_t added to the observed plan P_{obs_t}, the set of partial execution paths $Path_{Exe}$ is updated by extending, removing, or adding partial paths. A partial path can be extended if the new observed action a_t subsumes one of the next possible actions in the activity plan and if the extended partial path respects the constraints in the activity plan. If we can extend a partial path, we must keep a copy of the original partial path, since the new observed action could be not associated to the realization of the partial path's activity plan. A partial path is removed if the maximum delays for the next possible action in the activity plan are exceeded. A partial path is added is the observed action a_t subsumes one of the first actions in the activity plan.

The set of partial execution paths $Path_{Exe}$ is then used to generate behavioural hypotheses $\mathcal{B}$, according to the observed plan P_{obs_t}, concerning the observed behaviour of the patient when he realize some activities. A *behaviour hypothesis* $b \in \mathcal{B}$ for an observed plan P_{obs_t} is a subset of the partial execution path set $Path_{Exe}$ that respects the following conditions: (**i**) each partial path is associated with a different activity, (**ii**) some observed actions can be shared between partial paths, (**iii**) each partial path must at least have one action that is not shared. It should be noted that it is possible that some observed actions in the observed plan are not in the partial paths.

A behaviour hypothesis is *normal*, denoted by b_N, when each observed action in the observed plan is associated to at least one partial path. A normal behaviour represents a coherent realization, which can be partial or complete, of some activities by the patient. A behaviour hypothesis is *erroneous*, denoted by b_E, when some observed actions in the observed plan are not associated to a partial path. An erroneous behaviour represents an erroneous realization of some activities, while some others activities can still be carried out in a coherent way.

From this point, the behaviour recognition agent has determined the sets of plausible normal and erroneous hypotheses, $\mathcal{B}_N$ and $\mathcal{B}_E$, concerning the behaviour of the observed patient. In order to circumscribe the behaviour hypothesis set before sending theses hypotheses to an assistance agent, the possibility and necessity measures concerning the observation of each behaviour must be evaluated. Such measures are obtained from the behaviour possibility distribution, which also need the partial execution path possibility. The *partial execution path possibility distribution* at time t, π_{Exe_t}, is obtained by selecting, for each partial path $p \in Path_{Exe}$, the maximum values between the minimum action prediction possibility among the next possible actions and the minimum value among the action observation and activity possibilities for each observed action in the partial path. This partial path possibility distribution π_{Exe_t} is then used to evaluate the behaviour possibility distribution π_{bev_t}. The *behaviour possibility distribution* π_{bev_t} is obtained by selecting, for each behaviour hypothesis $b \in \mathcal{B}$, the maximum possibility value between the minimum partial path possibility for the partial paths of the behaviour, the minimum action observation possibility for the observed actions in the partial paths of the hypothesis, and the minimum action observation possibility for the observed actions not in the partial paths of the hypothesis.

The behaviour possibility distribution π_{bev_t} allows us to evaluate the possibility and necessity measures of behaviour observation, Π_{bev_t} and N_{bev_t}. Those measures, which allow us to indicate the possibility $\Pi_{bev_t}(Bev)$ and necessity $N_{bev_t}(Bev)$ that a behaviour b in a subset $Bev \subseteq \mathcal{B}$ is the behaviour of the observed patient according to the observed plan P_{obs_t}, are given by:

$$\Pi_{bev_t}(Bev) = \max_{\{b \in Bev\}} \left(\pi_{bev_t}(b)\right), \tag{4}$$

$$N_{bev_t}(Bev) = \max_{\{c \in \mathcal{B}\}} \left(\pi_{bev_t}(c)\right) - \Pi_{bev_t}(\overline{Bev}) \tag{5}$$

$$= \min_{\{b \notin Bev\}} \left(\max_{\{c \in \mathcal{B}\}} \left(\pi_{bev_t}(c)\right) - \pi_{bev_t}(b) \right) . \tag{6}$$

