Spatiotemporal knowledge representation and reasoning under uncertainty for action recognition in smart homes

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Abstract

We apply artificial intelligence techniques to perform data analysis and activity recognition in smart homes. Sensors embedded in smart home provide primary data to reason about observations and provide appropriate assistance for residents to complete their Activities Daily Livings (ADLs). These residents may suffer from different levels of Alzheimer disease. In this paper, we introduce a qualitative approach that considers spatiotemporal specifications of activities in the Activity Recognition Agent (ARA) to do knowledge representation and reasoning about the observations. In this paper, we consider different existing uncertainties within sensors observations and Observed Agent's activities. In the introduced approach if the more details about environment context be provided, the less activity recognition process complexity and more precise functionality is expected.

1 Introduction

Smart home mostly addresses the health-care problem of performing automated assessment of functional health for elder adults and provision of automated assistance that will allow people suffering from Alzheimer to remain independent [16]. In order to live independently at home, adults need to be able to complete key activities of Daily Living, or ADLs, however tracking of ADL accomplishment is a time consuming task for caregivers. To provide automated assistance we apply Activity Recognition Agent (ARA) to reason about observations provided by the embedded sensors in Smart Home.

In this paper, we deal with the activity recognition process performing in Activity Recognition Agent (ARA). Event Recognition Agent (ERA) detects realized events and report them to the ARA. ARA provides a report for the Plan Recognition Agent (PRA) about observed and inferred activities and finally the Assistance Provision Agent (APA) would provide appropriate assistance for the Observed Agent (OA). The schema1 shows the general process in the smart home.

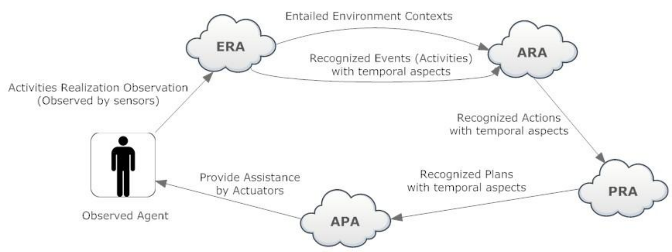
Although uncertainty and imprecision is included always with the action recognition field, in most of the performed researches up to now [1,6,11,13,14,15,16,23,24] the existing uncertainty and imprecision in OA's behavior and home state is not considered and they are not robust if activity realization models change. Furthermore, any small change in sensors network, sensors locations and sensors number could lead to restricting all their applied models and all the previous training tests would not be useful any more. Moreover, objects movement, which provides important information in activity recognition, has not been considered.

Most of the surveyed activity recognition approaches do not tolerate relatively detailed information about the real world and even they may avoid more sensors for not to receive complementary information about the activities. The reason is that increase in number of applied sensors could lead to process complexity and they would need a huge dataset for training. I contrast, the introduced approach in this paper welcomes the increase in input information and in the case of change in sensors network structure, and the old knowledge would be still valid. Furthermore, the increase in provided information would even cause to decrease in process complexity.

In this paper, we are explaining an intelligent agent that tries to explain the observations and detects anomalies in the case that there is no explanation. Applied knowledge representation and reasoning techniques that benefit from activities temporal and spatial specifications is discussed and we introduce fuzzy contexts that can briefly indicate the home state and possible events that could occur in contexts.

The art of ranking and classification between generated hypotheses inferred from available knowledge and present observations can lead to better adjustment between system's inference and the real world. In this way, reasoning can be less complicated and so it causes less

error to choose the right decision in decision-making process.
A brief explanation about general activity recognition process is that after that ERA provides ARA the current home state and happened events in fuzzy context and fuzzy events frame (knowledge representation), the possible hypotheses through time line are generated and ranked dynamically. Then in the reasoning process, the explanations about observations would be provided.



schema1- the general smart home process model

2 Knowledge Representation

A knowledge representation system is applied to interpret sentences in the logic in order to derive inferences from them. When we design a knowledge representation system, we have to make choices across a number of design spaces. The single most important decision to be made, is the expressivity of the KR. Our desire is to include more effective parameters in action recognition process who may make the knowledge representation enough expressive and may make the reasoning process not so relatively difficult. Brahman and Levesque [1984] introduced the mentioned desire as contradictory goals; however, we believe that applying fuzzy context can lead to more expressiveness and simpler reasoning in an intelligent agent. That is because fuzzy context holds more details at one hand and at the other hand the defuzzified context prevents to generate many relatively similar contexts that can make the reasoning process complicated. Here we introduce two key knowledge types and their representation methods.

