Cailhol, Simon and Fillatreau, Philippe and Fourquet, Jean-Yves and Zhao, Yingshen A multi-layer approach for interactive path planning control. (2014) In: 11th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2014), 1 September 2014 - 3 September 2014 (Vienne, Austria).

A multi-layer approach for interactive path planning control

Simon Cailhol, Philippe Fillatreau, Jean-Yves Fourquet and Yingshen Zhao
Laboratoire Génie de Production, INP-ENIT, 47 Av d'Azereix, 65000 Tarbes, France
{*simon.cailhol, philippe.fillatreau,jean-yves.fourquet, yingshen.zhao*}*@enit.fr*

Keywords: Interactive path planning, control sharing, virtual reality, manipulation tasks

Abstract: This work considers path-planning processes for manipulation tasks such as assembly, maintenance or disassembly in a Virtual Reality (VR) context. The approach consists in providing a collaborative system associating a user immersed in VR and an automatic path planning process. It is based on semantic, topological and geometric representations of the environment and the planning process is split in two phases: coarse and fine planning. The automatic planner suggests a path to the user and guides him trough a haptic device. The user can escape from the proposed solution if he wants to explore a possible better way. In this case, the interactive system detects the user's intention in real-time and computes a new path starting from the user's guess. Experiments illustrate the different aspects of the approach: multi-representation of the environment, path planning process, user's intent prediction and control sharing.

1 Introduction

The industrial product development process is going faster and faster with more and more complex products. This leads to a need of tools allowing to rapidly test a product at all the Product Lifecycle Management (PLM) stages during the design phase. There is a particular need for the tasks that involve human operator manipulation. Here comes the interest of Virtual Reality (VR) to run these tests with virtual prototypes instead of expensive and time consuming real ones (Fillatreau et al., 2013).

The main issue of tasks such as the ones involved in assembly, dismantling and maintenance is to find paths for the systems components and parts.

In this context, we propose a collaborative pathfinding system based on the interaction of a user immersed in a VR simulation and an automatic path planning process inspired from robotics.

Collaboration is defined as follows. The system provides a initial planned path and the user is guided along a computed trajectory through an haptic device. However, the user can disagree with the proposed path and try to go in another direction. The system must compute a new path every time the user tries to test another solution. Thus, it must be able to take into account the user's interactions in real-time to update the suggested path and it requires control sharing between the user and the planner while performing the task.

Robotics path planners mainly deal with geometric aspects of the environment. The VR context of our planner involves a human in the loop with a different environment representation. Thus, we chose to split the planning process in two phases: a coarse planning dealing with topological and semantic models of the environment (the places, their semantics and their connectivity) and a fine planning dealing with geometry and semantics (geometry of obstacles and places and their complexity). This planning process partitioning provides a framework compatible with the human path planning process described in (Ahmadi-Pajouh et al., 2007).

Thus, the originality of the proposed interactive path planner consists in using the information of a multi-layer environment representation (semantic, topological and geometric) for path planning, but also for control sharing. All these environment models are used by distinct planner layers to perform the coarse (semantic and topological aspects) and fine (semantic and geometric aspects) planning and to assist VR user. The actions of the VR user are also taken into account in real-time to update the proposed path.

This paper first gives, in section 2, an overview of the state of the art of the different fields involved (automatic path planning, sharing control, interactive path planning). The architecture of our novel multi-layer environment model and multi-layer interactive planner is presented in section 3. The implementation of this architecture on our VR platform is described in section 4. Proof of concepts experiments are presented in section 5. These experiments show that our novel multi-layer architecture finds more relevant paths with faster processing times than the purely geometrical approaches from the state of the art. Thus our original approach allows a better real-time interactive planning. Finally, section 6 summarizes the contribution of this paper and introduces the future steps of this work to handle real industrial manipulation tasks.

2 State of the art

2.1 Automatic path planning

The automatic path planning issue has been deeply studied in robotics. These works are strongly based on the Configuration Space (CS) model proposed by (Lozano-Perez, 1980). This model aims at describing the environment from a robot's Degrees of Freedom (DoF) point of view. The robot is described using a vector where each dimension represents one of his DoF. A value of this vector is called a configuration. So, all the possible values of this vector form the CS. This CS can be split into free space and colliding space (where the robot collides with obstacles of the environment). With this model, the path planning from a start point to a goal point consists in finding a trajectory in the free space between these two points in the CS.

The main strategies for path planning are given in Table 1 where we distinguish the deterministic from the probabilistic ones, but also, the ones involving global approach from the ones involving local one. More details on path planning algorithms and techniques are available in (LaValle, 2006).

2.2 Control sharing

There are already existing applications involving path planning with human interactions (robot teleoperation, semi-autonomous vehicles, virtual environment exploration,...). These applications allow us to identify two aspects in control sharing:

- Authority sharing: it aims at defining how the authority on the system is shared between automatic planner and human. To deal with this issue, different strategies can be found in the literature. The use of virtual fixtures (Marayong et al., 2003), the allocation of the authority to the automatic system for fine motion operations (Abbink and Mulder, 2010), the progressive transfer of authority to robot while reaching the goal (Weber et al., 2009), for an anthropomorphic robot, the control of Cartesian position and orientation of end effector by user and joint control by planner (You and Hauser, 2012). The authority sharing through haptic devices were studied for semi-autonomous vehicles driving. In this case, inspired from the horse riding experience, (Flemisch et al., 2012) suggests to use an haptic interface with a *H-mode* to perceive user's involvement and allocate the authority according to it (the higher the user involvement is, the more authority he has).
- Intent prediction: it aims at predicting the intent of the human to define the goal of an automatic controller and thus to assist the human performing the task. These techniques are strongly based on behavior or trajectory recognition (Aarno et al., 2005; Fagg et al., 2004; Li and Okamura, 2003; Yu et al., 2005), on minimum jerk criterion (Weber et al., 2009), on model predictive control (Loizou and Kumar, 2007; Anderson et al., 2010). Dragan also recently proposed to find the targeted goal among a set of potential ones from the current movement direction (Dragan and Srinivasa, 2013).