$\Pi_{bev_t}(Bev)$ is obtained by selecting the maximum behaviour possibility among the behaviours b in the behaviour subset $Bev \subseteq \mathcal{B}$. $N_{bev_t}(Bev)$ is obtained by selecting the minimum possibility among the values resulting from the subtraction of the maximum possibility in the distribution with the behaviour possibilities $\pi_{bev_t}(b)$ of the behaviour hypotheses b not in Bev ($b \in \overline{Bev}$). This allows to represent an interval of confidence $[N_{bev_t}(Bev), \Pi_{bev_t}(Bev)]$ concerning the possibility that a hypothesis behaviour $b \in Bev$ is the observed behaviour of the patient according to the observed plan P_{obs_t}. So, after each observation obs_t, the behaviour recognition agent selects the most possible and necessary behaviour hypotheses and sends them to an assistance agent, which will use it to plan an assistive task if needed.

By using the formal tools previously presented, we can formulate the Algorithms 1 and 2, which describe the principal steps in the recognition process.

Algorithm 1 Action recognition.

Input:
obs_t, obs_{t-1} previous and current observations
$\pi_{pre_{t-1}}$ previous action prediction distribution
$\mathcal{C}$ context set
C_{t-1} previous entailed contexts
$\mathcal{A}$, $\mathcal{P}$ action and plan libraries
Output:
a_t current recognized observed action
π_{pre_t}, π_{rec_t}, π_{obs_t}, π_{rel_t} current action prediction, action recognition, action observation, and activity possibility distributions

$C_t \leftarrow$ evaluateEntailedContexts($\mathcal{C}$,obs_t)
$\pi_{pre_t} \leftarrow$ evaluateActionPrediction($\mathcal{A}$, C_t)
$\pi_{rec_t} \leftarrow$ evaluateActionRecognition($\mathcal{A}$, C_t, C_{t-1})
$\pi_{obs_t} \leftarrow$ observationAddOperator($\pi_{pre_{t-1}}$, π_{rec_t})
$a_t \leftarrow$ selectObservedAction($\mathcal{A}$, π_{obs_t})
$\pi_{rel_t} \leftarrow$ evaluateActivityRelated($\mathcal{P}$, C_{entail})

To recognize the behaviour of the observed patient after the realization of an action at a time t, the recognition agent uses the environmental observations obs_t, to generate behavioural hypotheses that could explain the sequence of t observed actions. According to the Algorithm 1, the contexts C_{t-1} and C_t that are entailed by the previous and current observations obs_{t-1} and obs_t are used to evaluate the action observation possibility distribution π_{obs_t} on the action library $\mathcal{A}$ by using the observation addition operator $\oplus_{obs}$ on the previous action prediction possibility distribution $\pi_{pre_{t-1}}$ and the action current recognition possibility distribution π_{rec_t}. This action observation possibility distribution π_{obs_t} is then used to evaluate the action observation possibility and necessity measures Π_{obs_t} and N_{obs_t}, which are used, in conjunction with the action subsumption relation, to select the most possible and necessary observed action a_t. Also, the activity possibility distribution π_{rel_t} on the activity plan library $\mathcal{P}$, which indicates the possibility that the observed environment's state described in obs_t is related to a specific activity realization, is evaluated.

According to the Algorithm 2, the observed plan P_{obs_t}, which include the new observed action a_t, is used to generate a set of hypotheses $\mathcal{B}$ concerning the observed behaviour of the patient. The observed plan P_{obs_t} is used to update the set of partial execution paths $Path_{Exe}$, where each partial path is a partial (or complete) coherent realization of an activity plan. The set of behaviour hypotheses $\mathcal{B}$ is obtained by selecting subsets of $Path_{Exe}$ that respect the conditions in order to be a behaviour hypothesis. Each behaviour hypothesis $b \in \mathcal{B}$ can be a coherent realization of some activities ($b \in \mathcal{B}_N$) or an erroneous realization of some activities ($b \in \mathcal{B}_E$), according to its partial path subset and the observed plan. The behaviour possibility distribution π_{bev_t} is then evaluated by using the previous defined possibility distributions (π_{pre}, π_{obs}, π_{rel}) and the partial execution path possibility distribution π_{Exe_t}. This behaviour possibility distribution π_{bev_t} allows us to rank the set of behaviour hypotheses $\mathcal{B}$ according to the behaviour possibility and necessity measures Π_{bev_t} and N_{bev_t}. The recognition agent sends the most possible behaviour hypotheses B_t to an assistance agent, which plans an assistance task if needed.

