

Ontology Based Spatial Planning for Human-Robot Interaction

L. Belouaer and M. Bouzid and A.I. Mouaddib
GREYC (UMR 6072)

Université de Caen Basse-Normandie
Campus Côte de Nacre, boulevard du Marchal Juin
BP 5186 - 14032 Caen CEDEX, FRANCE

{lamia.belouaer,maroua.bouzid, abdel-illah.mouaddib}@info.unicaen.fr

Abstract

In the last decade, there has been significant progress on Robotics. This development has widened the intervention fields of robots, particularly the assistance and interaction with humans. Improving the quality of this interaction requires robots to be endowed with representation and/or reasoning system for spatial knowledge. Our goal is to develop a planner allowing us to use human robot interaction to solve space sharing problems. This work is original, in that the representation of the same space for humans (symbolic, fuzzy) and robots (numeric) is not the same. Our objective is to combine human and robots representations of space in order to develop a mixed reasoning. We propose here an ontology called *SpaceOntology* as a spatial knowledge representation and reasoning system. In this paper, we focus on this ontology, and show how this type of knowledge can be profitably used for task planning. Our objective is to incorporate this ontology into a planner by extending the planning language PDDL.

1 Introduction

Human-robot interaction (HRI) is not intuitive. This constitutes a barrier to the acceptance of some humans to interact with robots. Making this interaction intuitive and improving its quality requires endowing robots with representations and/or reasoning systems directly inspired by humans. Many works have been dedicated to this purpose, mainly on task planning for autonomous robots ([9], [4], ...). Task planning requires different types of knowledge encoded in the planner in a suitable way [7]. We focus here on spatial knowledge in task planning in HRI context. Our goal is to develop a planner allowing us to solve problems taking into account spatial information: *Spatial Planner* (Fig. 1). This planner consists of two sub-systems.

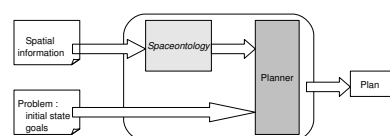


Figure 1. Spatial planner.

The first sub-system is *SpaceOntology*. It is defined as a knowledge representation and reasoning system, for modeling and managing spatial entities, spatial relations and imprecise spatial information. Moreover, *SpaceOntology* manages spatial semantic knowledge about spatial entities and how they are related. These are respectively represented in terms of *concepts* and *relations* which are organized into a hierarchy called an ontology [8]. Different spatial representation and reasoning techniques have been proposed; maps [15, 11], algebraic approaches [3], etc. However, these approaches can not manage quantitative, qualitative and imprecise knowledge at the same time. We choose an ontology since it leads to: (1) a complex spatial description, (2) an easy management of large amounts and different types of spatial information, (3) a structure easily extensible and especially (4) infer spatial information by deduction of spatial relations. As input, *SpaceOntology* takes a set of imprecise and incomplete spatial information. However, as output, it provides structured knowledge about the environment to explore in planning.

The second sub-system, *Planner* explores the potential uses of spatial information incorporated in *SpaceOntology*. It defines the set of actions to be executed by the robot in order to achieve its mission. We consider that all spatial knowledge can be associated with the execution of each action. Also, the actions may require navigation.

In this paper, we focus on spatial information, and show how this type of knowledge can be profitably used for task planning. This paper is organized as follows. In the next section we give a simple example to illustrate our work. Section 3 presents our ontology. Section 4 describes how

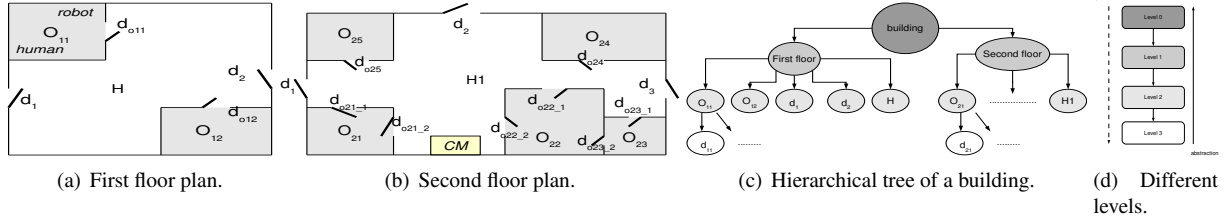


Figure 2. A building, its floors and its hierarchical organization.

our spatial representation and reasoning complements spatial information for task planning. Section 5 concludes.