2.1 Environmental parameters or context items

Embedded sensors in the smart home provide primary data for the Activity Recognition Agent (ARA). The received data by sensors that is raw and unprocessed introduce the environmental components (such as temperature, doors state, heater state, Observed Agent's position, etc) that may be effective on action recognition process. In fact, the mentioned components form the body of contexts and are named as context items. Unfuzzy context is a context that is constituted from a set of items and we define fuzzy context as context constituted from fuzzified items.

2.2 World state and fuzzy context

"Fuzzy Context" is the term used to express the home state with it. In this way, environmental parameters (called *items* and indicated by i_x) are measured and then fuzzified by fuzzy membership functions. To express a general form of fuzzy context, we apply the following form: $\tilde{C}(\tilde{i}_1, \tilde{i}_2, ..., \tilde{i}_n)$

Temperature is an example for item. For instance, when the thermometer indicates 37 degree it can be inferred that it belongs to "Warm" class (applying fuzzy roles and defuzzification functions) and finally warm is reported instead of 37 degree. Home state is finally formed by such this information. As a simple example for home state, consider a home that includes some embedded sensors to indicate the home state. These sensors indicate "OA location", "door state", "heater state", "oven state" and "temperature". Mentioned sensors generate continuously values along time axis. The following indicates the final defuzzified home state: $C_{obs_t}(OA: at\_oven, door: closed, heater: off, Oven: off, temperature: warm)$

2.3 Events

We define *events* as each meaningful change in sensors generated values. ERA simply receives generated values from the sensors and checks whether the value belongs still to a new class. A change in received values class means an event has happened and the event is reported to the ARA.

2.4 Discussion

Allen temporal logic is a famous temporal logic that introduced thirteen temporal relations between actions. Morchen argued that Allen's temporal patterns are not robust and small differences in boundaries lead to different patterns for similar situations [2]. Furthermore, the complexity increases if the OA performs multiple actions simultaneously. Moreover, it does not also indicate the actions beginning and terminating moments.
From the mentioned problems, we have inspired the idea that we can consider the beginning event (temporal point) instead of interval consideration and so in this way, it would be necessary just to compare beginning points of actions and their durations would be justified as their components that contain fuzzy, relative and estimative measures as value. So, in brief it can be said that only the before relation would be considered and the possible moments that other actions can begin on them.
To implement the mentioned idea we have applied the possibility theory that was first introduced by Zadeh[7,8,9,10]. In summary, it is assumed that after observation of an event, all the possible actions can begin simultaneously and the most possible moments for events occurrence is indicated. The farther from *most possible*

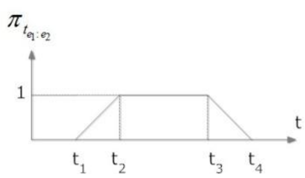
occurrence moments the less ranking value in hypotheses ranking introduced in "3.3" section.

The result is that multiple simultaneous running actions can be considered and it is enough flexible to consider different possible temporal relations between actions and gives an estimation (by defuzzifying the fuzzy time up to next Action's beginning moment) to predict the action termination moment.

For example, for the action entering to the kitchen, the table1 indicates the possible events (actions beginning points) that are possible to occur after previously assumed occurred events and their possible occurrence moments.

t_0 \ t_1	kitchen_door_open	kitchen_door_close	temperature_increase	temperature_decrease	heater_on	heater_off
kitchen_door_open	0	1	0	0.9	0	0
kitchen_door_close	0	0	0	1	1	0
temperature_increase	0	0	0	0	0	1
temperature_decrease	0	0	0	0	1	0
heater_on	0	0	1	0	0	0.2
heater_off	0	0	0.3	0.7	0	0

Table1. Possibility distributions for relations between events for action "entering to the kitchen"



Schema2. Possibility distributions for occurrence moments

In the table1 the possibility distribution for the "before" relation is indicated by the normalized numbers (from 0 to 1) and in schema2 the possibility distribution for *possible occurrence moments* of the next event is indicated by $\pi_{t_{e_1:e_2}}$ which is a trapezoid fuzzy number. In this digit t_1 is the soonest moment that event2 can occur after another event1, moments between t_2 and t_3 are the most possible moments that event2 can occur and t_4 is the latest moment that event2 can occur. (We have forborne to include the necessity distributions in our calculations, which is already dependent to the possibility distributions.)

The table1 is implemented as a data table in database and it indicates the effective environmental parameters to recognize the action "*entering to the kitchen*".

2.5 Temporal Knowledge Representation

We define the term temporal knowledge as a kind of knowledge that is dependant to the time and may lead to different inferences in different temporal contexts; however, this knowledge can include some temporal information about next possible contexts that can possibly happen in future. We refer to the first introduced type as absolute time and the second one as relative time.

To represent temporal dependency (absolute time), we insert a new item to the fuzzy context ontology that is called fuzzy time item. In this way, contexts for similar conditions but different temporal conditions are made. A function is implemented to check whether the current time is adjustable to the defuzzified *time item* existing in the fuzzy context.

