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A new qualitative spatial recognition model based on Egenhofer topological approach using C4.5 algorithm: experiment and results

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Abstract

Ambient technologies and ubiquitous computing constitute together an emerging trend of research bringing new possible solutions to many problems of human life. One of them is the technological assistance of the elders suffering from cognitive deficit with their everyday life activities inside what is called a smart home. The main issue in implementing such technology is the recognition of the activities of the resident. This problem consists in inferring the minimal set of possible ongoing activities using models defined in a plans library. To achieve that, most works propose to exploit different types of constraints (logical, temporal, etc.) in order to eliminate a maximum of incoherent hypotheses. However, very few works considered exploiting the spatial aspect related to the movement of objects and to their relations in space. In this paper, we propose to add a spatial pre-filter based on a topological approach from Egenhofer to discriminate implausible ongoing activities before applying a C4.5 decision tree to choose from the remaining hypotheses. Furthermore, this paper presents promising results we obtained from an experiment on that model using real case scenarios built from clinical trials that we conducted with Alzheimer's patients.

Keywords: Smart Homes, RFID, Activity Recognition, Spatial Constraints, C4.5

1. Introduction

Advance in ubiquitous computing and miniaturization of ambient technology has brought the scientist community in the era of smart home [1]. A smart home is an enhanced environment taking decisions from intelligent agents perceiving their environment using multi-modal sensors embedded in everyday life objects [2]. A smart environment could be used to help a human resident suffering from a cognitive deficit to complete his daily activities. In this context, it must take decisions and pose actions with different kinds of effectors (light, sound, screen, etc.) while remaining less intrusive as possible. To do so, the artificial intelligence of the smart home must first overcome the challenge of recognizing the ongoing inhabitant activity of daily living (ADL) [3]. This specific issue interests a growing community of scientist [4, 5, 6], like us [2], which recognizes the importance of investigating this problem. The recognition process in a smart home consists in the association of the observations made from distributed sensors with actions and plans in a library corresponding to the possible ongoing activities. The goal is to circumscribe a minimal set of plausible plans [7] (hypothesis) from this library by using constraints to eliminate the incoherent hypotheses. These constraints can be of different natures (logical, temporal, spatial, etc.). For example, the activity CookPasta

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could be constituted of the two steps BoilWater and PutPasta with a sequential (temporal) constraint specifying to do BoilWater before PutPasta. Most recognition approaches focus on exploiting only logical [2] or temporal constraints [1] while ignoring the fundamental spatial aspects related to objects in a smart home. Nevertheless, these aspects can play a significant role in the recognition process [8]. A spatial constraint can be defined as the spatial state of an object, in relation to its environment and other objects. For instance, each object has a size, which can be represented as a spatial zone (in 2D or 3D) that it occupies in the environment. Starting from here, constraints can be defined about objects implicated in an activity. For example, the zone of an object A should not intersect the zone of object B during step 2 of a certain activity. Spatial reasoning (SR) [9] is a theory that studies objects and their relations in space. It takes its sources in natural language [10] with expressions we use everyday such as ”under” or ”beside”. Qualitative spatial reasoning (QSR) is a particular type of spatial reasoning. It is better suited to abstract a complex reality and more feasible on computational complexity point of view [11]. In this paper, we propose the integration of topological qualitative spatial relations [12] to reduce the number of possible plan hypotheses before applying an activity recognition algorithm based on C4.5 decision tree. We present an implementation of this new algorithm and describe a first experiment conducted on it using a recognition platform based on passive RFID tags [13]. This experiment is based on real case scenarios obtained from previous experiments conducted by our team with subjects suffering from Alzheimer disease [14]. The goal of this paper is to show how to improve the efficiency of recognition algorithms by introducing spatial reasoning.

The paper is organized as follows. Section 2 presents the qualitative spatial reasoning and its importance in our context of recognition. It describes the relations of Egenhofer’s topological framework and how they are integrated together. Section 3 describes the new recognition model and how it uses the relations to circumscribe the agent’s plan hypotheses before inferring the correct activity with the C4.5 decision tree. Section 4 presents an implementation of the new model and an overview of the RFID platform used for the experiments. Section 5 details the experiments we conducted using real case scenarios and presents the promising results we obtained. Finally, section 6 concludes the paper by resuming the important aspects and by outlining future developments of this work.