2 Illustrative Example

In this section, we present an example to identify our problem. Throughout this paper, we rely on this example to illustrate our work.

Example 1 *A human robot team is to perform a task in the environment defined in the figures 2(a) and 2(b). The team is in the office O_{11} . The human asks the robot to pick up a book located in the office near the coffee machine.*

In our work, we consider that the robot has the ability to recognize objects, communicate and interpret orders. From this example, two problems requiring spatial information are identified: (1) in which position the robot should execute an action, for example to enter in the office *close to* the coffee machine, i.e how to evaluate that an office is close to the coffee machine? (2) how to move between different action areas? i.e to define the robot’s navigation during and between each action; for example, finding a path between the current position and the target position.

These problems can be resolved by focusing on how the human and the robot share and communicate information about space. However, this is not simple. Indeed, Humans and robots consider space differently. From the human’s point of view, space is generally considered in a symbolic (in, disjoint, above, etc) and fuzzy way (very close, very far, etc). Thus, we consider a symbolic representation by considering topological relations and an ontological definition. There are several topological representations, namely the *Intersection Method* (xIM [5]), *Region Connection Calculus* (RCC [13]). RCC is probably the best known model for spatial representation and reasoning. The limitations of this representation are both in the boundaries definition of regions and in the expressiveness. For instance, RCC method can not reason about cardinal relations such as an object north of an another. This is possible with other qualitative formalisms such as rectangles algebra [3]. This representation defines regions as rectangles. It contains 169 relations. This is very expressive but the number of relations slows

down computation. Moreover, we propose a fuzzy representation. From the robot’s point of view, space is considered in numerical way (angles, distances, etc). Thus, we consider a numeric representation by considering distance relations.

On the other hand, managing a considered space as a whole is difficult. One solution is to make a hierarchical organization [6] of said space. This organization reduces the amount of information considered for coping with a complex, high-detailed world: concepts are grouped into more general ones and these are considered new concepts that can be abstracted again. The result is a hierarchy of concepts that ends when all information is modeled by a single universal concept (in abstraction case) or when all information is modeled by several concepts to a desired level of specialization (in specialization case). Hierarchical space organization gives a structure easily manageable by humans and robots. In addition, it provides better performance than a flat representation [6], in particularly in path planning.

Considering these aspects, we give here an environmental description understandable by both humans and robots.

3 Our Formal Framework

As a formal language, we opted for the OWL DL formalism [2]. This formalism benefits from the compact and expressive nature of DL’s. Indeed, an important characteristic of DL’s is their capability of inferring implicit knowledge from the explicitly represented knowledge. In this section, we describe how we present and reason with regards to spatial knowledge.

3.1 Spatial representation

SpaceOntology allows a knowledge representation for modeling space (spatial entities, hierarchical organization), spatial relations and fuzzy information. To the best of our knowledge, no work has developed an ontology that takes into account all these aspects.

3.1.1 Spatial entities

A region in a considered environment is called a *spatial entity*. The environment itself is seen as a spatial entity. A spatial entity is localizable in a given space by one of its attributes or by its geometric transformation. From a geometric point of view, a spatial entity ϵ is defined by a rectangle $rect_\epsilon$, corresponding to its axis-aligned bounding rectangles.

Hierarchical representation Our organization is made from the highest abstraction level to the lowest (most detailed one) unlike the organization described in [6]. The highest level represents the environment with the maximum amount of detail available. The lowest level represents the environment by a single concept. From hierarchical organization two categories of spatial entities are derived. *Space* represents a global space ($Space \sqsubseteq T$) (T for Thing¹). This entity is the highest abstraction and the lowest level in the hierarchy organization. *Region* ($Regions \sqsubseteq Space$) represents any spatial entity belonging to different hierarchical levels (intermediate and final). A region is a sub-space included in the given space. A region itself considered as a space that can be decomposed into different sub-regions. For each region we specify the current hierarchical level and scale.

The hierarchical relationship between concepts *Space* and *Regions* given by subsumption is symmetrical and transitive. From these properties, we can compose these links and deduce new information.