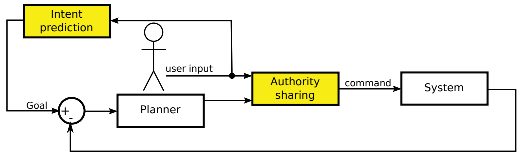


Figure 1: Sharing control model in semi-automated planning.

We summarize these two control sharing aspects in Fig. 1 where the yellow boxes illustrate the control sharing.

These techniques allow involving human and automatic planning system to perform a task. However, the user's actions do not affect the automatic planner strategy to compute the path.

2.3 Interactive path planning

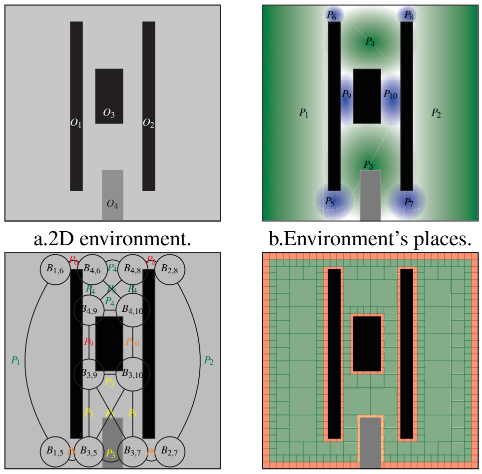
Some works propose collaboration between a human operator and an automatic planner in the path planning process. The simpler one (Ladeveze et al., 2010) uses a potential field strategy. An attractive field to the goal is computed and used to guide the user thanks to a haptic device. Another interactive planner from (Ladeveze et al., 2010) guides the user along a computed trajectory. To compute this trajectory in real-time, a cell decomposition of the free space is used to define a 3D tunnel. Then a RDT algorithm computes a path within this 3D tunnel. The whole trajectory

	Global approaches	Local approaches
Deterministic strategies	Cells decomposition Roadmap	Potential fields
Probabilistic strategies	PRM	RRT and RDT

Table 1: The main path planning approaches

computation process is restarted if user goes away from the proposed trajectory. Finally, an interactive planner built from a probabilistic strategy (Taïx et al., 2012), uses the users action to constraint the random sampling of the configuration space in the RRT growing.

These three planners do not involve the human user in the same way. The first one gives a strong responsibility to the user (it's up to him to deal with the obstacles and to avoid collisions). The second one suggests a whole trajectory the user can go away from to restart the whole planning process. The last one allows the user to point a direction that gives to the planner a preferred direction to explore.



a.2D environment. b.Environment's places. c.Topological graph. d.Free space decomposition.

Figure 3: Different perceptions of environment for user and planner.

3 Proposed interactive planner

This section presents the concepts of the strategy used in the interactive planner shown in Fig. 2 where colors are linked to the environment and planning layers: yellow for geometry, orange for topology and red for semantics. The same colors are used in the algorithms to specify the involved layer. The concepts used are illustrated here with 2D illustrations for clarity, but the model stands identical for 3D simulations.

We argue that involving semantic and topological aspects in path planning in addition to the common geometric ones allows adapting the planning strategy to the local complexity of the environment. To deal with it, a coarse planning is performed first using mainly semantic and topological information. Then, heavy geometric path planning strategies are used merely locally, (according to the place complexity). This allows us to plan path without disturbing user's immersion in the VR simulation, and to take into account user's action while performing the task to interactively update the planned path.

The contribution of the work presented here is thus two-fold:

- Guidance is provided in real-time to the user by improving the path planning processing times thanks to the semantic and topological information of the environment.
- User's actions are integrated in real-time in the planning process and used to update the planned path, and so, the guidance submitted to the user.

3.1 Environment representation

The topological information of the environment is represented as a set of *Places* (P_1 to P_7 in Fig. 3.a) and transition areas between those places, which we call *Borders*; $B_{i,j}$ denotes the transition area between places P_i and P_j. The topological layer of our environment model is made of a *Topological graph* (Fig. 3.c) connecting places and borders. In this *Topological graph*, the nodes correspond to the *Borders*, and the edges to the *Places*. Fig. 4.a shows the distance between the borders' centers in place P_4. These distances are attributes set to the edges of topological graph (Fig. 4.b for place P_4).

The semantic information is attached to places. Semantic attributes are assigned to the places to describe their complexity (size, shape, cluttering,...) for path planning.

The geometric environment representation consists in a geometric description of the environment's objects and a cell decomposition of the *Free space*. The *Objects* are described with meshes; the free space decomposition is made thanks to a quadtree (an octree in 3D) (Fig. 3.d).

