

SPATIAL KNOWLEDGE IN PLANNING LANGUAGE

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Abstract: This paper describes the integration of spatial knowledge in a planning problem. For example, in the case of evacuation problem of a building during a fire, we must know the fastest paths (the shortest, least congested, ...). Such applications require spatial knowledge to perform spatial planning. This planning task becomes more complex when knowledge are shared by many actors. Indeed, our interest concerns collaborative work between agents, in particular the case of human-robot interaction. In such contexts, considering the space information in planning, we use a spatial ontology called *SpaceOntology* which handles different representations and abstraction levels of spatial information. We integrate this ontology in the planning by defining a formal language planning: Spatial-PDDL. Spatial-PDDL combines PDDL concepts with this ontology. Also, we distinguish between three types of actions: non spatial, spatial and navigation actions.

1 INTRODUCTION

In this paper, we focus on the spatial knowledge management in planning problem where the tasks consider spatial and non-spatial representations. Such problems could be met in human-robot interaction. Most typical scenarios include a human instructing a robot to perform some actions on some objects in the environment. To achieve this task, the human and the robot establish a similar description of the concerned environment. This requires not only that the scene descriptions created by the robot and the human match but also needs a system which can successfully mediate between these descriptions. However, the space representation from human's and robot's points of view is not the same. Indeed, the robot's spatial representation is numeric and the human's spatial representation uses natural language. The natural language employs incomplete and fuzzy information about space (for example, the book is near the bottle). Thus, we propose to find a representation for planning problems that can be used by robots to communicate with humans, analyze scenes and build maps.

To do this, we use an ontology called *SpaceOntology* (Belouaer et al., 2010). It permits a knowledge representation for modeling space, spatial relations and fuzzy information. This ontology allows us: a complex spatial description, an easy management of various spatial aspects, an easily extensible structure and to infer spatial information. It provides a struc-

tured knowledge about the environment to explore in planning process.

Planning process in artificial intelligence is decision making about the actions to be taken. As input, this process takes a planning problem (initial state and goal state) returns a plan (a sequence of ordered actions) to solve this problem (achieve the goal state from the initial state). To express spatial knowledge in planning process, we need a formal language. We use language PDDL (Ghallab et al., 1998) (Planning Domain Definition Language).

We propose a planner incorporating spatial representation and reasoning by integrating *SpaceOntology*. *SpaceOntology* in the planning, is not used for verification or control, but as information needed for planning. We adapt the PDDL actions and concepts definition to express spatial information if it is necessary. In other words, we extend PDDL to spatial knowledge: Spatial-PDDL.

The rest of paper is organized as follows. Section 2 gives an overview about different approaches to solve planning problems taking spatial knowledge into account. Section 3 describes the spatial representation and reasoning. Section 4 describes the planning process with spatial knowledge and its impact on complexity. Section 5 presents some results. Finally, we conclude in Section 6.

2 RELATED WORK

Different techniques for spatial representation and reasoning have been proposed. Most are based on constraints, logical and algebraic approaches (Balbani et al., 1999). However, these approaches can not manage numeric, topological and imprecise knowledge at the same time. In planning, we need to combine these knowledge. Thus, we must use a unified framework to cover large classes of problems and to give rise to instantiations adapted to each particular application. Ontologies appear as an appropriate tool toward this aim.

Spatial ontologies can be found in some fields such as Virtual Reality (Dasiopoulou et al., 2005), Robotics (Dominey et al., 2004), etc. All these ontologies are focused on the representation of spatial concepts according to the application domains. A major weakness of usual ontological technologies is their inability to represent and to reason with imprecision. An interesting work presented in (Hudelot et al., 2003) overcomes this limit.

The concept of exploiting ontology to represent spatial knowledge in planning has been explored. (Bouguerra et al., 2008) describes a new approach for monitoring the execution of plans where spatial knowledge is defined by an ontology called LOOM. This ontology permits a region classification and verifies the plan execution. However, it does not describe spatial relations and it is not used in planning.

To express spatial knowledge in planning process, we use PDDL (Ghallab et al., 1998). The first version of PDDL is extended to consider several aspects in a planning problem definition that improve the quality of the solution, such as the temporal dimension (Fox and Long, 2003). Despite the importance of the spatial dimension in planning problem, PDDL with spatial definition is not yet integrated.

Our main contribution is the extension of PDDL to spatial knowledge: Spatial-PDDL. To do this, we use *SpaceOntology* that considers several spatial knowledge aspects; the space hierarchy, spatial relations (numeric, topological and fuzzy).

3 SPATIAL REPRESENTATION AND REASONING

In the following, we present *SpaceOntology* (Belouaer et al., 2010), a framework for spatial representation and reasoning.

3.1 Spatial Representation

We opted for OWL¹ DL² (Baader, 2003) as a formal language³. An important characteristic of DL is its expressivity and its capability of inferring knowledge from the known information.

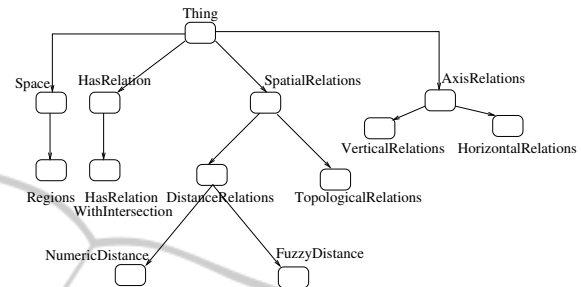


Figure 1: Graphical representation of *SpaceOntology*.