2. Qualitative Spatial Reasoning

From researches in the field of activity recognition [2, 3], we can find many situations where exploiting spatial relationships between objects is necessary to obtain efficient and precise recognition results. For instance, imagine that a resident has just executed a certain action named *BoilWater*. Let’s say that this observation can lead to two plausible explanations (activities), according to the plans’ library, which are *MakeCoffee* or *CookPasta*. Considering the topological relations between objects, we can detect that a cup is present in the activity zone, while there is no box of pasta nearby. Without that spatial information, it would be impossible to discriminate between the two activities. We propose a new qualitative spatial reasoning recognition (QSRR) model able to deal with such situations. A QSR model should abstract the quantitative description of objects and their relations in space in a discrete and simple form. Works published on QSR has been mostly derived from Allen’s temporal reasoning [11] but according to Cohn [12], it is much more complex because it works in greater dimension (2 or 3) than in the temporal reasoning. In the context of activity recognition, it seems intuitively appropriate to use purely QSR because of its reduced calculation complexity, and because it better describes the relations between objects [15]. In his paper, Cohn [12] listed frequent spatial problems (distance, position, orientation) that we can encounter in real life activities. Here is an example of distance problem between objects: *The subject is correctly executing the step to prepare his coffee. Then he has to put hot water in the cup. He correctly takes the water jar but instead of moving it near the cup, he placed it farther on the table.* It is clear that the problem will not be detected without considering the increasing distance between the cup and the jar. Therefore, if the activity is correctly identified, the system will believe that everything is going fine. The second type is the position issue and it occurs when the system does not considerate that some type of object should never be in certain regions (*shampoo* is never used in kitchen activities!). The last type of problems happens when an object is incorrectly oriented in space so that might cause anomalies. For instance, if a cup is under water to be filled, without considering the spatial aspect, one cannot detect if the cup is upside down, which can lead to false conclusions. In this paper, we decided only to address the first two spatial problems, which are distance and position, in our context of activity recognition. The reason is that we used RFID tags as main inputs for our recognition algorithm. This kind of tags does not allow us to get precise information about the object orientation.

2.1. A topological spatial framework

The spatial model we exploit is a specialization of Egenhofer's work [16], which is primarily based on general topology [17]. We chose this model because the description of spatial relations in terms of general topology is simple and also because it was demonstrated that any topological spatial relations fall within that framework. First, one must understand the basic concept of *interior* and *boundary* from general topology, because they are the base of our topological spatial relations. Imagine each object with a projected sphere around them defining the primitive *region* for the establishment of our relations. If the boundary of the spoon touches the boundary of the cup, it might imply the two objects are in relation for the execution of an activity such as *MakeCoffee*. If the interior and the boundary of the spoon are inside the interior of the cup region then it is probably because the spoon is used to stir something inside the cup. This framework exploits the topological relations between two regions/subsets (A and B). It takes into account eight relations representing all the different ways an object A can intersect an object B in a two dimensional plan according to their interiors and boundaries [16]. A visual representation of the possible relations between two objects can be seen on figure 1.

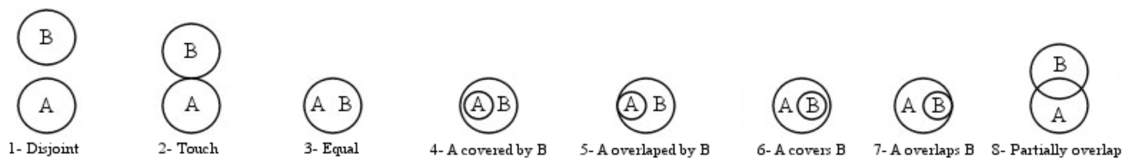

Fig.1. The eight exploited topological spatial relations.

In our recognition context, each object will be represented in the environment with an associated zone area. The plans in the library will have a list of constraint K where a constraint k is a spatial relation r_i (o_1, o_2) between two objects area (ex: A overlaps B). The relation between two objects will be used to circumscribe the plans' library in our recognition model. We will often refer to them with their name and their number by writing r_i where i is the relation number. It might be noted that the same relations exist in a three dimensional context.