This muli-layer environment model is built as

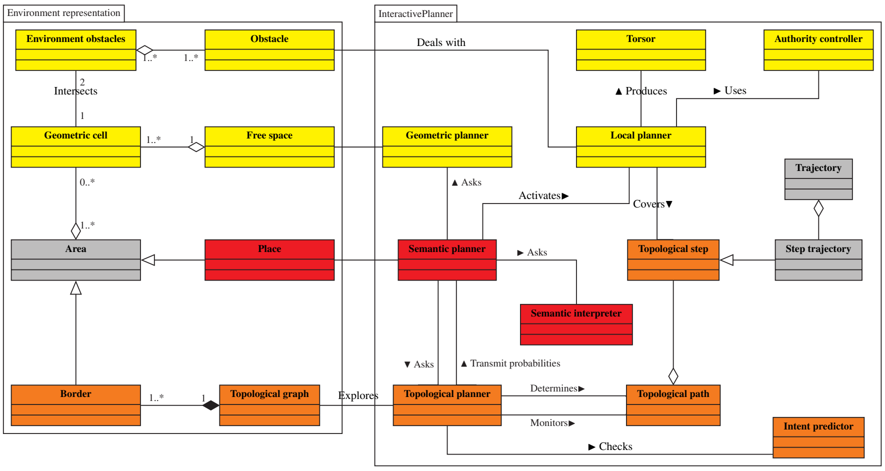
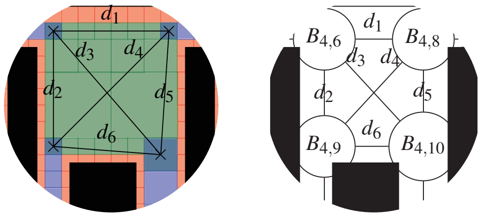


Figure 2: UML Domain model of environment representation and interactive planner.



a.Place P_4 distances. b.Place P_4 topological graph.

Figure 4: Topological graph building for place P_4.

given in algorithm 1. First (line 2), the 3D mesh of environment *Objects* are loaded. Second (line 3), the *Free space* decomposition is computed. Third (line 4), the free space decomposition is used to identify the place. Fourth (line 5), the *Places* found are used to define the *Borders*. Then (line 6), the *Borders* are connected building the *Topological graph*. Last (line 7), semantic attributes are set to the *Places*.

Algorithm 1: build environment model

1 **begin**
2 load *Objects* 3D Meshes ;
3 build *Free space* decomposition ;
4 build *Places* ;
5 build *Borders* ;
6 build *Topological graph* ;
7 assign attributes to *Places* ;

3.2 Planning aspects

According to these environment models, the planning process is split in two stages: the coarse planning involving semantic and topological layers and the fine planning involving semantic and geometric layers

3.2.1 Coarse planning

To adapt the geometric planning strategy to local complexity, the whole path is split in steps. A step refers to a place of environment representation. A step also refers to a border to reach to fulfill the step. The geometric planning strategy is thus chosen according to the semantic information of step's place.

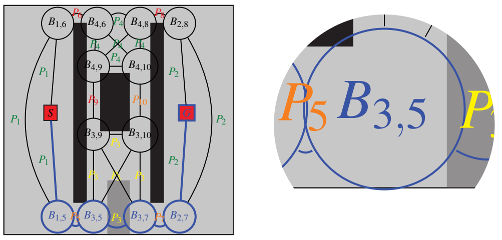
Algorithm 2: coarse planning

1 **begin**
2 update *Topological graph* (start & goal) nodes ;
3 update *Topological graph*'s costs ;
4 explore *Topological graph* ;
5 build *Topological path* and *Topological steps* ;
6 **for** *Topological step* ∈ *Topological path* **do**
7   define milestone for *Topological step* ;

Algorithm 2 describes this stage. Two nodes corresponding to start (S) and goal (G) configurations are added to the topological graph (line 2). To direct the graph exploration the *Semantic planner*, thanks to the *Semantic interpreter*, assigns costs (C) to graph's nodes ($n_{i,j}$) and edges (e_k) (line 3). These costs are chosen accordingly to the semantic information of involved places (see (1)).

$$\begin{aligned} C_{n_{i,j}} &= f(sem(P_i), sem(P_j)) \\ C_{e_k} &= f(d_k, sem(P(e_k))) \end{aligned} \tag{1}$$

Where $sem(P)$ is the semantic information of place P, e_k is a graph's edge, d_k its distance attribute



a.Topological path found. b.Second topological step.

Figure 5: Steps of a topological path.

and $P(e_k)$ its place attribute; $n_{i,j}$ is the node linked to the border $B_{i,j}$ between P_i and P_j.

These costs make the cost of a path (C_{path}) computation possible (see (2)).

$$C_{path} = \sum_{n_{i,j} \in path} C_{n_{i,j}} + \sum_{e_k \in path} C_{e_k} \tag{2}$$

Then the *Topological planner* explores the graph (line 4) thanks to a Dijkstra algorithm (Dijkstra, 1959) to find the less expensive *Topological path* between start and goal nodes. This *Topological path* is used to split the trajectory in *Topological steps* (line 5), each step corresponding to a place to cross (a edge of *Topological path*) and a *Border* to reach (a node of topological path). Fig. 5.a shows the *Topological path* found in the environment of Fig. 3.a. Fig. 5.b focus on the edge and the node corresponding to the second step of this path.

3.2.2 Fine planning

This planning stage consists in finding the concrete geometrical path. To do so, each *Topological step* is used to define a milestone configuration within the border to reach (line 6-7). Then, accordingly to the semantic information of the place to cross, we adapt the geometric path planning strategy. Indeed, the aim of our architecture is to be able to choose the best geometric planning method among a set of available ones for each step. For now, we use two geometric planning strategies. These two strategies deal with the two distinct geometric environment models (*Obstacle*s and *Free space* description). Depending on the semantic attribute describing the place's cluttering, the geometric planner can perform an A* algorithm (when the place is cluttered) on the part of the octree corresponding to the step's place to set intermediate milestones within the step. When all the milestones have been defined, the *Local planner* guides the user toward the next milestone. It computes a linear interpolation between current configuration and milestone's configuration, and uses this interpolation to apply a torsor on a haptic device.

3.2.3 Coarse and fine planning organization

The coarse and fine planning are used to manage the whole planning. The *Topological path* and its steps are concepts allowing saving the necessary information for each planning layer. When the *Topological path* is found and the *Topological steps* are defined, the steps information is used by the *Semantic planner* to set the geometric layer accurately.