A spatial entity is described by two concepts: Regions and Space. The concept Space ($\text{Space} \sqsubseteq \text{Thing}$) is used to model space: the name of places, the hierarchical level, the boundaries definition, etc. It represents a global environment (a country, a city, a building, ...). The concept Regions ($\text{Regions} \sqsubseteq \text{Space}$) is a sub-space included in a given space. A region is itself considered as a space that can be decomposed into different sub-regions. From a geometric point of view, a region rg is defined by the smallest rectangle $rect$ corresponding to its axis-aligned bounding rectangles. These concepts include some attributes. The hierarchical space organization has an impact on the distance evaluation. Indeed, the distance of 10 meters in a city is considered as *close*, however in a corridor this distance is considered as *far*. Each region has the attributes alpha and beta depending on the scale of its level. These two parameters evaluate the distance between two spatial objects (Belouaer et al., 2010) (section 3.2.3).

A spatial relation is defined by the concept $\text{SpatialRelations} (\text{SpatialRelations} \sqsubseteq \text{Thing})$ which includes $\text{TopologicalRelations}$ and DistanceRelations . A spatial relation is a concept on its own. A $\text{TopologicalRelations}$ is an ABLR relation (Laborie et al., 2006). This relation is a couple $\langle r_X, r_Y \rangle$, where: $r_X \in \{L, O_L, C_x, I_x, O_R, R\}$ and $r_Y \in \{A, O_A, C_y, I_y, O_B, B\}$. A DistanceRelations can be an Euclidean distance (NumericDistance) between the symmetry points of two rectangles representing two regions (r referent object and ϵ target object) noted $d(\epsilon, r)$ (in \mathbb{R}^+).

¹Web Ontology Language

²Description Logics

³All notations used here are defined in the DL.

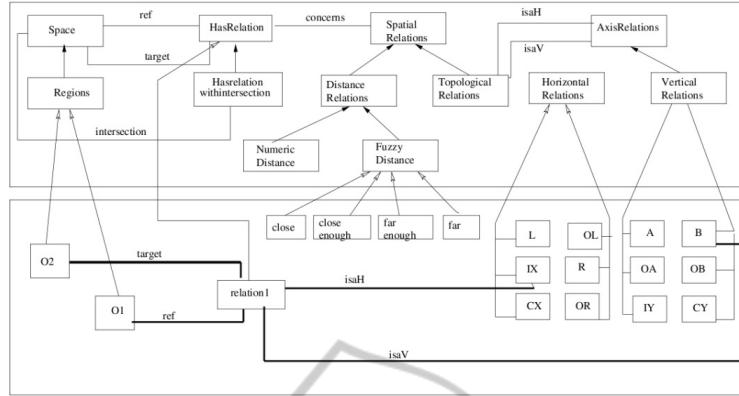


Figure 2: Graphical illustration of *SpaceOntology* to describe structures in specific domains.

or fuzzy distance (*FuzzyDistance*) evaluating a distance between the symmetry points of two rectangles representing two regions. A fuzzy distance is defined by four linguistic variables: close to, close enough, far enough and far.

To define a spatial relation between spatial entities, we use the concept *HasRelation*. This concept links with a spatial relation between a reference region and one or more target regions (Example 1).

There are several relations (or predicates) to link these concepts to provide a spatial semantic. For example to express a hierarchical relation between two regions, we consider the links:

- consistsOf:

$$\text{Space} \sqsubseteq \text{Thing} \sqcap \exists \text{ consistsOf.Regions} \\ \sqcap \geq 1 \text{ consistsOf}$$

- isPartOf:

$$\text{Regions} \sqsubseteq \text{Space} \sqcap \exists \text{ isPartOf.Space} \\ \sqcap \geq 1 \text{ IsPartOf}$$

Example 1. Let us consider a part of a floor with two offices (*O1*, *O2*) and a hall (*H1*) (Fig. 3).

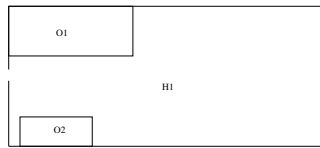


Figure 3: Partial Map.

Figure 2 models⁴ the space domain defined in Figure 3 by using *SpaceOntology*. We consider that each spatial entity is a *Regions* concept. Then, spatial relation between these different spatial entities are described by combining *SpatialRelations* and *HasRelation*.

⁴For more readability, we omit certain classes and attributes.

In Example 1, the *relation1* is an instance of the concept *HasRelation* describing the topological relation between offices *O2* and *O1*:

```
relation1:HasRelation
  ⊑ concernsSpatialRelation.inside_below
  ⊑ hasReferent.O1 ⊑ hasTarget.O2
```

The relation *inside_below* is defined as follow:

```
inside_below:TopologicalRelations
  ⊑ isAnHorizontalRelation.Ix
  ⊑ isAVerticalRelation.B
```

3.2 Spatial Reasoning

The reasoning methods infer spatial information in order to enrich the description of the environment and/or to manage the lack of information.