3. A New QSRR Model

Given that overview of our spatial primitives, the new qualitative spatial reasoning recognition model (a 4-tuple $< A, O, E, P >$) will be introduced properly. $A = \{$*take, turnOn, open,* $\ldots\}$ constitutes the set of all basic actions that can be done in the environment. $O = \{$*coffee, cup, spoon,* $\ldots\}$ is the set of all the observed (tagged) objects in the environment. With these two sets, we can define the basic structure of observable actions, which is a pair $(a, o \mid a \in A, o \in O)$, referring to the fact that we can observe the application of a certain basic action a to a certain object o in the environment. For instance, it can be (*take, cup*), which means that the cup has been taken by the resident. The set E represents the events observed by the recognition agents. An event $e \in E$ is composed of a timestamp linked to a basic observable action structure. For instance, the set E might be equal to $\{(1,$ *take, cup*$), (2,$ *take, coffee*$), \ldots\}$. For the agent, an activity is a partially ordered set of actions in time that correspond to a certain plan. The set of possible plans P represents the knowledge base of our agent. A plan $p \in P$ is defined by a list of actions on objects $\{(a_1, o), \ldots, (a_n, o)\}$ and a list of spatial constraint $\{k_1, \ldots, k_n\}$. It should be noted that the agent believes P to be exhaustive and will only search within his library. A plan is believed to be completed when all actions corresponding to his definition have been observed by the intelligent agent. The list of spatial relations from the Egenhofer's framework is added to the definition of a plan in order to enhance the plans' discrimination process efficiency. For instance, the plan *MakeCoffee* has a spatial constraint *(Cup [covers] Spoon)* which literally says that a cup zone should (but not must) contains a spoon and its zone at the end of the activity. Observing this relation or a similar one between a spoon and a cup, the recognition agent would give more plausibility to the plan *MakeCoffee* so it could be determinant to the discrimination of other plans such as *CookPasta*.

3.1. Addressing the position issue

The position issue should be addressed before beginning to circumscribe the knowledge base to ignore some noisy observations that could lead to misjudgement of the plans' plausibility and consequently, restrain the agent from elimination of many impossible activities. To do so, we have to verify the relations of the objects that have taken part in events set E with the smart home logical zones. More precisely, we have to verify that an object and his area are not completely contained in a forbidden place. If the object is in spatial relation of type 3 to 7 (inclusively) with a forbidden area (the object is entirely covered by the area or equal it), we will ignore this observation in the inference of the ongoing plan. In an assisting system, it could have triggered the assisting agent or sent a report to a caretaker in charge. To be sure that our point is rightfully expressed, let's take an example where we have Peter, an Alzheimer's patient, in earlier stage of the disease. Peter wants to make a coffee. Therefore, his first action is to open a panel cabinet and take a cup. Hence, the system observes the event (1, *take, cup*). Then, he goes to the bathroom and instead of washing his hands, he took the bottle of soap with him in the kitchen. Thus, the new events set look like this: $E = \{(1,\ take, cup), (2,\ take, soap)\}$. It is rather simple for a human to see that it is a mistake, because soap should never be part of any kitchen activity. But in the system, we translate it by verifying the relation of the soap with the forbidden areas (the kitchen) that are specified in the library to finally conclude that we should ignore this observation. If not ignored, the system would not have eliminated the plans related to the bottle of soap that were obviously incoherent, and it might have led in significant errors in the recognition process.

3.2. Plan hypotheses circumscription

The goal of the model is to circumscribe the plans' library into a limited set of activity hypotheses based on observed actions (events). To do so, we must evaluate the plausibility of all plans in the library with a certain function. For each plan, we calculate plausibility based on every event. These events are ordered in time from the newest to the oldest in order to give more weight to the newest observations made by the agent. We do this because the newest observation can be the beginning of a new plan or even contradict previous ones. For example, suppose the following set $E = \{(1,\ Take, Coffee), (2,\ Take, Cup)\}$ the subject seems to be making coffee but then he changes his mind while thinking about his health and the system observe (3, *Take, Tea*). Without variable weighting based on time, the plans *MakingCoffee* and *MakingTea* would seem to be equally probable.

Each event can increase or decrease the plausibility of a plan. To determine the influence of an event, the model is using the spatial relations described in the previous sections. For an event, it searches for each relationship (r_1 to r_8) between the object altered by the event and every object used in the plan. The relations can be divided into two groups: those who increase the plausibility of a plan and those who decrease it. Fortunately, the relations can be split easily because only the first one (two objects are disjoints) does the contrary of the others. Therefore, r_1 have a negative impact when the others have a positive one. The only problem remaining is to determine when a group should increase the plausibility or when it should decrease it. It is really straightforward because when an object is used in the realization of a plan, it should be in relation with the other objects and then r_2 to r_8 would be favorable to the plan. Otherwise we just need to reverse the value from positive to negative and vice versa. Finally, it is important to understand that some relations are stronger than others. For example, two objects that are in relation r_8 (partially overlaps) have a stronger bond than in r_2 (touch) but weaker than r_{3-7} (equal, covers and overlaps). Using this information, the influence of an event on the plausibility of a plan will be the sum of the influence of his relations with the objects of the same plan. The algorithm evaluates the plausibility of every plan in the agent's knowledge base. The goal is to use this information to eliminate unlikely plans from further consideration. The set of inferred plan hypotheses $P_h \subseteq P$ is defined as follows:

$$P_h = \bigcup_{p_i \in P}^{d} Near(p_i^{\varphi}, p_{i-1}^{\varphi})$$

In order to circumscribe the set of weighted plans, we first need to order them from the highest plausibility to the lowest. We will always take the one with the highest plausibility because we want at least one hypothesis. Then, the next plans will be considered only if their plausibility φ is near the precedent one. The function Near verify if $p_i^{\varphi} - p_{i-1}^{\varphi} < 0.25 * p_{i-1}^{\varphi}$. In other word, it verifies if the difference in plausibility is less than 25% of the precedent plan. This condition is used for the next plans until the difference between the current plans plausibility and the first plan is d elevated (d is the upper limit of the union where $p_1^{\varphi} - p_i^{\varphi} < d$). In the end, the new set P_h contains every plan with a high plausibility.

3.3. Application of the C4.5

Our model is a pre-filter that we use on the plans set before applying the C4.5 algorithm [18] that uses data drawn from data mining to generate a decision tree to classify (training) and then to predict missing class attribute in a dataset. We decided to use the C4.5 because we had already a working implementation, and we wanted to keep this part simple. However, since the C4.5 works with a training dataset to recognize the activity, we must use our reduced set of plans to minimally restrain the training data. The C4.5 uses these records to conclude which plan is the most plausible. It is rather simple; we just need to use a restrained training set where all training data concerning a plan not contained in our hypotheses should be ignored. Once it is done, the remaining of the process is really straightforward. We only need to build a decision tree that will use the remaining data in order to decide which activity the agent will believe to be ongoing. Figure 2 graphically illustrates the steps of our model that we have been explaining. In the next section, we will give a complete example using our model.