Algorithm 2 Behaviour recognition.

Input:
a_t current recognized action observed
$P_{obs_{t-1}}$ previous observed plan
$\mathcal{A}$, $\mathcal{P}$ action and plan libraries
π_{pre}, π_{obs}, π_{rel} sets of possibility distributions
$Path_{Exe}$ partial execution path set
Output:
P_{obs_t} current observed plan
$Path_{Exe}$ updated partial path set
$\mathcal{B}$ current behaviour hypotheses
π_{bev_t} current behaviour possibility distribution
B_t set of most possible behaviour hypotheses

$P_{obs_t} \leftarrow$ appendObservedAction(a_t, $P_{obs_{t-1}}$)
$Path_{Exe} \leftarrow$ updatePartialPathSet($Path_{Exe}$,$\mathcal{P}$, P_{obs_t})
$\mathcal{B} \leftarrow$ generateBehaviourHypotheses($PathExe$, P_{obs_t})
$\pi_{Exe_t} \leftarrow$ evalPartialPath($Path_{Exe}$,P_{obs_t}, π_{pre}, π_{obs}, π_{rel})
$\pi_{bev_t} \leftarrow$ evaluateBehaviourPossibility($\mathcal{B}$, π_{Exe_t}, π_{obs})
$B_t \leftarrow$ selectBehaviourHypotheses($\mathcal{B}$,π_{bev_t})

3 RELATED WORK

A number of researchers have investigated activity recognition as plan recognition. Logical based approaches (Kautz, 1991) define a theory using first–order logic, in order to formalize the recognition activity into an inference process. But to alleviate to the equiprobability problem of logical models, where an hypothesis cannot be privileged within the set of possible activities, probabilistic models (Liao et al., 2004; Philipose et al., 2004), mainly Bayesian or Markovian based, or hybrid models (Avrahami-Zilberbrand and Kaminka, 2007; Geib, 2007; Roy et al., 2009), that use logical and probabilistic reasoning, were proposed. The limit of the vast majority of these previous approaches is that they were focused exclusively on the concept of probability where the inference itself requires large numbers of prior and conditional probabilities. For example, in the context of assistive cognition within smart homes, requiring humans to specify the habitat's object involvement probabilities is time consuming and difficult when we consider all the potential objects involved in each stage of an activity, given the large numbers of activities performed. Moreover, the probabilities do not allow us to represent complete ignorance; besides, there are numerous situations where it is not possible to give the agent probabilities based on statistical measures, but only qualitative information provided by experts or deduced from previous experiences. Our proposed model, by using possibility theory, allows to mitigate those limitations by taking into account partial belief and by handling the behaviour hypotheses as a partially ordered set.

4 CONCLUSIONS

This paper has presented a formal framework of activities recognition based on possibilistic DL as the semantic model of the observed agent's behaviour. This framework constitutes a first step toward a more expressive ambient agent recognizer, which will facilitate to support the fuzzy and uncertainty constraints inherently to the smart environment. Currently, the proposed is under implementation in the software framework of our smart home infrastructure, which consists of a standard apartment with a kitchen, living room, dining room, bedroom, and bathroom, equipped with multiple sensor devices. Moreover, the next logical step 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. Finally, we clearly believe that considerable future work and large scale experimentations will be necessary, in a more advanced stage of our work, to help evaluate the effectiveness of the model in the field.

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