3.1.2 Spatial relations

A spatial relation is not considered in our ontology as a property between two regions but as a concept on its own ($SpatialRelations \sqsubseteq T$). This concept represents a set of all spatial relations between two regions. A spatial relation subsumes topological ($TopologicalRelations$) and distance relations ($DistanceRelations$).

The semantic of the relation *office O_{22} is left of the coffee machine* is not the same depending on whether the reference system is the coffee machine itself or an external observer. In order to have a unique meaning and to remove the ambiguity, each spatial relation is linked explicitly to a given reference system that can be *intrinsic* or *egocentric* [10].

We consider a 2D space representation given by (O, \vec{i}, \vec{j}) . A rectangle denoted ϵ represents a region. X_ϵ (resp. Y_ϵ) denotes the projection of ϵ on the \vec{i} axis (resp. the \vec{j} axis). Additionally, a symmetry center of a rectangle will be known as the region name. $P_x(\epsilon)$ (resp. $P_y(\epsilon)$) denotes the projection of ϵ on the \vec{i} axis (resp. the \vec{j} axis).

¹Thing is an OWL class that represents the set containing all individuals. Because of this all classes are subclasses of OWL:Thing.

Topological relations We consider the **ABLR** (Above Below West Right) [12] relations. This algebra balances between expressiveness and the number of relations (reasoning/complexity). **ABLR** reduces the number of relations while preserving the directionality property of the representation defined there in [1]. It can represent the topological relations themselves (overlaps, etc) and express the cardinal relations. A topological relation is an **ABLR** relation. This relation is a couple $\langle r_X, r_Y \rangle$, where:

$$\begin{aligned} r_X &\in \{Left(L), OverlapsLeft(O_L), Contains(C_x), \\ &Inside(I_x), OverlapsRight(O_R), Right(R)\} \\ \text{and} \\ r_Y &\in \{Above(A), OverlapsAbove(O_A), Contains(C_y), \\ &Inside(I_y), OverlapsBelow(O_B), Below(B)\}. \end{aligned}$$

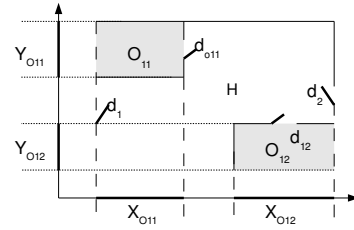


Figure 3. ALBR relation.

Consider the floor in figure 2(a). Offices O_{11} and O_{12} are defined by rectangles having the same names. In figure 3, $X_{O_{12}}$ is right of $X_{O_{11}}$ (R) and $Y_{O_{12}}$ is below $Y_{O_{11}}$ (B):

```
relation1:HasRelation  $\sqcap$   $\exists$ 
concernsSpatialRelation.right_below  $\sqcap$   $\exists$ 
hasReferent.O11  $\sqcap$   $\exists$  hasTarget.O12
```

The topological relation (*right_below*) is given by $O_{12}\langle R, B \rangle O_{11}$:

```
right_below:TopologicalRelations  $\sqcap$   $\exists$ 
isAnHorizontalRelation.R  $\sqcap$   $\exists$ 
isAVerticalRelation.B
```

Distance relations We consider (fig. 4) four linguistic variables to describe distance relations. Consider the building given in figure 2(a) and 2(b). The office O_{11} is far from the office O_{23} is expressed as follows:

```
relation2:HasRelation  $\sqcap$   $\exists$ 
concernsSpatialRelation.far  $\sqcap$   $\exists$ 
hasReferent.O11  $\sqcap$   $\exists$  hasTarget.O23
```

3.1.3 Fuzzy representation

In HRI under spatial constraints, fuzzy information is a key point. Indeed, a human may have an imprecise request such as *take a book in the office close to the coffee machine*. The fuzziness is due to the imprecision of spatial description using linguistic variables such as close to, far from, etc. In this

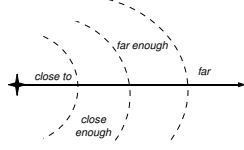


Figure 4. Organization of distance.

work, vagueness and ambiguity concern the relation itself. They mainly concern distance.