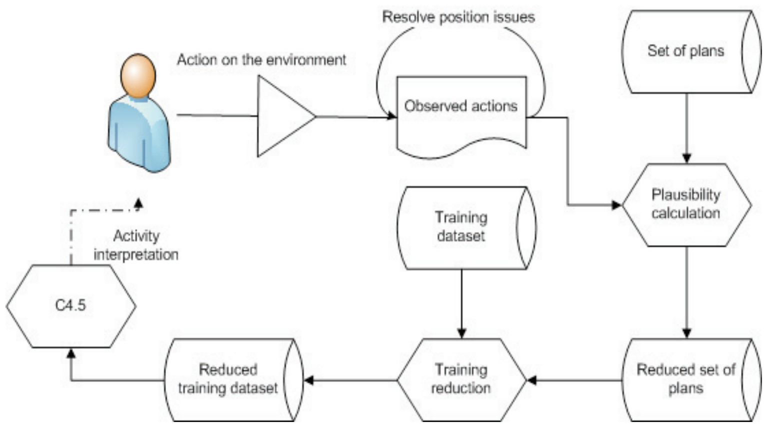

Fig.2. QSRR model using C4.5

3.4. Execution example

This section will display with a simple example how it helps to determine the ongoing activity with the distance criterion. Let $P = \{MakeTea, MakeCoffee, MakePasta\}$ be our complete plans' library. Again, we have Peter living in his smart apartment doing is everyday life activities. His position, detected by a tactile mat, is believed to be right in front of the kitchen counter. Then, he opens the tap to fill the kettle with water. Until now, the system has observed the events $E = \{(1,\ open,\ tap), (2,\ close,\ tap), (3,\ turnOn,\ kettle)\}$ and it believes that the three plans in its library are possible. Peter now takes a coffee cup from one of the cabinets and deposes it on the countertop of the kitchen. The observation (4, *take, cup*) is added to the set and the recognition process begins. While calculating the plausibility of each plan, we get the relation r_8 (partially overlap) between the object cup and kettle that are both part of the plans *MakeTea* and *MakeCoffee*. Thus, it increases the plausibility of these two plans. The result is that the plan *MakePasta* is ignored for the latter part of the recognition (this iteration at least). The C4.5 now determine with his training set which activity is ongoing. For now, he has many chances to be wrong if Peter usually drank tea, but today he wants to drink coffee. Next, Peter takes a spoon, which again does not influence the odds, but after that, the system observes (6, *take, tea*) so obviously Peter seems to prepare tea. Then, the system observes (7, *take, coffee*) which would have re-established the initial plausibility to be equal between the two plans. However, during the spatial analysis, the relation r_1 (disjoint) has been observed between the items *((tea, kettle), (tea, spoon))* and this relation reduces the plausibility of the plan *MakeTea*. Furthermore, the system observes the relation r_8 (partially overlap) between the objects *((coffee, kettle), (coffee, spoon))* and it benefits to the performance of the plan *MakeCoffee*, so it increases his plausibility. At the end, the system might observe the plausibility is much higher for the latter plan and then reduce the set of plan hypotheses to $P_h = \{MakeCoffee\}$. In reality, the action of taking the tea done by Peter could have been a misjudging error so it was put back to his initial position and the coffee was taken right after to replace it.

The example shown was a really simple version of what might happen in the reality. However, it was really clear in that case, without observing the distance between related objects, we would not have been able to adequately discriminate the different hypotheses.

4. Validation

To experiment our new approach, we chose to use a recognition test platform recently developed and presented in [13]. This platform is based only on RFID tags that are characterized by their light weight and their low cost. The figure 3 illustrates the hardware comprising two RFID antennas that we set up on a table of 1.5meter by 0.75meter. We defined a two dimensional Cartesian coordinate to express the position of objects on the table. To do so, we measure the distance of the objects from each antenna, and we use it as a radius to create two virtual circles around the antennas. Then, using the equation of both circles, we find the coordinate (x,y) where the circles intersect. If there are two intersection points, we know that only one can be on the table because the position of the center of both virtual circles is in the corner of the first quadrant that covers the entire table. Therefore, the second point is not in this quadrant. This problem could also have been solved by adding a third antenna to do a triangulation calculus.

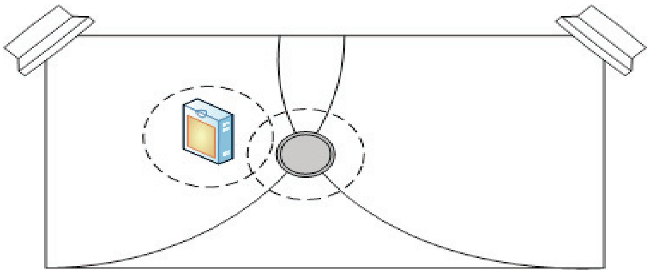

Fig. 3. The table with the two antennas (upper corner), the objects and their zones.

The basic recognition algorithm worked using data mining with a decision tree (C4.5) to identify the possible ongoing ADL. As we used data mining, a certain amount of training has been done on each possible activity in our library. Everything was implemented using Java with a data mining library named Weka [19]. To understand the efficiency of the spatial constraints, we made our experimentations with and without the spatial analysis. Everything in our environment was defined as region beginning by the two RFID antennas. The zone covered by the antenna wave is considered as the antenna zone. Then we associated a logical region to every physical object and saved it in the database. These regions were defined in 2D to reduce the complexity in order to improve the precision of our results. We tested different shapes of region *(convex hull, disc, elliptic)* and we rapidly concluded that convex hull would be far too complicated to implement and not necessarily the best choice to be considered to use. Besides, elliptic shape would have been a good solution (probably the better), but as we cannot know the orientation of the objects for sure, we would not be able to determine the orientation of the axis of the ellipse in a Cartesian plane. Thus, it must be eliminated too. Therefore, we created the regions in the shape of a projected disc under the objects. The radius of a region is about the size of the diameter of the corresponding object. The elongated objects (spoons, forks, etc.) are no exception to this condition. We use their longest diameter as the radius.

5. Experiment and Results

For our experiment, we had to choose the right activity that would be simple to put in place, would require a little organization and would cover at least few spatial characteristics. We noticed that a lot of examples in the literature imply kitchen activities such as cooking [3], washing hands [7] and preparing tea or coffee [20]. We needed at least few steps for the chosen activity and to be shorter than fifteen minutes. For these reasons and because it is a well known activity by patients, we chose to use the activity *Preparing a coffee*. For our experiment, we wanted to use real data from clinical trials. To achieve that, we signed a formal collaboration agreement with our regional rehabilitation center, which provided us with an adequate group of cognitively-impaired people, such as Alzheimer's patients. We cooperated with our colleague, a neuropsychologist researcher, who helped us obtaining the ethical authorizations and setting of the test. The chosen activity and the experimental protocol are based on a well-known cognitive test used by therapists and named the "Naturalistic Action Test" [21]. We conducted the experiment with both normal and cognitively impaired subjects who did the NAT chosen activity. As shown on figure 4, these tests were filmed and the data recorded.