3.2.1 Spatial Hierarchical Reasoning

To express a hierarchical relation between two regions (for example, a region includes another region, or a region is in another one), we use the predicates *consistsOf* and *isPartOf*. The predicate *isPartOf* is the inverse of the relation *consistsOf*. These relations are transitive. The transitivity rules for the predicate *consistsOf* and *isPartOf* are:

$$\text{consistsOf}(r_1, r_2) \sqcap \text{consistsOf}(r_2, r_3) \\ \longrightarrow \text{consistsOf}(r_1, r_3)$$

$$\text{isPartOf}(r_1, r_2) \sqcap \text{isPartOf}(r_2, r_3) \\ \longrightarrow \text{isPartOf}(r_1, r_3)$$

To consider a space as a whole with the different abstraction levels is not always necessary and makes spatial reasoning very expensive. The hierarchical organization can simplify this reasoning, depending on abstraction level. To do so, we exploit the two predicates: *consistsOf* and *isPartOf* in order to define the function *hierarchical interest zone* denoted $Z^l(r)$.

This function $Z^l(r)$ defines an *interest zone* (An *interest zone* defines a region in a considered space to be reached and/or localized) of a region r in the hierarchical level l . To compute this function we query *SpaceOntology* (details in Section 4.2.1).

3.2.2 Spatial Reasoning based on Topological Relations

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

The Combination Mechanism. The combination concerns topological relations. As mentioned, a topological relation is a couple $\langle r_X, r_Y \rangle$. This mechanism consists of combining horizontal relation r_X with vertical one r_Y ($r_X \oplus r_Y$). This mechanism is defined by a set of rule proposed in *SpaceOntology*. Rules definition for the combination mechanism is used in order to define the 36 topological relations of ABLR (*Neighborhood graph* (Laborie et al., 2006)), dynamically. These relations express topological relations (overlaps, touch, ...) and orientation relations. Indeed, by this mechanism we can represent the 8 cardinal relations (left, above, above left, ...) and other directional relations as at the same level, between, etc. Figure 4 presents a rule which allows the combination of the horizontal relation $L(Left)$ and the vertical relation $A(Above)$.

```
isATopologicalRelation(?t_relation)
□ isAVerticalRelation(?t_relation, "A")
□ isAnHorizontalRelation(?t_relation, "L")
→ is(?t_relation, "left_above")
```

Figure 4: Rule definition for left_above.

The Composition Mechanism. The composition mechanism infers new spatial information. Let us consider three regions defined by three rectangles $rect1$, $rect2$ and $rect3$. The idea is to infer which relation $R3$ links between $rect1$ and $rect3$ where $R1$ is a relation between $rect1$ and $rect2$ and $R2$ is a relation between $rect2$ and $rect3$. The topological relation $R3$ is defined by $R3 = R1 \otimes R2$, then

$$\langle rx3, ry3 \rangle = \langle rx1, ry1 \rangle \otimes \langle rx2, ry2 \rangle \quad (1)$$

$$= \langle rx1 \otimes rx2, ry1 \otimes ry2 \rangle \quad (2)$$

The composition results of $\langle rx1 \otimes rx2 \rangle$ and $\langle ry1 \otimes ry2 \rangle$ are given by the composition table of rectangle algebra by preserving the directionality property as defined in ABLR. Formally, we define in *SpaceOntology* a set of rules reflecting the composition table. The composition mechanism returns a disjunction of possible relations between two rectangles. However,

not all inferred relations are valid. To reduce the number of possible relations between two rectangles, by keeping only the valid relations, we proceed as follows. First, we select the necessary knowledge for the inference and we formalize it as a constraint network called spatial relation network. Then, we apply the required rules, and we complete this network. Thus, a network is defined by :

- V a set of nodes representing rectangles describing regions,
- C a set of constraints representing topological relations. An arc is labeled by a topological relation (constraint) between two rectangles connected to this arc. Arcs labeled with disjunctions are arcs that are inferred by composition.

The idea is to remove all spatial relations does not ensure the consistency of the network. Thus, we aim to establish arc consistency in this network. We produce an equivalent network to the first one which checking the arc consistency property (Def. 1).

Definition 1. A network is arc consistent if all its arcs are arc consistent

Thus, the network produced is arc-consistent, *i.e.* it does not contain topological relations does not ensure the arc consistency of the network. Practically, for the rules application, we use the Pellet inference engine (Sirin et al., 2007), and for the verification of the arc consistency, we rely on the MAC algorithm (Prosser, 1995).

Example 2. Let us consider the following problem, a robot is in the office $o2$. Its mission is to go to the office $o3$. However, it has no spatial information enabling it to define its trajectory between $o2$ and $o3$.

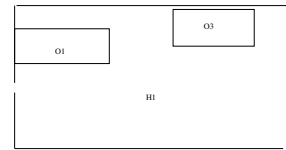


Figure 5: Spatial Relation Between $o1$ and $o3$.

We have a set of spatial information, depicted in Figure 5: the office $o3$ is right and overlaps above the office $o1$: $o3 \langle R, O_A \rangle o1$. Also, in Figure 3, the office $o2$ is inside and is below of the office $o1$: $o2 \langle I_x, B \rangle o1$.