Time elapse as a possible *fuzzy event* is also applicable. An example for defuzzified item of fuzzy time can be like "morning".

To represent temporal information (relative time) using a fuzzy trapezoidal digit, we indicate the possible transition moments to different possible contexts and it is implemented by a simple table containing the concerning data. This relative data is converted to the real time at the running time.

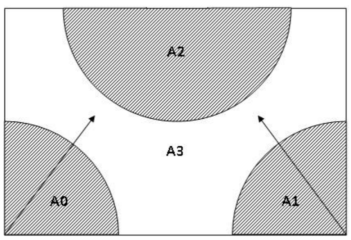
2.6 Spatial Knowledge Representation

Another key knowledge that is helpful to do better reasoning is spatial knowledge that indicates the context dependency to the objects locations. As it was mentioned earlier, movement of objects in the real world provides noticeable information for the activity recognition process. There can be considered two general spatial knowledge forms. The first one, which would be referred to as absolute position, indicates the objects positions in the real world and the second one that would be referred to as relative positions indicates the position of objects to each other. In the fuzzy context, a section is dedicated for the objects positions in the home (first spatial knowledge type) and the second spatial knowledge type is indicated in the Event Recognition Agent (ERA). One example for absolute position application in activity recognition is that, to infer the *cooking activity* it is necessary to observe the pan on the oven. An example for the relative position inference is that if approach of pot to glass be observed it can inferred that OA has fulfilled the glass with the pot's containing liquid such as coffee. ERA provides this information as recognized event for the ARA.

2.6.1 Discussion

To recognize objects movements we have applied RFID tags and antennas. This process is done in ERA and we would have a short introduction of it in here.

In a brief description, we have attached RFID tags on the objects and used RFID antennas to recognize the OA's activities. We have made a program in Java to recognize the performed activities by the OA. Every six microseconds applied RFID antennas check the environment to detect the RFID tags. By having just one RFID antenna and attaching RFID tags on the objects, we are able to recognize if the object is close or far from the antenna. By adding the second antenna, we would be able to make four regions. The first region is the region around the first antenna, the sec ond region would be around the second antenna, and the third region is the region in front of both antennas and the region that both antennas show equal signal strength to detect the objects and the fourth region is the region that no antenna can easily detect the object (see schema3).



Schema3. Regions defined by RFID antennas

In ERA, entering and exiting a region is recognizable by the available equipments and the concerning events are reported to the ARA. In the absolute position recognition, it‘s enough to find the object's location in one of the mentioned regions, however in relative position recognition we should find two target objects in one region.

2.7 Spatiotemporal Knowledge Representation

Spatiotemporal knowledge is key environmental information to do activity recognition; however, there is other effective environmental information such as temperature, door's position and other items that are also useful for controlling affairs in smart home. to represent such this knowledge we have divided fuzzy context into three major sections. One section for temporal knowledge, another section for spatial knowledge and third section for controling items is provided.

Introduced fuzzy context let us consider different knowledge types in action recognition and the controlling affairs (using checking functions) are done at the transition moments. Transition between contexts is also indicated by the observed fuzzy events reported by ERA.

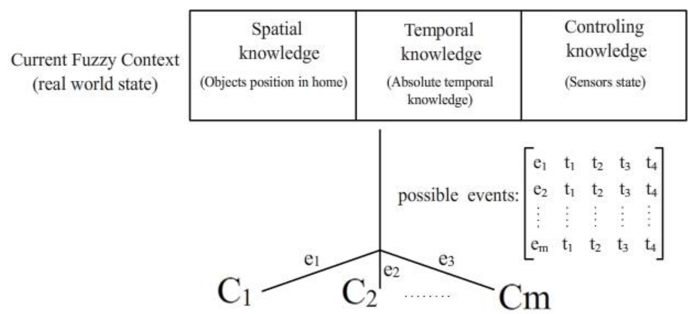
3 Reasoning

The reasoning process in activity recognition follows the observation, hypothesis generation and hypothesis pruning steps.

3.1 Hypothesis Generation

Hypotheses are generated only in the case of event recognition reported by the ERA. Movement of objects, elapse of time and a switch in controlling sensors states are possible observable events. In fact, the generated hypotheses indicate the possible future contexts could possibly be observed in the future.

The hypothesis generation process in summary is that at first hypotheses are generated based on a table named as possible fuzzy events (see table1) that could have been generated in future in the current context. At the second step, they are assigned the possible observation moments by the use of trapezoidal fuzzy digit (see schema2) and finally they are ranked or weighted (see part 3.3). the mentioned process is illustrated in schema4.