Fig. 4. A subject with dementia doing the NAT activity with tagged objects

5.1. *Obtained results*

We have defined three scenarios, from the 50 execution sequences we had filmed, that both versions of our algorithm tried to recognize five times. The first one was the normal execution of *Preparing a coffee*. The second one was incorporating distance problem, and the last one have included a position problem in the sequence. Before the execution, each object was replaced in their initial position near the two antennas (far from the subject). The objects on the table were the same for each type of scenario. The list is as follows: water jar, coffee pot, spoon, sugar, milk and cup. The results we obtained were very promising; even though our first algorithm gave good results, the second with spatial constraints did clearly better. A summary of the result can be seen on figure 5.

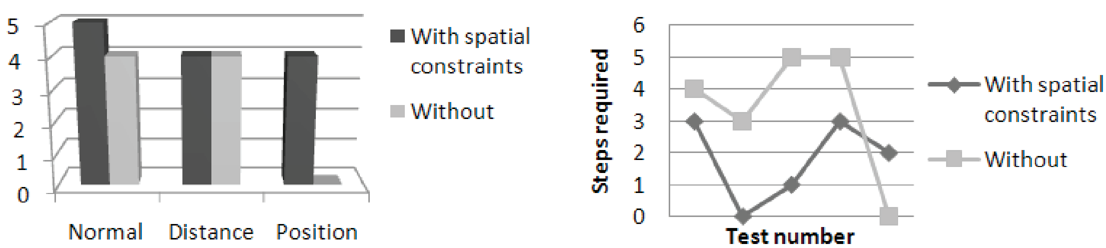

Fig. 5. (a) Number of success in recognition; (b) Number of steps required to recognize the plan for distance test (zero for unrecognized)

The recognition success rate for the normal and the distance execution sequence were almost the same for the two algorithms (fig. 5(a)), but through the steps of the activity, the spatial constraints helped a lot in the elimination of incoherent plans. Thus, even if the recognition was a success without the spatial constraints, it took more steps to conclude at the correct plan. This can be seen on fig. 5(b) for the five distance test. The recognition speed is very important to be able to seek for anomalies and help the resident as soon as possible. In a real smart home, the performance will diverge even more due to the far greater complexity of the activities than in our case. For the distance criterion, 4/5 activities were identified accurately by both algorithm. However, in the spatial case, we could see that because of a distance anomaly the plan was not taking place correctly. That is the spatial algorithm provides us with new information that we would not have otherwise. The anomaly did not only help us, in a case it makes the algorithm eliminates the plan *Preparing a coffee* and led to incorrect recognition. A tweak in the spatial algorithm should help to better handle these situations. In the last scenario, the anomaly was to produce noise by introducing an interfering object that could never be implied in the kitchen activity. By introducing shampoo, our first algorithm was deceived and never recognizes the activity. However, the spatial constraint helped us identify the noise and simply eliminate it from the activity sequence (in a real context it might have helped the subject to correct his mistakes). To conclude, the results obtained are very promising and tend to confirm that spatial constraints are a very important feature for the process of recognizing ADL in a smart environment.

6. Conclusion

Through this paper, we have shown the importance of exploiting spatial constraints in the recognition process are. For this sake, we proposed an extension to the well-known C4.5 [18] decision tree algorithm, which incorporates qualitative topological spatial relations based on the framework of Egenhofer [16]. We also presented the implementation of the new algorithm and the first experiment results that we obtained based on real data gathered in a former experiment with cognitively-impaired subjects. Very few papers present an analysis of the integration of qualitative spatial reasoning in a context of activity recognition, even if it is especially important from a smart home point of view [8]. In the future, we intend to improve the coverage of our spatial recognition algorithm and to address the issue of disorientation of objects. Then we will proceed to a larger experiment with new scenarios of new activities covering each type of spatial attributes (including the one of disorientation). We also plan to introduce new fuzzy spatial constraints that will help dealing with the imprecision of sensors and will enhance the decision process in our algorithm.

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