Our goal is to find the spatial relation between the offices $o3$ and $o2$. First, we apply a symmetry rule, then, $o1 \langle L, O_B \rangle o3$ is the inverse of $o3 \langle R, O_A \rangle o1$. Second, we apply composition rule between $o2 \langle I_x, B \rangle o1$ and $o1 \langle L, O_B \rangle o3$ (Fig. 6).

Thus, from this information we can plan our trajectory to reach the office $o3$ without considering

```

translate(?link,?t_link)  $\sqcap$  translate(?relation, ?t_relation)  $\sqcap$  concerns(?link,?relation)
 $\sqcap$  hasTarget(?link,?tgt)  $\sqcap$  hasReferent(?link,?ref)  $\sqcap$  isANumericDistance(?relation)
 $\sqcap$  isPartOf(?ref,?region)  $\sqcap$  isPartOf(?tgt,?region)
 $\sqcap$  swrlb:greaterThan(distanceValue(?relation),0)
 $\sqcap$  swrlb:lessThanOrEqual(distanceValue(?relation),alpha(?region))
 $\rightarrow$ 
[concerns(?t_link,?t_relation)  $\sqcap$  hasTarget(?t_link,?tgt)  $\sqcap$  hasTarget(?t_link,?tgt)
 $\sqcap$  hasReferent(?t_link,?ref)  $\sqcap$  isAFuzzyDistance(?t_relation)  $\sqcap$  is(?t_relation,"close")]
    
```

 Figure 7: Rule Definition of *Def_close.relation*.

```

isATopologicalRelation(?t_relation1)
 $\sqcap$  isAnHorizontalRelation(?t_relation1,"LX")
 $\sqcap$  isAVerticalRelation(?t_relation1,"B")
 $\sqcap$  isATopologicalRelation(?t_relation2)
 $\sqcap$  isAnHorizontalRelation(?t_relation2,"L")
 $\sqcap$  isAVerticalRelation(?t_relation2,"O.B")
 $\rightarrow$  [isATopologicalRelation(?t_relation3)
 $\sqcap$  isAnHorizontalRelation(?t_relation3,"L")
 $\sqcap$  isAVerticalRelation(?t_relation3,"B")]
    
```

 Figure 6: Rule definition for *left_below* with composition.

the entire second floor but only the northeastern part of the floor from the office *o2*. The information $o2 \langle L, B \rangle o3$ is added in *SpaceOntology*.

3.2.3 Spatial Fuzzy Reasoning

In this work, the fuzzy representation concerns only distance relations. Indeed, we use linguistic variables to evaluate a distance (close, close enough, far enough and far). We aim to give a numeric representation to each variable and vice versa. *SpaceOntology* allows this translation, by defining some rules based on functions $N_{\alpha,\beta}$ and $F_{\alpha,\beta}$ (Schockaert, 2008). The function $N_{(\alpha,\beta)}(p,q)$ (resp. $F_{(\alpha,\beta)}(p,q)$) measures the degree with which p is close to q (resp. the degree with which p is far from q) ($\alpha, \beta > 0$).

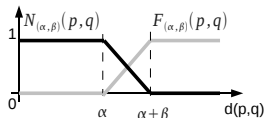


Figure 8: Distance evaluation. (1) if $d \in [0, \alpha]$, then d is close, (2) if $d \in [\alpha, \alpha + \frac{\beta}{2}]$ then d is close enough, (3) if $d \in [\alpha + \frac{\beta}{2}, \alpha + \beta]$ then d is far enough, (4) if $d \in [\alpha + \beta, +\infty[$ then d is far.

Figure 8 illustrates the translation of a distance from a numeric definition to symbolic definition and vice versa. The parameters α and β allow us to evaluate the numeric distance. These parameters depend on the current region. Figure 7 is a rule allowing us to evaluate a distance relation.

The rule *Def_close.relation* (fig. 7) translates a numeric distance (NumericDistance) (*distanceValue* (?*relation*)) in symbolic evaluation (FuzzyDistance) given by the instance *close* which indicates the close

relation. This rule is apply for distance (*distanceValue* (?*relation*)) between 0 and α .

4 SPACEONTOLOGY BASED PLANNING

Now, we explore the potential uses of spatial representation and reasoning offered by *SpaceOntology* in planning. Our goal is to propose a planner incorporating spatial representation and reasoning: *Spatial Planner* (Fig. 9).

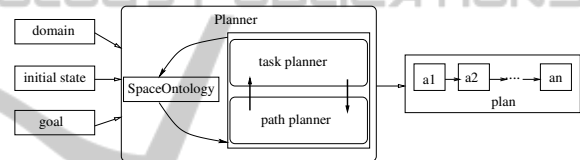


Figure 9: Spatial Planner.

As input, the spatial planner (Fig. 9) takes a *planning problem* defined by:

- a *domain* is a set of actions. Each action specifies *preconditions* that must be present in the current state so it can be applied, and *effects* on the current state,
- a description of the *initial state* of a world,
- a description of a *goal*.

As output, it generates a *plan*: a sequence of actions.

This planner consists of a task planner and a path planner and *SpaceOntology*. The task planner's aim is to define the sequence of actions which will be executed to achieve the goals of the entry problem. Path planner defines possible paths to reach the execution of tasks to accomplish. It finds a path between two positions (fuzzy positions or well defined positions). *SpaceOntology* manages spatial information about the space.