3.3 Process monitoring

The *Topological path* and its steps are concepts allowing the different planning layers sharing the information. When the *Topological path* is found and the *Topological step*s are defined, the step information is used by the *Semantic planner* to accurately set the geometric layer.

Algorithm 3 shows how the planning layers are involved to monitor the planning process. While the user is performing the task, he is guided toward the next milestone configuration thanks to the haptic device. This next milestone is updated while the user moves along the path. On the geometric layer, the next milestone is set to the *Local planner* for the guidance computation when the current one is considered as reached (line 11-12). The goal is considered as reached when the distance between the goal and the current position is smaller than θ_d. On the topological layer, the milestone is a *Border*, so even if the user is guided toward a geometric configuration set within the *Border*, the milestone is considered as reached as soon as the user enters the *Border*. When the target *Border* is reached (line 2), the next *Topological step* is used to set the *Local planner* (line 7-9), except if the current step was the last one. In this case, the last milestone must be reached to consider the task as achieved (line 3-5).

3.4 Control sharing aspects

The planner provides user with a guidance torsor through the haptic device used for object manipulation. This *Local planner* computes the guidance torsor.

For each layer of such a planner architecture, specific ways to share control can be proposed as shown in Table 2.

In Table 2 it appears that the intent prediction for the geometric layer is directly linked to the authority sharing of topological layer. Indeed, within a *Place*, the set of potential goals to get out of this *Place* is made of the corresponding *Border*s. The intent prediction is made with geometric movement and geo-

	Authority sharing	Intent detection
Semantic layer	Learn from users action new semantics information or means to deal with them to accurately set the topological and geometric planners	Interpret planning query expressed in natural language (*assemble this part on this one, bring this object on this one,...*)
Topological layer	Check if user agrees with the proposed topological path. Trying to predict his intents on the topological layer (which place he is targeting)	Learn the kind of paces the user prefers to cross to advantage them during the topological path planning process
Geometric layer	Dynamically balance the authority on the object manipulation (between human and automatic planner) by modulating the automatic planner guidance norm	Find the targeted next place to redefine the geometric planner goal

Table 2: Interaction means on the diferent layers

Algorithm 3: process monitoring

```
begin
    if Topological step = achieved then
        if current step = last step then
            if Milestone reached then
                achieved = true;
        else
            set next Topological step in Local planner;
            if Topological step's Place cluttered then
                run A* on Topological step;
    else
        if Milestone reached then
            set next milestone to Local planner;
```

metric information on *Borders*. The re-planning is made by the *Topological planner* for a new *Topological path* definition.

The same logic applies for the intent prediction of the topological layer and the authority sharing of the semantic layer. Cost functions of (1) may be learned from the places the user prefers to cross. Indeed the preferred places attributes can be identified from all the re-planning done due to users action. The new cost values defined with these functions will thus change all the incoming topological re-planning.

The control sharing of the proposed planning architecture is focused on the geometric and topological layers. We implemented A H-mode from (Flemisch et al., 2012) for geometric authority control. We also developed an intent prediction inspired from (Dragan and Srinivasa, 2013) to make the topological path re-planning available.

3.4.1 Authority sharing

To share authority, we chose to use a strategy inspired from *H-mode* introduced in (Flemisch et al., 2012). This strategy aims at modulating the guidance torsor $\mathcal{G}$ norm according to the user's involvement as shown in equation 3.

$$\mathcal{G}_{user} = g_{mod} \cdot \mathcal{G} \tag{3}$$

Where g_{mod} is a measure of user's involvement from $g_{mod_{min}}$ (not involved) to 1 (strongly involved). The lower limit $g_{mod_{min}}$ is chosen to keep the user aware of automatic planner state as suggested by (Marayong et al., 2003). In our application of *H-mode*, we chose to compute g_{mod_i} on each process loop i from the scalar product of instantaneous guidance force $(\overrightarrow{g_i})$ by the instantaneous movement direction $(\overrightarrow{m_i})$ as shown in equation 4.

$$g_{mod_i} = \frac{1 - g_{mod_{min}}}{2}\left(\frac{\overrightarrow{g_i}.\overrightarrow{m_i}}{\|\overrightarrow{g_i}\|\|\overrightarrow{m_i}\|} + 1\right) + g_{mod_{min}} \tag{4}$$

The coefficient obtained with 4 is filtered to obtain a smooth transfer of the authority with g_{fmod_i} computation given in equation 5.

$$g_{fmod_i} = \alpha_{mod} \cdot g_{fmod_{i-1}} + (1 - \alpha_{mod}) g_{mod_i} \tag{5}$$

Where α_{mod} is chosen from 0 to 1 accordingly to the loop rate and the transfer time needed. The g_{fmod_i} coefficient obtained is applied to equation 3 to have our effective authority control given in equation 6.

$$\mathcal{G}_{user_i} = g_{fmod_i} \mathcal{G}_i \tag{6}$$

3.4.2 Intent prediction

Algorithm 4 shows the process used to define if a coarse re-planning is necessary or not. On line 2, if the user is not following the guidance (angle between guidance direction and movement direction greater than threshold angle and movement amplitude greater than a given threshold), it means the user does not agree with the proposed path. He may have found another one or at least needs a new proposal.

To deal with it, the intent prediction we use allows us to define, in a step, for each border of the current *Place*, the probability that the user is targeting it (line 3). These probabilities are used to define if the user is targeting another border than the one defined in his current step (line 4). In this case a new

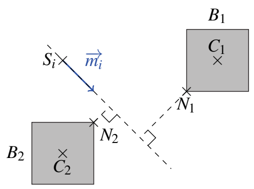


Figure 6: Border representative point problem.

topological path is defined taking into account user's will.

