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A simple path optimization method for motion planning

Mylène Campana\textsuperscript{1,2}, Florent Lamiraux\textsuperscript{1,2} and Jean-Paul Laumond\textsuperscript{1,2}

Fig. 1: In this motion planning problem, PR2 robot has just to exchange the positions of its arms. The task is simple, however, in absence of explicit indication, any probabilistic motion planner will compute a path that makes the PR2 mobile basis purposelessly moving. This is the case of RRT-connect algorithm (left). Path optimization is expected to remove unnecessary motions. The popular random shortcut algorithm fails in this case (middle). Our algorithm succeeds (right).

Abstract—Most algorithms in probabilistic sampling-based path planning compute collision-free paths made of straight line segments lying in the configuration space. Due to the randomness of sampling, the paths make detours that need to be optimized. The contribution of this paper is to propose a gradient-based algorithm that transforms a polygonal collision-free path into a shorter one, while both:

- requiring mainly collision checking, and few time-consuming obstacle distance computation,
- constraining only part of the configuration variables that may cause a collision, and not the entire configurations, and
- reducing parasite motions that are not useful for the problem resolution.

The algorithm is simple and requires few parameter tuning. Experimental results include navigation and manipulation tasks, e.g. an robotic arm manipulating throw a window and a PR2 robot working in a kitchen environment, and comparisons with a random shortcut optimizer.

I. INTRODUCTION AND PROBLEM STATEMENT

Motion planning for systems in cluttered environments has been addressed for more than thirty years \cite{1}, \cite{2}. Most planners today randomly sample the system configuration space \cite{3} in order to find a collision-free path. The main issue using these techniques is that the computed path makes unnecessary detours and needs to be post-processed before being executed by a virtual or real robot. Alternative strategies exist however.

- Planning by path-optimization \cite{4}, \cite{5} where obstacle avoidance is handled by constraints or cost using computation of the nearest obstacle distance. Most of these planners are using non-linear optimization \cite{6} under constraints. Such planners provide close-to-optimality paths and have smaller time computation for easy problems, but they are mostly unable to solve narrow passage issues.
- Optimal random sampling \cite{7} are also close to an optimal solution, but computation time is significantly higher than classical approaches. Moreover the roadmap is only valid for a given motion planning problem.

In this paper, we propose a method aimed at shortening path length after a path planning step. Note that we do not address path planning, but that we take the result of a probabilistic motion planner as the input to our path optimization method.

For this shortening purpose, random shortcut methods are still very popular \cite{8}, \cite{9}. However, random shortcut requires fine tuning of the termination condition (see Algorithm 2) and is no efficient due to randomness for long trajectories where only a small part needs to be optimized. Figure 2 presents another situation where random shortcut will always fail to optimize the initial path, since it cannot decouple the robot degrees of freedom (DOF) on which the optimization occurs, contrary to our algorithm.
On the other hand, numerical optimization methods like CHOMP [10] can be used as a post-processing step. They have clear termination conditions, but collision avoidance is handled by inequality constraints sampled at many points along the trajectory. These methods therefore require a pre-processing step of the robot (and/or environment) model in order to make it simpler: [10] covers PR2 bodies with spheres, while [11] needs to decompose objects into convex subsets. Moreover, in the applications we address, optimality is not desirable as such since the shortest path between two configurations in a cluttered environment usually contains contacts with the obstacle, or is most of the time out of the scope of numerical optimization algorithms [12].

The idea of our method is to find a good trade-off between the simplicity of blind methods like shortcut algorithm, and the complexity of distance based optimization techniques. The method iteratively shortens the initial path with gradient-based information. When a collision is detected at a given iteration, the method backtracks to the latest valid iteration and inserts a linearized transformation constraint between the objects detected in collision. Only few distances between objects are evaluated, therefore no pre-processing of the robot or environment models is necessary. The underlying optimization algorithm is a quadratic program.

Related work is presented in Section II. Section III explains how the path-optimizer works, from the formulation of the problem to the implemented algorithm. Finally, we conclude on experimental results in Section IV.