We note $d(\epsilon, r)$ in \mathbb{R}^+ , the Euclidean distance between the point of symmetry of two rectangles representing two regions (r referent object and ϵ target object). The aim is to find a way to represent the four linguistic variables in figure 4 by a numerical distance and vice versa. To do so, we consider two degrees, defined in [14], $N_{(\alpha, \beta)}(p, q)$ (1) and $F_{(\alpha, \beta)}(p, q)$ (2). The degree N represents how near two points p and q are to each other and the degree F represents how p is far from q ($\alpha, \beta > 0$).

$$N_{(\alpha, \beta)}(p, q) = \begin{cases} 1 & \text{if } d(p, q) \leq \alpha \\ 0 & \text{if } d(p, q) \geq \alpha + \beta \\ \frac{\alpha + \beta - d(p, q)}{\beta} & \text{otherwise } \beta \neq 0 \end{cases} \quad (1)$$

$$F_{(\alpha, \beta)}(p, q) = \begin{cases} 1 & \text{if } d(p, q) > \alpha + \beta \\ 0 & \text{if } d(p, q) \leq \alpha \\ \frac{d(p, q) - \alpha}{\beta} & \text{otherwise } \beta \neq 0 \end{cases} \quad (2)$$

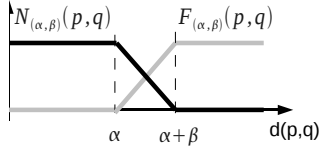


Figure 5. Graphical representation of relationship between $N_{(\alpha, \beta)}(p, q)$ and $F_{(\alpha, \beta)}(p, q)$.

From equations 1 and 2 and organization given in figure 4, it is easy to deduce that: (1) if $d \in [0, \alpha]$ then d is considered as *close*, (2) if $d \in]\alpha, \alpha + \frac{\beta}{2}]$ then d is considered as *close enough*, (3) if $d \in]\alpha + \frac{\beta}{2}, \alpha + \beta]$ then d is considered as *far enough*, (4) if $d \in]\alpha + \beta, +\infty[$ then d is considered as *far*.

We have defined a hierarchical space organization. This has an impact on the distance evaluation. Indeed, the distance of 2 meters in a city is considered *close*, however, 2 meters in an office is considered *far*. From this information, we define for each hierarchical level an α and a β depending on the scale of this level. Consider a building, a first floor and an office O_{11} given in figure 2. From an ontological point of view, the hierarchical aspect taking into account the α and β is modeled as follows:

building:Space $\sqcap \ni$ level.0 $\sqcap \ni$ α .10 $\sqcap \ni$ β .15

floor1:Regions $\sqcap \ni$ level.1 $\sqcap \ni$ α .5 $\sqcap \ni$ β .10

O_{11} :Regions $\sqcap \ni$ level.2 $\sqcap \ni$ α .1 $\sqcap \ni$ β .1

The exploitation of the fuzzy representation is described in section 3.2.3.

3.2 Spatial reasoning

The reasoning methods infer spatial information in order to enrich the description of the environment with new knowledge and/or to manage the lack of spatial information. The reasoning methods proposed are related to the abstraction with hierarchical organization and the deduction with spatial relations composition.

3.2.1 Reasoning on the hierarchy

Consider example 1. A solution plan is to move between the current position (in office O_{11}) and the target position (in the office close to the coffee machine), take the book and go to the human position's. Finally, give the book to a human. Now, consider the navigation problem between the initial position and the target. The target position is defined in a fuzzy way.

Computing a path, by considering a global map of an environment (with all the corridors and all access, ...), quickly becomes expensive. Hierarchical organization of space simplifies the path computation. Indeed, it helps to decompose this problem into 3 sub-problems: (1) from initial position to reach an access point to the second floor, (2) from this access point plan to reach the second floor and (3) from arrival position on the second floor, plan to reach the coffee machine. In each hierarchical level, we want to reach an intermediate target position (interest zone). An *interest zone* I_Z defines a region in a considered space to be reached and/or localized. Thus, we combine the notions of hierarchy and interest zone: *hierarchical interest zone*.

In example 1, as a first goal, we want to reach a coffee machine. This target region defines an *interest zone*. Considering the hierarchy of the environment, we define the interest zone as $I_Z^l(r)$, where l is the hierarchy level and r the target region. Thus, we can deduce from *SpaceOntology* a hierarchy for an interest zone. This determines the most abstract interest zone ($I_Z^0(r_{CM}) = \text{building}$) and the more detailed one ($I_Z^3(r_{CM}) = \text{current region of coffee machine}$).