Algorithm 4: intent prediction and replanning

```
1 begin
2     if user's movement ≠ guidance then
3         compute Borders' probabilities ;
4         if prediction ≠ proposal then
5             coarse planning;
6             set first Topological step in Local planner ;
7             if Topological step's Place cluttered then
8                 run A* on Topological step ;
```

To manage it, we decided to adapt Dragan's strategy (Dragan and Srinivasa, 2013) using the set of border of the current step's place as the set of potential goals. Indeed, to predict user's intent, Dragan computes probabilities for all potential goals thanks to a scalar product of the movement $\overrightarrow{m_i}$ by the goal direction $\overrightarrow{S_iG_n}$ (where S_i is the current position and G_n the position of n^{th} goal). In our simulations, the potential goals (the borders) are not punctual. Thus the point chosen to compute the scalar product must be carefully chosen. Indeed, as shown in Fig. 6, if the centers C_i of borders B_i are taken as representative points, the probability to target borders B_1 and B_2 will be the same. However, it seems that B_2 is more suited to the user. To deal with this issue, we chose to select the borders' nearest points N_i of the movement axis.

With such elements, the probability that the border $B_{j,k}$ is targeted is given in (7) where a scalar product is scaled to fit between 0 and 1.

With such elements, the probability that the border $B_{j,k}$ is targeted is given in equation 7 where a scalar product is scaled to fit between 0 and 1.

$$P(B_{j,k}) = \frac{1}{2}\frac{\overrightarrow{m_i}.\overrightarrow{S_iN_{j,k_i}}}{\|\overrightarrow{m_i}\|\|\overrightarrow{S_iN_{j,k_i}}\|} + 0.5 \tag{7}$$

Fig. 7 is an example of the points chosen for intent prediction in place P_4 where S_i is the instantaneous position on sample i, $\overrightarrow{m_i}$ its movement direction, and N_{j,k_i} the point chosen to consider border $B_{j,k}$. In this

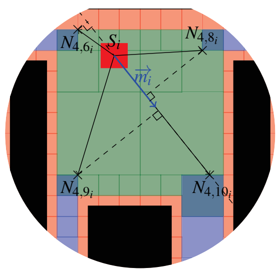


Figure 7: Border probability computation elements

example, the borders classified by probability to be targeted are: $B_{4,10}$, $B_{4,9}$, $B_{4,8}$ and $B_{4,6}$.

When the probability of all the borders have been computed, if the following condition of (8) is satisfied, a new topological path computation in done.

$$max(P(B_{i,j}))–P(B_{step}) \geq \theta_{replanning} \tag{8}$$

Where $P(B_{step})$ is the probability computed for the border chosen as goal of the current step and $\theta_{replanning}$ is the threshold used to decide if a topological re-planning is needed or not.

3.4.3 Coarse re-planning

When a coarse re-planning is necessary (line 5 of Algorithm 4) the start node of the topological graph is updated to match with the current object position. The borders' costs are also updated to add costs $C_{n_{k,l_i}}$ corresponding to the intent prediction (see (2)). These new costs direct the next topological graph exploration toward the user's targeted border. The new topological path computation is done adding new costs $C_{n_{k,l_i}}$ to the nodes linked to the borders. The costs added are chosen accordingly to the corresponding borders as given in (2).

$$\begin{cases} C_{n_{k,l_i}} = k\dfrac{max(P(B_{i,j}))–P(B_{k,l})}{max(P(B_{i,j}))} \text{ if } B_{k,l} \neq B_{step} \\ C_{n_{k,l_i}} = C_h \text{ if } B_{k,l} = B_{step} \end{cases} \tag{9}$$

Where k is a multiplicative coefficient and C_h a specific cost used to avoid the border of previous *Topological path* when computing a new one.

These new costs, being heavy on the previously chosen border, and light on the high probably targeted ones will tend to explore paths through user's targeted borders and thus define a topological path crossing one of these borders.

3.5 Interactive path planning simulation

Algorithm 5 summarizes the operations made for the interactive path planning. First, an initialization process including environment building and first coarse planning is processed (line 2-7. Then, the proper interactive planning is done in a loop (line 9-14). This loop includes the performed trajectory recording (line 9), the user's intent prediction and the replanning to fit with his intent (line 11), the process monitoring (line 12) and the guidance modulation and update (line 13-14).

Algorithm 5: Interactive planning simulation

```
1  begin
2      build environment model;
3      coarse planning;
4      achieved = false;
5      set first Topological step in Local planner ;
6      if Topological step's Place cluttered then
7          run A* on Topological step ;
8      while achieved = false do
9          record sample configuration ;
10         compute user's movement direction ;
11         intent prediction and replanning;
12         process monitoring;
13         update authority ;
14         update guidance ;
```

4 Implementation

We implemented our proposed path planning and environment modeling architecture in Virtools^{TM}4.1 software through libraries developed in C++ language. We developed 3 distinct libraries: 2 autonomous libraries corresponding to *environment model* and *path planner* and an interface library.

4.1 Environment representation built

The environment model is implemented in a dedicated library interfaced to Virtools^{TM}with a specific library.

The environment representation we use is made of 4 models:

- The objects of the environment represented through meshes and positioning frames. To build this part of environment model, we use the CGAL project (CGAL, 2014). Semantic attributes are attached to the objects. One of them describes if the object is fixed or not to be able to exclude the moving ones while identifying the places (static mapping of the environment).
- The free space description through an octree decomposition of the 3D scene (in this case also, the nodes colliding with fixed object are distinguished from those colliding with only moving objects)
- The topological graph to model the places connectivity (the graph's nodes are the borders, and the edges the places)
- The set of places and their borders. We defined some procedures to automatically identify the places from the octree structure. The semantic attributes are characters strings. Their attachment to the places is manually made, choosing for each place the right attributes among a set of available ones. One attribute is automatically set: "cluttered" if the place contains moving obstacles

The attributes available in our simulations allow describing the level of complexity of a place as "low", "average", "high", and "very high". Another attribute is used to define if a place is "cluttered". Finally, "square", "triangular", "round" and "pentagonal" attribute can be set to describe place's shape.