There is a communication between these components (Fig. 9). This communication is in the form of queries/answers. These one is in charge of planners which at some steps require spatial preconditions to be satisfied. To this end, it sends a query to *SpaceOntology* to answer to the request.

Example 3 (Study Case). A team (human and robot) is in the office $O_{11}^{B_1}$ in the first floor of the building B_1 (the human position is h) (Fig.10). The human asks the robot to pick up a book (b) located in the office (o) close to the coffee machine. This machine is on the second floor of the building B_6 (Fig.10).

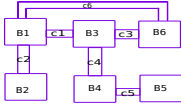


Figure 10: Abstract Map.

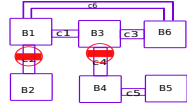


Figure 11: Deadlocks.

The robot's goal is to fulfill this mission. A classical task planner provides: (1) $go\text{-}to(o_{11}^{B_1}, o)$, (2) $take(b)$, (3) $go\text{-}to(o, h)$, (4) $give(b)$ as a plan. Several problems requiring spatial information are identified: (1) in which position the robot should execute an action ($go\text{-}to(o_{11}^{B_1}, o)$). The office o is defined as the office *close to* the coffee machine, i.e. how to evaluate the relation *close to the coffee machine*? (2) how to move between different areas to accomplish actions? i.e to define the robot's navigation during and between each action; for example, finding a path between the current position o and the human position h . (3) how to order the action execution with respect to navigation?

To solve this problem, we use the *Spatial Planner* (Fig. 9). This planner requires different types of knowledge encoded in Spatial-PDDL. It is an extension of PDDL with spatial information made by the communication between planners (task and path planner) and *SpaceOntology* (Fig. 9). We focus here on Spatial-PDDL definition and the planner operation.

4.1 From PDDL to Spatial-PDDL

We extend PDDL with spatial knowledge using *SpaceOntology* in order to improve the expressiveness of the planning language. Formally, *SpaceOntology* is a triple (Φ, R, I) , where Φ is a set of concepts, R is a set of relations (or predicates) between concepts and I is a set of instances which depends on the described environment.

Our planner takes three inputs (Fig. 9). (1) An initial state S_0 , (2) a goal state S_G ; these states describe a set of objects (O) by specifying their type (T) and relations between them (Π), (3) A set of actions (A) described in a domain (D). We extend PDDL language with *SpaceOntology*.

4.1.1 Notations

The main extensions are summarized in Table 1.

Table 1: Extended Notions with *SpaceOntology* Elements.

Notions	PDDL	Extend PDDL with <i>SpaceOntology</i>
Predicate	Π	$\Pi \leftarrow \Pi \cup R$
Type	T	$T \leftarrow T \cup \Phi$
Domain	D	use of extends and @ns
Objects	O	spatial/non spatial objects
Actions	A	non spatial/spatial/navigation actions

A concept, a relation or an instance always has a prefix. (Dou, 2008) expresses that the domain is extended by an ontology, where the notion of “: extends” and “@ns1 :” were introduced. Each concept in *SpaceOntology* defines a spatial type. All the concepts defined in *SpaceOntology* (Φ) are introduced and exploited for extending PDDL (Table. 1). A predicate π ($\pi \in \Pi$) expresses a relation. All the relations (R) defined in *SpaceOntology* are introduced and exploited for extending PDDL (Table. 1).

Our contributions concerning the action definition consist of the extension of geometric preconditions/effects in order to take the different spatial representations (topological and fuzzy information) into account. In addition, it consists of the definition of the spatial fuzzy actions (Def. 2).

Definition 2 (A Spatial Fuzzy Action). A *spatial fuzzy action* a is defined by $a = (at, pr, q, e)$, where at , pr and e are respectively parameters for the action, preconditions, effects as defined in the extended action (Guitton, 2010) and q is a set of queries.

Example 4. The semantic of the action $take$ (Fig. 12) is: the robot r takes the book b located in the office defined in a fuzzy way $?o$. The office $?o$ is defined in Spatial-PDDL as a query variable (Dou, 2008).

```

take(r,b,?o)
(robot r) (book b) (empty-arm r)
(¬(has r b)) (region ?o) (At r ?o)
(:query
  (freevars (?o - Region ?α ?β ->xsd:int
    ?rel - SpatialRelations ?hr - HasRelation)
    (and(@ns:isPartOf ?o ZLevel(CM)-1(CM))
      (@ns:hasTarget ?hr ?o) (@ns:hasReferent ?hr CM)
      (@ns:concernsRelation ?hr ?rel)
      (if(instanceOf ?rel NumericDistance)
        (and(owl:DatatypeProperty rdf:ID="α" ?α ZLevel(CM)(CM))
          (owl:DatatypeProperty rdf:ID="β" ?β ZLevel(CM)(CM))
          (bounded-int owl:DatatypeProperty rdf:ID="distance" ?α (?α+ ?β))))
      (if(instanceOf ?rel FuzzyDistance) (= ?rel "close_to"))))
  (At r p_r) (@ns:isPartOf p_r ?o)
  (bounded-int distance(p_r.r.arm , b), ?α_r, ?β_o)
  (:query
    (freevars (?α_o ?β_o ->xsd:int)
      (and(owl:DatatypeProperty rdf:ID="α" ?α_o ?o)
        (owl:DatatypeProperty rdf:ID="β" ?β_o ?o))))
    (frontOf r.arm, b) (sameLevel r.arm,b)
    (¬(empty-arm r) (has r b)

```

Figure 12: Modeling the Action $take$ in Spatial-PDDL.