This organization enables reasoning partitioned according to the hierarchical levels considered for a navigation action. The exploitation of this reasoning is described in section 4.1.1.

3.2.2 Reasoning on spatial relations

In order to enrich *SpaceOntology* with new knowledge and/or to manage the lack of spatial information, we consider two different aggregations of spatial relations: composition \otimes and combination \oplus .

Composition mechanism This mechanism infers new information about a spatial configuration. Consider three regions ϵ_1 , ϵ_2 and ϵ_3 defined by rectangles with the same name. The idea is to infer which relation R_3 links between ϵ_1 and ϵ_3 where R_1 is a relation between ϵ_1 and ϵ_2 and R_2 is a relation between ϵ_2 and ϵ_3 . The topological relation R_3 is defined by $R_3 = R_1 \otimes R_2$, then

$$\langle r_{X_3}, r_{Y_3} \rangle = \langle r_{X_1}, r_{Y_1} \rangle \otimes \langle r_{X_2}, r_{Y_2} \rangle \quad (3)$$

$$= \langle r_{X_1} \otimes r_{X_2}, r_{Y_1} \otimes r_{Y_2} \rangle \quad (4)$$

The composition results of $r_{X_1} \otimes r_{X_2}$ and $r_{Y_1} \otimes r_{Y_2}$ are given by the composition table of rectangle algebra by preserving the directionality property as defined in ABLR.

Combination mechanism This mechanism consists of combining horizontal relation with vertical one $r_{X_1} \oplus r_{Y_1}$. With this mechanism, we can deduce 36 topological relations given in *Neighborhood graph* of the ABLR relations [12]. This mechanism makes possible to enrich topological relations (for example overlaps, touch, ...) and orientation relations. Indeed, by this mechanism we can represent the 8 cardinal relations and other directional relations as at the same level, between, ...

Example 2 : Composition and exploitation of its results.

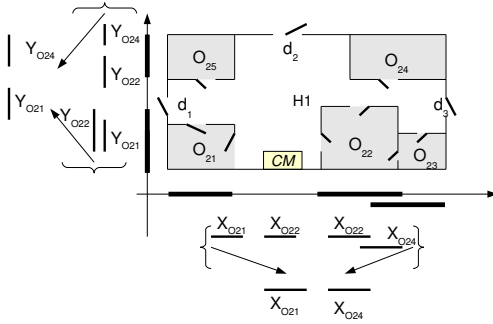


Figure 6. Projection and composition.

In the second floor (fig. 2(b)), we assume that the team is in the office O_{21} . The human asks the robot to go and stay in the office O_{24} . From *SpaceOntology*, the robot has only this information: (1) $O_{21} \langle L, I_Y \rangle O_{22}$, $O_{22} \langle O_L, B \rangle O_{24}$ and (2) the office O_{24} is on the current floor.

The spatial information the office O_{24} is on the same floor as the office O_{21} allows the robot to limit its interest

zone to the second floor ($I_Z^1(r_{O_{24}}) = \text{second floor}$). However, this information is not sufficient to find O_{24} . Indeed, to find the target the robot will look through all the floor in order to find its target. Based on the composition mechanism (fig. 6), we can deduce that $O_{21} \langle L, B \rangle O_{24}$ (equation 6).

$$\langle L, I_Y \rangle \otimes \langle O_L, B \rangle = \langle L \otimes O_L, I_Y \otimes B \rangle \quad (5)$$

$$= \langle O_L, B \rangle \quad (6)$$

Based on the symmetry of spatial relations, we have $O_{24} \langle R, A \rangle O_{21}$. Thus, from this information the robot can plan its trajectory to reach the office O_{24} without considering the entire second floor but only the northeastern part of the floor from the office O_{21} . This information is added in *SpaceOntology*.

3.2.3 Reasoning on fuzzy representation

In the previous section, we relied on symbolic information to reach a defined interest zone (a portion of the corridor where the coffee machine is). We consider that the current region of the robot is the interest zone. However, it does not reach its target position. To achieve/define its target position, the use of distance relations (imprecise and precise) is necessary. Indeed, in the example 1, a robot must enter the office *close* to the coffee machine. However, there are several offices near the coffee machine (fig. 2(b)).