4.2 Planner implementation

The planner is also implemented in a dedicated library and interfaced to VirtoolsTM using the same interface library used to interface the environment.

4.2.1 Planning classes

Four classes had been defined corresponding to the four planners. Each of these planner classes deals with an environment model. The local planner provides the user with the guidance. The geometric planner finds, if necessary, a path on the octree. The topological planner explores the topological graph to build the path and the steps managed by the local and the geometric planner. The semantic planner coordinates the whole planning process, asking the topological planner for the topological path and planning which strategy will be used on the geometric layer.

For the weights computation, we defined the function of (1) assigning the weights as given in (10).

$$\begin{aligned} C_{n_{i,j}} &= \frac{C_{complexity}}{2} \\ C_{e_k} &= d_k.C_{complexity} \end{aligned} \qquad (10)$$

Where $C_{complexity}$ sums two costs:

- the first one is set according to the traversability of the involved places 0, 0.5, 1 and 5 for low, average, high and very high complexity.
- the second one is set according to the shape attribute: 0 if empty, 0.5 if the shape match with the handled object's shape, and 5 if not.

4.2.2 Control sharing classes

Two main classes improve the planner for the control sharing. The first one is related to the *Authority Controller*. It aims at modulating the guidance norm according to the user's involvement. It allows user to feel free when he is exploring others ways. The second one is the *Intent Predictor*. It detects the user intents to compute a new *Topological Path* when the user goes away from the proposed one. These two classes and there computation are strongly based on the instantaneous movement computation made thanks to the Trajectory Step Trajectory.

The geometric authority sharing is set as follow:

- the minimal guidance norm is set to 10% of the nominal norm. Thus the $g_{mod_{min}}$ parameter of equation 4 is set to 0.1.
- the guidance modulation filter parameter α_{mod} of equation 5 is set to 0.9 to process the filtering on some twenty samples

4.2.3 Processes and threads

The guidance submitted to user being provided in real-time through a haptic device, the corresponding computations are done in the main thread of simulation. This inclusion in the simulation loop updates the guidance about 60 times per second.

The intent prediction and the new topological path computation are run when needed on a dedicated thread to not disturb the main thread and thus not decrease the sample rate. Both processes are synchronized thanks to flags notifying states changes.

5 Simulations and results

The following simulations were implemented on our VR platform (Fillatreau et al., 2013) (see Fig. 8). The VR devices used here are a large screen using passive stereoscopy for the 3D visualization and immersion, an AR Track system for the user view-point capture and a Virtuose 6D 35-45 as haptic device for the part handling.

The first simulation is a 3D instance of the 2D example used to illustrate the principles of our planning

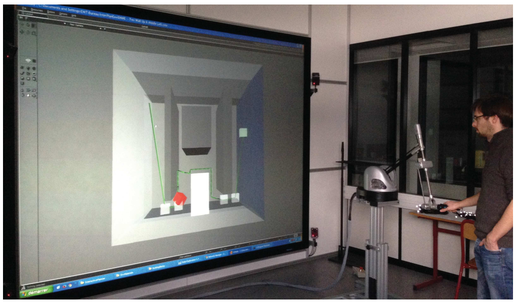


Figure 8: Simulation on VR platform.

strategy. It has been used for development and allowed to test the collaboration of the planners. The second simulation shows a richer semantics of the environment (semantic attributes that describe the shape of objects and places). This has allowed showing how the control of the planning process, thanks to the semantic information, increases the reliability of the planned path while reducing the processing time.

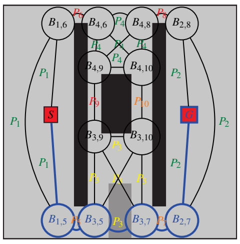
5.1 First simulation

5.1.1 Simulation scene

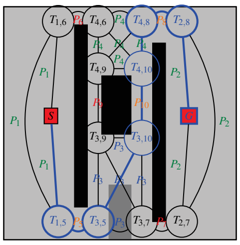
To test the multi-layer structure on the laboratory's VR platform, the environment used is a 3D instance of the environment described in section 3. This environment is a cubic workspace with four obstacles cluttering the scene (3 fixed and 1 moving). Different environment configurations have been tested moving the fixed obstacles to change the complex passages locations (O_1 and O_2 are moved vertically and O_3 horizontally). The corresponding topological graphs are given in Fig. 9. This figure also illustrates the planning query in these environments. It aims at bringing a piece from a start point S in place P_1 to a goal point G in place P_2. The topological paths found by the topological planner are also displayed in bold blue lines in the topological graphs.

5.1.2 Path planning

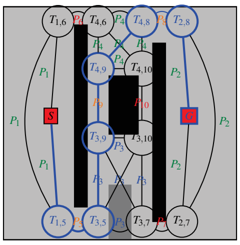
Fig. 10 shows the real path computed in the environment illustrated in Fig. 9. The object to move is the red cube and the targeted goal is the green one. The path is displayed in green. The paths on place P_3 avoid mobile obstacle O_4 thanks to the A* algorithm performed on this cluttered place. To find such paths, the computational time for the Dijkstra algorithm in the topological graph was about $1ms$, and the A* algorithm when necessary to cross the cluttered place took from $50ms$ to $750ms$ depending on the path to find. Thus, the whole path is find in less than $1s$ when



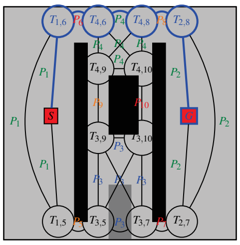
a.Environment 1.



b.Environment 2.