To delimit this region, we query *SpaceOntology* (details in Section 4.2.1). The fuzzy relation *close* can be described in a numeric way. So, we seek an

office satisfying the fuzzy relation close by translating it in a numerical representation (Belouaer et al., 2010). Moreover, the action execution requires that the precondition ($\text{At } r \ p_r$) is satisfied. However, the satisfaction of this precondition requires the definition of the position p_r . This position is defined as follows. First, it must be in the office $?o$. Then, it must allow us to reach the target; the book. This requires that the robot is at a position p_r close to the book. The evaluation of this distance is made by the function `bounded-int`. Also, there are two functions like `frontOf` and `sameLevel` which must be satisfied in order to grab the book.

4.1.2 Integrating *SpaceOntology* in PDDL: Spatial-PDDL

We translate any spatial knowledge described in *SpaceOntology* to the domain and problem definitions in PDDL. *SpaceOntology* has an open world assumption and PDDL a closed one. To overcome this difficulty, the translation concerns only known types.

Our model requires as an input : (1) a planning domain describes each action of a system in Spatial-PDDL, (2) a planning problem describing the initial state and goals in Spatial-PDDL, (3) *SpaceOntology* gives spatial description of space, and (4) some required information.

Definition 3 (A Domain). *A planning domain $D = (A, \Pi)$, where $A = \{a_1, a_2, \dots, a_n\}$ a set of actions, where a_i is an action and Π set of relations between objects O .*

Definition 4 (A Spatial Planning Problem). *A Spatial Planning Problem $P = \langle O, S_0, S_G \rangle$, where O is a set of spatial and non-spatial objects, S_0 is an initial state that could be associated to fuzzy position and S_G is the goal state that could be associated to fuzzy position.*

In Figure 13, some objects are spatial (`:regions O_{11}^{B1} CM ?o), others are non spatial (:objects human robot book). The initial state expresses an initial symbolic situation human has not the book ((not (has human book))). Also, it expresses the initial spatial situation the robot is in the office O_{11}^{B1} ((At robot O_{11}^{B1})).`

Note by “ $?α$ ” and “ $?β$ ” query variables to determine the $α$ and $β$ of the current level. The relation `owl:DatatypeProperty rdf:ID="β" ?α $Z_{Level(cm)}$ (cm)` identifies for a given region the $β$ (Fig. 13).

The fuzzy spatial information *the office close to the coffee machine* is defined by a query variable: “ $?o$ ”. There are some functions. (`distance?ip?tp – position`) used to compute the Euclidean distance between two positions. (`maxhdistance`) (resp.

```
(define (problem bookmissionpb)
  (:domain bookmission)
  (:objects
    Arnaud - human
    Bobo - robot
    book table - item
    o11b1 - region
    ?target - region ;; fuzzy region)
  (:init
    (on book table)
    (At Arnaud o11b1)
    (At Bobo o11b1)
    (At table ?target)
    (Empty Arnaud)
    (Empty Bobo)
    (= (maxhdistance) 1)
    (= (minhdistance) 0.5)
    (not (Holding Arnaud book))
  )
  (:query
    (freevars (?target - region ?α ?β -@xsd:int)
      (and ( In ?target  $Z_{Level(cm)}$ -1(cm)
        (owl:DatatypeProperty rdf:ID="α" ?α  $Z_{Level(cm)}$ (cm))
        (owl:DatatypeProperty rdf:ID="β" ?β  $Z_{Level(cm)}$ (cm))
        (bounded-int distance(?o,cm) ?α (?α+ ?β))))
    )
  (:goal ( and
    (not (on book table))
    (Holding Arnaud book))))
```

Figure 13: An Example of Spatial-PDDL Problem.

(`minhdistance`)) indicates the maximum distance (resp. minimum) from which the interaction with humans can not be executed. *path* (Fig. 14) checks the existence of a path and computes it.

```
(define (domain bookmission)
  (:requirements :typing :fluents)
  (:extends
    (uri "../SpaceOntology.owl" :prefix sponto))
  (:types actor - object
    item - object
    human robot - actor)
  (:spatial-types region - @sponto:Regions)
  (:predicates (Empty a - actor) (Holding a - actor i - item)
    (on i - item t - item))
  (:spatial-predicates (At o - object p - region))
  (:functions (distance ip tp - position) (maxdist) (mindist)
    (maxhdist) (minhdist) (path irg trg - region))
  (:action go
    :parameters(r - robot irg - region trg - region )
    :precondition (and(At r irg) (not(At r trg)))
    :spatial-precondition (= (path irg trg) true))
    :effect (and(At r trg) (not(At r irg))))
  (:action pick-up ...)
  (:action put-down ...)
  (:action give ...)
  (:action take ...))
```

Figure 14: An Example of Spatial-PDDL Domain.

4.2 Communication between Components

The planner has three components: task planner, path planner and *SpaceOntology*. The communication between them is in form of request/response. Planners (task and path) formulate queries to spatial ontology. They are encapsulated in the preconditions of the actions or they are directly in the problem definition.