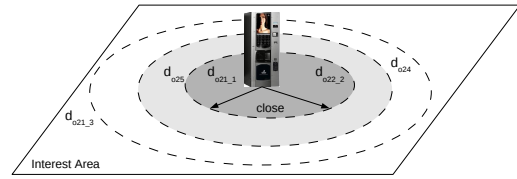


Figure 7. Distance evaluation.

Denoted by $d(O_i, CM)$ the Euclidean distance between the office O_i and coffee CM . The selection of the closet office is as follows: The distance $d(O_i, CM)$ should allow that the degree $N_{\alpha, \beta}(CM, O_i) = 1$. The evaluation of distance is made by the data α and β for the current hierarchical level.

By applying this system of evaluation, the offices O_{21} and O_{22} are close to the coffee machine. Thus it selects the corresponding gates $d_{O_{21},1}$ and $d_{O_{22},2}$ (fig. 7). We note that O_{21} and O_{22} verify the close relation to the coffee machine. In this case, the robot may request additional information. The robot asks the spatial direction. The human answers *the office in left of the coffee machine*. This allows the 2 direction and distance relations to combine by superimposing the 2 representations as defined in figure 8.

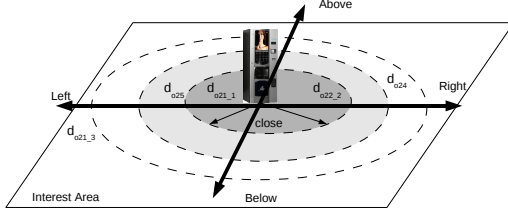


Figure 8. Superimposing representations.

From a planning perspective, let us consider the action of `enter_office`, these spatial constraints must be expressed in terms of preconditions for action `enter_office` (see section 4).

4 Application Context: Planning

Now, we explore the potential uses of spatial representation and reasoning offered by *SpaceOntology* in planning. A planning process searches for a sequence of ordered actions that transform the initial state into the goal state. Let us consider the problem defined in section 2. This problem involves the use of spatial planner (Fig. 9). This planner consists of a task and a path planner. The task planner is used to define the sequence of actions performed to achieve its objectives. The path planning is used to define the trajectory of the robot, i.e trying to define the robot's navigation during and between each action.

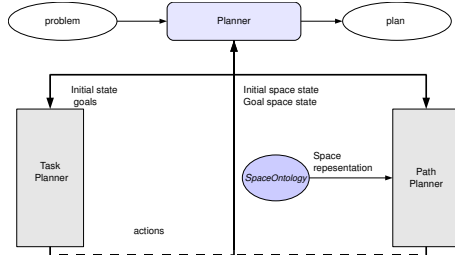


Figure 9. Spatial planner in details.

In [9], the task and path planners are interlacing. The navigation actions are not considered as actions but as preconditions for actions. For example, to take the book in the office, the robot must be able to access this area and to position itself correctly. We offer the same planner structure in [9]. However, the definition of these planners is not the same. Future work will concern the spatial planner and how to link between sub planners. Moreover, our planner manages symbolic, numerical and fuzzy spatial information in spite of managing only numeric information in [9].

The task planning focuses on defining the actions to be executed from an initial state of world and an initial state of

the system, the purpose of this planning is to reach a final state in which all objectives are achieved.

The path planning focuses on geometric aspects of motion planning (avoidance of collisions with fixed obstacles in the environment). The planner must be able to provide a path between two points or two regions of space. The initial position/region is the current position. We suppose it is known. However, the definition of the target position/region is defined vaguely, for example, *the office near the coffee machine*.

In this paper, we focus mainly on how to exploit *SpaceOntology* in path planning between a precise and imprecise position.

4.1 Using spatial knowledge for path planning

In the example 1, the robot must reach the office close to the coffee machine from its initial position then enter into the office and take the book. To do so, the robot must: (1) reach the region in which the coffee machine is, (2) select the office close to it, and (3) enter into this office, position itself and take the book. The goal of path planning is to define the path between the robot's current position and the interest zone, i.e a region in which it will execute the action of taking the book, defined imprecisely.

Our contributions to the path planning focused on taking into account: (1) space hierarchy, (2) topological relations (touche, left, ...), (3) distance and fuzzy information. We can summarize the path planning in three points: (1) acquisition of the environmental model; it is based on *SpaceOntology* for spatial representation and reasoning in order to define the *interest zone* for the fuzzy position (denoted \tilde{t}_p) and generate a structure called *Crossing Network Graph*; (2) in this graph we try to define the path between the current position and the *interest zone*; (3) then to define/delimit the fuzzy position. The last step is described in the section 3.2.3, we develop here the first two steps.