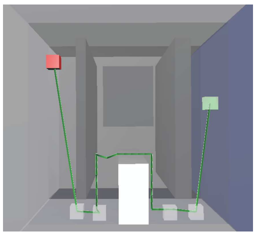


c.Environment 3.

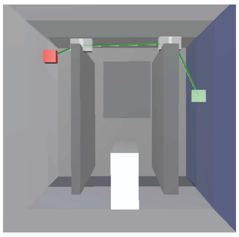


d.Environment 4.

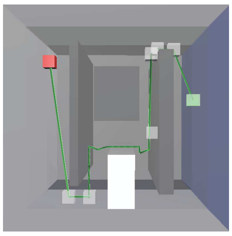
Figure 9: Experimental environments.



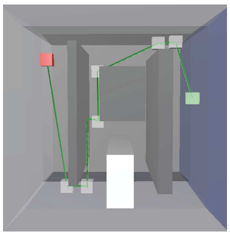
a.Environment 1.



b.Environment 2.



c.Environment 3.



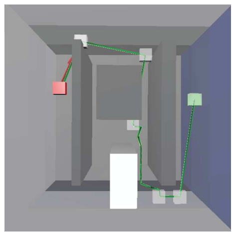
d.Environment 4.

Figure 10: Planning results.

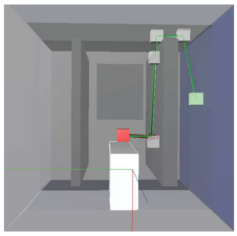
using the A* algorithm alone without any semantics or topology planning process takes about 3.5s without avoiding complex passages (in this case the past computed is the shortest but not the easiest to perform).

5.1.3 Path re-planning

Fig. 11 illustrates the topological re-planning including real-time detection of user's intent. In Fig. 11.a, in the first step, the user seems to prefer the narrow passage. Detecting it, the topological path is recomputed taking into account this intent. In Fig. 11.b, the user doesn't follow the guidance along the A* path in the third step. Thus, the topological planner computes a new topological path. The path re-planning including



a.Re-planning in step 1.



b.Re-planning in step 3.

Figure 11: Topological re-planning in environment 1.

A* process is done in less than 150ms in this case.

5.2 Second simulation

5.2.1 Simulation scene

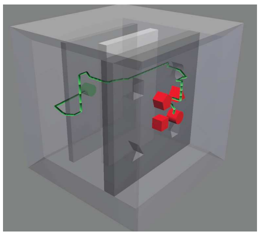
Our simulation scene (see Fig. 12) is made of a cubic workspace divided in three large places by two walls. The wall in the foreground is an obstacle with four holes. Each hole has a characteristic shape (square, triangular, round and pentagonal). The wall in the background is an obstacle leaving a passage on each side (a large one on the left and a narrow one on the right). A moving obstacle clutters the place between these two walls.

The topological places of this environment are: the three large places, the two passages around the background wall, and the holes through the foreground wall (each hole corresponds to a place). The semantic attributes attached to the places are: "low complexity" for the three large places; "high complexity" for the large passage around the background wall, and "very high" for the narrow one. Attributes are also set to the wall holes to describe their shape ("square", "triangular", "round" and "pentagonal"). The additional "cluttered" semantic attribute is assigned to the places containing moving objects.

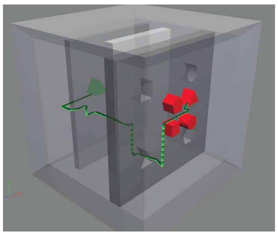
The planning query here consists in passing the two walls to move the shaped object (in red) from one side of the cube to the other.

5.2.2 Path planning

Fig. 12 shows the path computed with our proposed architecture. Fig. 12.a shows the path planned for the red cylindrical object, and Fig.12.b the path planned for the triangular one. In both cases, a path is found, and the computed path crosses the wall in the foreground through the hole having the same shape as the moved object. Furthermore, the computed path goes through the large passage beside the wall in the background rather than the narrow one.



a.Path for cylinder.



b.Path for triangle.

Figure 12: Planning results.

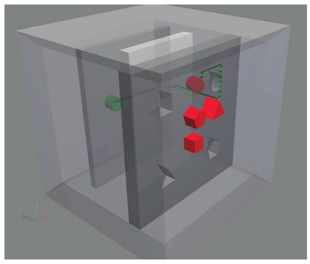


Figure 13: Coarse re-planning with cylinder.

The computational time to find these paths is $1s$ when moving the triangular object and $7s$ when moving the cylindrical one. The A* search is more complex for the cylinder. In Fig. 12.b, after the triangular moved object has crossed the triangular hole, the path through the large passage besides the wall in the background is quite simple. The path computed for the cylinder is more complex. When the cylinder has crossed the round hole, it is located on the wrong side of the background wall to reach the large passage.

We compared our results to the results obtained using the A* planning algorithm. The processing times obtained were $24s$ and $26s$ for the triangle object and the cylinder respectively; in both cases, the A* algorithm failed to find a feasible path as the proposed hole to get through the wall in the foreground had the wrong shape.

These results show the advantage brought by our architecture; controlling a classical geometrical path planner using the semantic and topological information leads to improve the planning results qualitatively (success vs failure), while reducing drastically processing times.