Schema4.hypothesis generation

3.2 Hypothesis Generation through the time line

Considering uncertainties for unrecognized but in reality happened events (there are several reasons for it), it is possible that it defects the reasoning process and so ARA wrongly detects normal actions or activities as anomaly. To improve the activity recognition efficiency we consider that possible events may have happened but not observed and they are generated and pruned through the time line. A question that may arise in here is that what could be the occurrence time of undetected event? The answer is that the defuzzified value of the fuzzy trapezoid number can indicate the possible moment that the event has happened. In the case of anomaly detection, it would be checked whether there have been no undetected event and there is no previously generated hypotheses that can explain the occurred events.

3.3 Hypothesis Ranking

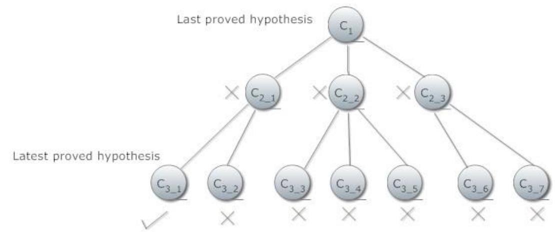
When new hypotheses are generated, they are inserted as tree leafs (we can call it also decision tree) and then they are ordered by defuzzified occurrence moment from left to right. To describe briefly the ranking process, we assign each observed and proved a higher point and in contrast unobserved or not yet proved hypotheses are assigned lower points.

The rank and weight of generated hypotheses ($w_i(t)$) can change dynamically by elapse of time. The primary assigned weight is derived from the possibility distribution for occurrence of event ($\pi_{e_1:e_2}$ existing in table1) and as the fuzzy trapezoid number affects it, so by elapse of time it can differ to the past weights ($\pi_{t_{e_1:e_2}}$, schema2). The third parameter to affect the hypotheses rankings is the possibility distribution of the upper node occurrence (W_u). Finally, γ affects the ranking value. γ is a value that is resulted from a trade-off between smart home precision in event detection and uncertainties about behaviours of Observed Agent (OA) or in other words Alzheimer severity degree. At one side, the more severity in Alzheimer illness the less confidence on the OA and at the other side the more precision in event recognition, the more confidence on the reports and so it would be less necessary to trace the tree down to a lot of levels. The ranking formula is indicated as:

$$w_i(t) = \gamma . W_u . \sqrt{\pi_{e_1:e_2} . \pi_{t_{e_1:e_2}}}$$

3.4 Hypothesis Pruning

To prevent the increase in number of less possible hypotheses, pruning is necessary. Pruning is applied in the case of low possibility distribution of event occurrence. In addition, observation of a possible event that could have happened calls the pruning function[1]. Another way is to limit the pruning to a fix number of levels. Whenever a hypothesis be proved, the concerning weight for that node is assigned one.



schema5.hypothesis pruning, reasoning and explication of observation

In the schema5 the sequence of C1 and C2_1 and C3_1 indicate an explanation about the latest observations.

3.5 Reasoning Process

Our goal in reasoning process is to find an explication that can explain the observations. Observation of a fuzzy event is a good reason to decide whether there are anomalies or not. However, the more OA be conscious the more rely on unproved hypotheses. The sequence of observed events can explain the current activities and actions. Furthermore, the contexts can explain the precedence of home states. So, recognition of current context from the previously generated hypotheses can well explain the observations and current activity(ies). Whenever no explanation for the observation is found or the explanation does not include minimum acceptance weight (dependent to γ), so the observed action would be recognized as abnormal action.

4 Implementation and Conclusion

The ARA was implemented in VB.net environment and it was simulated in SIMACT [27]. The activity "*entering to the kitchen"* was simulated in different scenarios (but the same old embedded sensors) and some uncertainties in event recognition (see picture1). Anomaly detection would not be better than 50% done if the unproved hypotheses grow deeper than three levels in decision tree. In spatial reasoning it can be said that the more antennas be applied, the more precise hypotheses would be generated. It can be inferred that in the introduced approach, in the case of increasing the sensors number, more precise hypotheses would be generated and proved. Fuzzy context at one hand can express well the real world state and it can decrease reasoning complexity if it be well defuzzified.

[1] To estimate the closeness of new observation to the previously generated and assumptive hypotheses, we applied the $\pm\frac{1}{\gamma}$ formula to check the difference between values of the observed and assumptive context items. If all the differences between all the items be more than $\pm\frac{1}{\gamma}$ then no explain is found.

Picture1- the activity "*entering to the kitchen*" simulation in SIMACT

5 Future Works

We recommend the interested researches to survey the Activity Recognition in the case of multiple residents in smart homes and also to introduce an optimization model for fuzzy roles to decrease the activity recognition mistakes.

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