In this section, we start by specifying the types of queries necessary for the planner function. Then, we describe the operation.

4.2.1 Requests for *SpaceOntology*

Several types of queries that are needed for the system operation. We can classify them into three categories: **Adjacency query**, **Proximity Query** and **Hierarchical Interest Zone Query**

Adjacency Query. We assume that each region is adjacent to its neighbors with access points (doors, intersection of corridors, ...) called *gates*. A gate allows transitions between adjacent regions (in the same hierarchical level or in different hierarchical levels). A gate allows us to connect more than two regions.

Two regions are adjacent if there is a/or a set of transition between these two regions. Two types of adjacency: *direct adjacency* (i.e, the longer of the path between these two regions is equal to 1 (number of gates), of course several possibilities may exist, this represents a multiple choice of paths) and *indirect adjacency* (i.e, the longer of the path between these two regions is more than 1 (number of gates))

To extract the gates between regions or neighbors for a given region, we use adjacency query to *SpaceOntology*.

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

This query takes as parameter a gate (*gate*) and defines the regions connected to this gate. The *indirect adjacency* is inferred by the existence of a path (of length greater than one see next section).

Proximity Query. A proximity query defines regions that are close to a given region or if a region is near or far from another region.

```
SELECT ?referent ?target "
WHERE {"?x ns:concerns \"close\"."
      "?x ns:hasReferent ?referent."
      "?x ns:hasTarget ?target."}
```

This query takes a parameter relation (*close*) and defines the regions that are close.

Hierarchical Interest Zone Query. To define the function $Z^l(r)$, we define the hierarchical interest zone query.

```
SELECT * "
WHERE {"?region rdf:type ns:Regions ."
      "?region ns:label \"\" + rg + "\" ."
      "?region ns:isPartOf ?father ."
      "?father ns:level ?level."
      "Filter ( ?level = \" + level + ") ."
```

This request is used to return the area of interest for the region *rg* level hierarchical *level*.

4.3 Spatial Planning Process

During the selection of these actions, the planner asks the satisfaction of these preconditions using *SpaceOntology*. Then, it calculates the required displacements and returns an answer to the result thereof. If the navigation is possible so action can be executed. Otherwise another action must be found to achieve the mission. The execution of the action *take the book* (Fig. 12) requires that the robot is in the office close to the coffee machine (in which the book is). However, the robot is in another office : O_{11}^{B1} . Thus, a navigation between the current position and target position is required. The target position is defined in a fuzzy way. Formally, we assume that the general planning problem includes a *fuzzy path planning problem*.

Definition 5 (Fuzzy Path Planning Problem.). *Let us consider two fuzzy positions (\tilde{i}_p, \tilde{t}_p) and a spatial description given by SpaceOntology (Φ, R, I). A path solution P_{th} between \tilde{i}_p, \tilde{t}_p is a continuous sequence of positions/regions that allows the robot to move from the initial state to the goal state while avoiding obstacles.*

4.3.1 Path Planning

Our main contributions to the path planning focus on using space hierarchy, topological spatial relations and spatial fuzzy information.

Let us consider that the initial position i_p is accurate⁵ and the target position \tilde{t}_p is fuzzy. The path planning operation is detailed in the following.

Generation of Crossing Network Graph. A *Crossing Network Graph* Γ_G is a directed graph. Nodes are organized hierarchically. Edges represent hierarchical relation between nodes. A node in this graph represents a *Crossing Network* or a region.

Definition 6 (Crossing Network Γ). *A graph $\Gamma = (V, E)$, where; $V = (v_1, \dots, v_n)$ is a set of vertices, each v_i is a crossing network and $E = (e_1, \dots, e_n)$ is a set of*

⁵To simplify the explanation, the initial position is crisp. This work may well be applied in the context of precise positions.

edges, each e_i defines an adjacency relation, a gateway and a congestion.

Each element of Crossing Network Graph is related to the mission. This graph defines all possible paths between i_p and t_p .

Example 5. In example 3, the team is in office O_{11}^{B1} and the target is in floor E_2^{B6} . These offices are not in the same hierarchical level. In addition, these regions (O_{11}^{B1} and E_2^{B6}) are not adjacent. Thus, finding a path between these two regions exploits the space hierarchy and adjacency links defined in SpaceOntology.

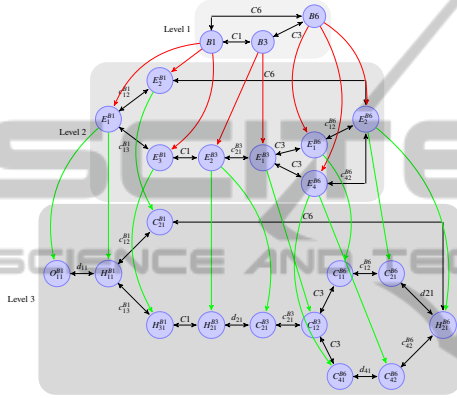


Figure 15: Crossing Network Graph.