5.2.3 Path re-planning

Fig. 13 illustrates the topological re-planning in the case of the cylinder manipulation. Here, the user does not follow the haptic guidance along the A* path between the two walls, and targets the narrow passage to perform a simpler path. Thus, the topological planner computes a new topological path, through the narrow passage instead of the large one, according to the user intent. The path re-planning (topological re-planning and geometrical A* re-planning) is done in less than $2s$ in this case.

6 Conclusion

This paper presents a novel multi-layer architecture for interactive path planning in VR simulations. This architecture is based on a multi-layer environment model and a multi-layer planner. Each layer deals with specific information (semantic, topological and geometric). The contribution of such an architecture is two-fold :

- First, it provides the user with real-time manipulation guidance thanks to path planning involving the semantic and topological information. The path planning process is accelerated by splitting the path in steps and then by adapting the geometric planning strategy to the local complexity of each step.
- Second, it integrates efficiently a human in the loop: path re-planning is computed based on real-time user's intent detection and motion control is shared by the user and the planner.

The interest of such a planner architecture had been demonstrated here with semantic information of the environment based on "complexity", "shape" and "clutter". This information allowed this novel architecture to deal efficiently with an abstract example using only simple geometrical path planning techniques.

However, real manipulation task for industrial processes involves more complex semantic information (functional surface, multi-physics interactions, surfaces or material properties). Future work will be done to further define both the meaningful semantic information needed for such tasks and the corresponding planning strategies. The proposed architecture meets the requirements for such semantic information. For instance, in assembly tasks, sliding motions are commonly used. We are planning to develop interactive geometric path planning methods with contact. We also plan to enrich the topological and semantic layer of our environment model in order to use our global architecture to choose to interactively plan paths with or without contact according to the functional context of the assembly tasks (or subtasks) to be performed.

Moreover, with an accurate semantic description, such a planner structure seems also well suited for off-line path planning allowing to rapidly find hard passages using the topological planning and to rapidly adapt the geometric planning strategy according to the local planning context.

REFERENCES

Aarno, D., Ekvall, S., and Kragic, D. (2005). Adaptive virtual fixtures for machine-assisted teleoperation tasks. In *International Conference on Robotics and Automation, ICRA. Proceedings*, pages 1139–1144. IEEE.

Abbink, D. A. and Mulder, M. (2010). Neuromuscular analysis as a guideline in designing shared control. *Advances in haptics*, 109:499–516.

Ahmadi-Pajouh, M. A., Towhidkhah, F., Gharibzadeh, S., and Mashhadimalek, M. (2007). Path planning in the hippocampo-prefrontal cortex pathway: An adaptive model based receding horizon planner. *Medical hypotheses*, 68(6):1411–1415.

Anderson, S., Peters, S., Iagnemma, K., and Overholt, J. (2010). Semi-autonomous stability control and hazard avoidance for manned and unmanned ground vehicles. Technical report, DTIC Document.

CGAL (2014). CGAL, Computational Geometry Algorithms Library. `http://www.cgal.org`.

Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. *Numerische mathematik*, 1(1):269–271.

Dragan, A. D. and Srinivasa, S. S. (2013). A policy blending formalism for shared control. *International Journal of Robotics Research*.

Fagg, A. H., Rosenstein, M., Platt, R., and Grupen, R. A. (2004). Extracting user intent in mixed initiative teleoperator control. In *Proc. American Institute of Aeronautics and Astronautics Intelligent Systems Technical Conference*.

Fillatreau, P., Fourquet, J.-Y., Le Bolloch, R., Cailhol, S., Datas, A., and Puel, B. (2013). Using virtual reality and 3d industrial numerical models for immersive interactive checklists. *Computers in Industry*.

Flemisch, F., Heesen, M., Hesse, T., Kelsch, J., Schieben, A., and Beller, J. (2012). Towards a dynamic balance between humans and automation: authority, ability, responsibility and control in shared and cooperative control situations. *Cognition, Technology & Work*, 14(1):3–18.

Ladeveze, N., Fourquet, J.-Y., and Puel, B. (2010). Interactive path planning for haptic assistance in assembly tasks. *Computers & Graphics*, 34(1):17–25.

LaValle, S. (2006). *Planning algorithms*. Cambridge University Press.

Li, M. and Okamura, A. M. (2003). Recognition of operator motions for real-time assistance using virtual fixtures. In *11th Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems. HAPTICS. Proceedings.*, pages 125–131. IEEE.

Loizou, S. G. and Kumar, V. (2007). Mixed initiative control of autonomous vehicles. In *International Conference on Robotics and Automation.*, pages 1431–1436. IEEE.

Lozano-Perez, T. (1980). Spatial planning: A configuration space approach. *IEEE Transactions on Computers*, 100(2):108–120.

Marayong, P., Li, M., Okamura, A. M., and Hager, G. D. (2003). Spatial motion constraints: Theory and demonstrations for robot guidance using virtual fixtures. In *International Conference on Robotics and Automation, Proceedings. ICRA*, volume 2, pages 1954–1959. IEEE.

Taïx, M., Flavigné, D., and Ferré, E. (2012). Human interaction with motion planning algorithm. *Journal of Intelligent & Robotic Systems*, 67(3-4):285–306.

Weber, C., Nitsch, V., Unterhinninghofen, U., Farber, B., and Buss, M. (2009). Position and force augmentation in a telepresence system and their effects on perceived realism. In *EuroHaptics conference, 2009 and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems. World Haptics 2009. Third Joint*, pages 226–231. IEEE.

You, E. and Hauser, K. (2012). Assisted teleoperation strategies for aggressively controlling a robot arm with 2d input. *Robotics: Science and Systems VII*, page 354.

Yu, W., Alqasemi, R., Dubey, R., and Pernalete, N. (2005). Telemanipulation assistance based on motion intention recognition. In *International Conference on Robotics and Automation, ICRA Proceedings*, pages 1121–1126. IEEE.