4.1.1 Acquisition of the environment model

Spatial modelisation A spatial relation is given by the concept *SpatialRelations*. We define a concept *HasRelation* which refers to the spatial relation for which target and reference entities are defined.

```

HasRelation ⊆ T ⊔ ∃
concernsSpatialRelation.SpatialRelations ⊔
= 1 concernsSpatialRelation ⊔ ∃
hasReferent.Regions ⊔ ≥ 1 hasReferent ⊔ ∃
hasTarget.Regions ⊔ = 1 hasTarget

```

Figure 10 models a part of a first floor with the office O_{11} and a corridor H (fig. 2(a)). We consider that each spatial entity is a *Regions* concept. Then, spatial relation between these different spatial entities are described

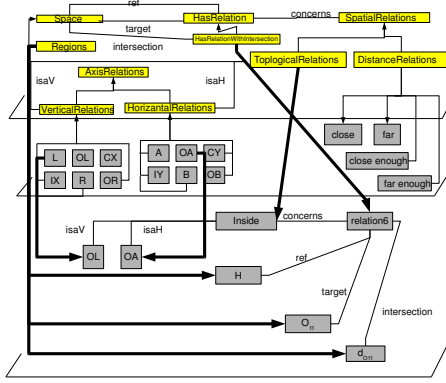


Figure 10. Graphical illustration.

by combining the *SpatialRelations* (inside) and *HasRelation* (relation6) concepts.

Topological relations: Gateways A spatial relation allows, given an environment, description of its spatial configuration using a direct description or by deduction. From topological relations, we can define for two regions if they are in contact or not and if there are points for direct passage between them: *gateways*. A gateway (i.e door, passing lane, ...) allows transitions between adjacent regions and adjacent regions from different hierarchical levels. A gateway allows us to connect more than two regions. To extract the gateways between regions, we query our knowledge base.

Example 3 : Querying SpaceOntology Let us consider the first floor (fig. 2(a)). As the door $d_{O_{11}}$ is already recognized, we can query SpaceOntology.

```
"SELECT ?referent ?target " +
"WHERE {" ?x ns:label ?relation." +
" ?x ns:hasintersection \"door1\"." +
" ?x ns:hasReferent ?referent." +
" ?x ns:hasTarget ?target." +"}";
```

The goal is to recognize if there are regions connected to this door and return them. We deduce that the corridor H contains the office O_{11} and a gateway d_{11} exists allowing passage between these two regions (table 1).

Table 1. Query results.

relation	referent	target
relation7	$d_{O_{11}}$	H

Graph generation from SpaceOntology A *Crossing Network Graph* (Γ_G) is a directed graph. A node in this graph represents a *Crossing Network*. Nodes are organized hierarchically. Edges represent relations between nodes.

A *Crossing Network* (Γ) is a graph whose nodes are *Crossing Network*. Edges represent spatial adjacency relations between two nodes described in *SpaceOntology* giving a gateway. Edges are labeled by a couple (*pass*, *dist*), where *pass* gives the gateway connecting these regions (or networks) and *dist* is the distance separating these regions (or networks) passing through this gateway.

Definition 1 (Crossing Network Γ) A graph $\Gamma = (V, E)$, where :

- $V = (v_1, v_2, \dots, v_n)$ set of vertices, each v_i being a crossing network,
- $E = (e_1, e_2, \dots, e_n)$ set of edges, each e_i is a spatial adjacency relation indicating a gateway and a distance.

4.1.2 Path computing : Algorithm 1

From *SpaceOntology*, we can compute the path between the initial position and the target position according to the space hierarchy. As stated, path computing between two positions can be decomposed into sub problems by defining hierarchical interest zone.

Each sub-problems requires a different level of detailed spatial information. To reach the most abstract interest zone, we must ignore the details given in others steps. However, considering the intermediate position as block boxes does not guarantee the path quality. Consider that the quality is related to speed; passing through certain corridors with big distances can be faster than through the ones with short distances but many obstacles. Our goal is to find the best path between two positions, according to the hierarchy of space, complying with two criteria: (1) minimize the Euclidean distance in the most abstract level, (2) facilitate access to a region, to ensure fast and simple actions. These two criteria allow us to have a quality path solution.