First, we consider the most abstract regions for O_{11}^{B1} and E_2^{B6} in the same level, there are $B1$ and $B6$. Then, we look for the adjacency links between $B1$ and $B6$. We assume that each region is adjacent to its neighbors with *gates*. To extract gates between regions, we query the ontology. So, we generate all possible paths between buildings $B1$ and $B6$ by considering $B2, B3, B4$ and $B5$. However, the passing through the buildings $B2, B4$ and $B5$ is not necessary (Fig. 11). For $B2$ and $B5$ they are not included in the mission; they are a deadlocks regions (one gate to exit/entrance). For $B4$, it is not included in the mission. Also, this region is connected to a deadlock region $B5$. So, $B4$ is also a deadlock region. By combining all these concepts we generate a directed graph: *Crossing Network Graph* (Fig. 15). Nodes are organized hierarchically. Edges represent hierarchical relation between nodes. A node in this graph represents a *Crossing Network* (a graph given the adjacency relations between regions in the same hierarchical level). Each node of one level l is developed until reaching the target hierarchical level. We assume that N^l is a subset of regions in the level l . E^l is a set of edges. Edges represent spatial adjacency relations between two nodes giving gateways. For each $n \in N^l$, n must satisfy the selection criteria.

Path Computing. We search a path between two positions i_p (accurate position) and t_p (fuzzy position) in the Crossing Network Graph, based on two criteria measures (Mouaddib, 2004): (1) minimize the Euclidean distance between i_p and t_p and (2) facilitate access to a region, to ensure fast and simple actions. We combine these concepts in order to improve the path solution quality. These criteria, allow the robot to execute its actions in an easy and quick way (the choice of paths that are short in terms of distance) and to maintain the speed of navigation. We define a measure: $\Theta(p_1, p_2) = (d(p_1, p_2), c(p_1, p_2))$, where $d(p_1, p_2)$ is the euclidean distance between p_1 et p_2 and $c(p_1, p_2)$ measures the congestion in the region between p_1 and p_2 . Pathfinding in crossing network graph consists of path search in crossing network for each hierarchical level. A path solution is a sequence of paths pth_0, \dots, pth_k , where pth_i contains nodes of the i -th level and that are a specialization of nodes on pth_{i-1} (i.e the path solution in level 1 is $B1 - B6 - B6$, the pathfinding in level 2 will not consider the sub nodes of the node $B3$ (Fig. 15). In each level, we use multi-criteria Dijkstra's algorithm with a single source $Z^l(i_p)$. It returns the shortest path between the source node and the target one $Z^l(t_p)$ (i is the abstract level). The shortest path is the path minimizing the measure $\Theta^i = (d, c)^i$, where d is the Euclidean distance and c is a congestion measure. In order to minimize Θ^i , we compute it as described in (Mouaddib, 2004): $\Theta^i = \sum_{crit \in \{d, c\}} Regret(crit)$. The concept is to minimize the regret (Fig. 16).

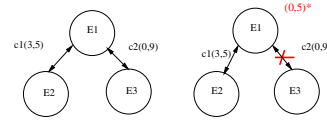


Figure 16: Regret Based Path Selection.

We compute θ^* , where this measure is $\theta^* = (0, 5)^* = [Min(3, 0), Min(5, 9)]$. Then, for each edge e , we compute the distance between θ^* and θ_e :

$$Min(Dist) = \begin{cases} Dist(\theta_{c_{12}^{B6}}, \theta^*) = Dist((3, 5), (0, 5)) = 3 \\ Dist(\theta_{c_{42}^{B6}}, \theta^*) = Dist((0, 9), (0, 5)) = 4 \end{cases}$$

Finally, we select the edge allowing us the minimum distance with θ^* : edge c_{12}^{B6} (Fig. 16).

We are not interested in the global network in level i . Indeed, we consider that the nodes and edges belonging to the path solution of level $i - 1$. We can generate the path for each node in the next level and exploit the hierarchical aspect of space which reduces the search time. Indeed, only nodes of the at level i are extended in level $i + 1$ and thus some edges in the graph are not explored.

5 EXPERIMENTS

We present some experimental results to solve planning described with Spatial-PDDL.

5.1 Experimental Results

The computation time to solve a spatial planning problem described in Space-PDDL depends on computing time of answering to queries.

Table 2: Computation Time of Plan Solution Generation Solving the problem in Example 3 (seconds). The path computation time is less then one second.

Queries		Solving problem
Queries number	Answer to query	
[2-8]	< 1	< 1
[9-13]	[1-2.2]	[1 - 3.08]
[14-20]	[3.01-4.8]	[4.01 - 7]
[21-30]	[5.05-10.09]	[8.07 - 15.01]

Table 2 shows that the computation time depends on the number of requests and the response time. The latter depends on the rules number defined in *SpaceOntology*. This computing time is very reasonable even if we have a large number of requests. Indeed, in Table 2, for a query number between 21 and 30, solving the problem is done in 15.01 seconds.

6 CONCLUSIONS

Our main contribution was the extension of PDDL to spatial knowledge: Spatial-PDDL. To do this, we uses *SpaceOntology* that considers several spatial knowledge aspects; the space hierarchy, spatial relations (numeric, topological and fuzzy). This permits to consider not only numeric spatial information in pre-conditions but also topological and fuzzy information. Moreover, spatial reasoning (the inference mechanisms) provided by this ontology permits a complex reasoning. *SpaceOntology* in the planning, is not used for verification or control, but as information needed for planning.

Future work will concern the improvement of spatial interaction between human and robots. In other words, we aim to formalize communication between them, especially in the case where the set of fuzzy rules are not sufficient to find a solution.

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