Path computing in *Crossing Network Graph* consists of path research in *Crossing Network* for each hierarchical level. Algorithm 1 gives computing path function. A first step (line 1) consists in generation of a *Crossing Network Graph* (*graph*). A second step (from line 6 to line 19) consists in finding a path between current region and the interest zone in this structure respecting our criteria.

First, we verify if there is a path between the most abstract regions ($I_Z^{l'_{ip}}(i_p)$, $I_Z^{l'_{tp}}(\tilde{t}_p)$) corresponding respectively to different positions (i_p , \tilde{t}_p) such as $I_Z^{l'_{ip}}(i_p)$ and $I_Z^{l'_{tp}}(\tilde{t}_p)$. Secondly, we select g and g' two gateways (line 7). The first one allows exiting of the initial abstract region. The second one allows entrance to the target abstract region. The path (*mostabstractpath*) between these gateways must respect the optimality criteria. Now, we consider that our target is the gateway g . Our goal is to find a path between i_p and g . If

Algorithm 1 pathComputing

Require: *Position* i_p, \tilde{t}_p , *SpaceOntology* O

- 1: $graph \leftarrow \text{createCrossingNetworkGraph}(i_p, \tilde{t}_p, O)$
- 2: $l''_{i_p} \leftarrow$ the lowest level corresponding to i_p , $l''_{\tilde{t}_p} \leftarrow$ the lowest level corresponding to $\tilde{t}_p \mid I_Z^{l''_{i_p}}(i_p) \neq I_Z^{l''_{\tilde{t}_p}}(\tilde{t}_p)$
- 3: $l_{i_p} \leftarrow$ the current level corresponding to i_p
- 4: $l_{\tilde{t}_p} \leftarrow$ the current level corresponding to \tilde{t}_p
- 5: $path \leftarrow \emptyset$
- 6: **if** \exists a path between $I_Z^{l_{i_p}}(i_p)$ and $I_Z^{l_{\tilde{t}_p}}(\tilde{t}_p)$ in $graph$ **then**
- 7: select g and $g' \mid g \leftarrow G(I_Z^{l_{i_p}}(i_p)), g' \leftarrow G(I_Z^{l_{\tilde{t}_p}}(\tilde{t}_p))$ and the path between g and g' respects optimality criteria
- 8: $mostabstractpath \leftarrow \text{abstractPath}(g, g', graph)$
- 9: $localpath \leftarrow \emptyset$
- 10: **if** $i_p, g \in$ the same current region **then**
- 11: $localpath \leftarrow \text{path}(i_p, g, graph)$
- 12: **else**
- 13: $localpath \leftarrow \text{pathComputing}(i_p, g, O)$
- 14: **end if**
- 15: $path \leftarrow localpath \cup mostabstractpath$
- 16: **else**
- 17: no path
- 18: **end if**
- 19: $\text{refinePath}(path, graph)$
- 20: **return** $path$

i_p and g belong to the same current region then we compute the local path between these positions. Else, we call recursively the pathComputing function in order to compute the path between i_p and g using O as ontology. Then, we construct path solution $path \leftarrow localpath \cup mostabstractpath$. To improve the solution quality (ie, accessibility, distance, ...), we perform a phase of post treatment: path refining (line 19). This technique changes locally optimal portions by direct lines; in other words, paths allowing an easy access and having a positive impact on the portion of the path in next hierarchical level. We start from one extremity of the solution: initial position. For each node in the solution, we check whether we can reach the next node by a direct line. If this happens, then the linear path between the two node replaces the original optimal order among these nodes. Then we update the path in lower hierarchical level.

5 Conclusion

This paper shows spatial knowledge exploitation for improving planning efficiency, an issue that is rarely considered in HRI in spite of its relevance when we have to deal with large amounts of information with different representations. This work can be further improved by incorporating

methods such as classification of regions for a better delimitation of interest zone areas. The planning aspect in this paper is not finished since we present only the path planning. Future work will concern integrating concepts defined in *SpaceOntology* in planning by extending the planning language PDDL. This is an innovative concept. We will use this model in ANR² project AMORCES³.

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³Algorithms and Models for Collaborative Eloquent and Social Robot.