II. RELATED WORK

CHOMP algorithm [10] optimizes an initial guess provided as input. It minimizes a time invariant cost function using efficient covariant hamiltonian gradient descent. The cost is quantified by non-smooth parts (with high velocities) and an obstacle avoidance term, provided by the distance to the nearest obstacle for each iteration of the trajectory. Calculating these nearest distances however is time-consuming because the distances between all pairs of objects must be computed at each time step along the path. To reduce the computation time, the method starts by building offline a map of distances that will be called during the optimization at the requested time. Besides, meshes are pre-processed into bounding spheres so that distances are computed faster at the cost of a geometry approximation.

STOMP method [13] avoids to compute an explicit gradient for cost optimization using a stochastic analysis of local random samples. But as for CHOMP, the obstacle cost term requires a voxel map to perform its Euclidian Distance Transforms, and represents the robot bodies with overlapping spheres. Such technique provides lots of distance and penetration information but remains very time consuming and is not as precise as some distance computation techniques based on the problem meshes as Gilbert-Johnson-Keerthi [14].

Some optimization-based planners may not require an initial guess but some naive straight-line manually or randomly-sampled initialization as TrajOp [15]. Its trajectory is iteratively optimized with sequential convex optimization by minimizing at each step its square length, linear and non-linear constraints considered as penalties. To compute the collision-constraints, nearest obstacle distances are calculated at each discrete time of the trajectory vector. This can be a burden for a high-dimensional robot or a complex environment as we propose to use, and may be compensated with a short path composed of only one or two waypoints.

The elastic strips framework [16] is also an optimization based method. The path is modeled as a spring and obstacles give rise to a repulsive potential field. Although designed for on-line control purposes, this method may be used for path shortening. In this case however, the number of distance computation is very high. The authors also proposed to approximate the robot geometry by spheres.

Some heuristics use random shortcuts on the initial guess combined with a trajectory re-building that returns $C^1$ shortcuts made of parabolas and lines (bang-bang control) [9]. These local refined trajectories are time-optimal since they comply with acceleration and velocity constraints.

In some way, our method shares similarities with [17] since this latter method relies on collision checking and backtracks when an iteration is detected in collision, instead of trying to constantly satisfy distance constraints. Unlike our method however, the iterations are composed of Cubic-B-splines. The benefit of this method is that the result is a differentiable path.

III. PATH OPTIMIZATION

A. Kinematic chain

A robot is defined by a kinematic chain composed of a tree of joints. We denote by $(J_1, \cdots, J_m)$ the ordered list of joints. Each joint $J_i$, $1 \leq i \leq m$ is represented by a mapping from a sub-manifold of $\mathbb{R}^{n_i}$, where $n_i$ is the dimension of $J_i$ in the configuration space, to the space of rigid-body motions...
The rigid-body motion is the position of the joint in the frame of its parent. In the examples shown in this paper, we consider 4 types of joints described in Table I. A configuration of the robot

\[ \mathbf{q} = (q_1, \ldots, q_{n_1}, q_{n_1+1}, \ldots, q_{n_1+n_2}, \ldots, q_n), \quad n \triangleq \sum_{i=1}^{m} n_i \]

is defined by the concatenation of the joint configurations. The configuration space of the robot is denoted by \( \mathcal{C} \subset \mathbb{R}^n \).

Note that the configuration of the robot belongs to a submanifold of \( \mathbb{R}^n \).

The velocity of each joint \( J_i, 1 \leq i \leq m \) is defined by a vector of \( \mathbb{R}^{p_i} \), where \( p_i \) is the number of DOF of \( J_i \). Note that the velocity vector does not necessarily have the same dimension as the configuration vector.

The velocity of the robot is defined as the concatenation of the velocities of each joint.

\[ \dot{\mathbf{q}} = (\dot{q}_1, \ldots, \dot{q}_{p_1}, \ldots, \dot{q}_{p_1+p_2}, \ldots, \dot{q}_n), \quad p \triangleq \sum_{i=1}^{m} p_i \]

a) Operations on configurations and vectors: by analogy with the case where the configuration space is a vector space, we define the following operators between configurations and vectors:

\[ \mathbf{q}_2 - \mathbf{q}_1 \in \mathbb{R}^p, \quad \mathbf{q}_1, \mathbf{q}_2 \in \mathcal{C} \]

is the constant velocity moving from \( \mathbf{q}_1 \) to \( \mathbf{q}_2 \) in unit time, and

\[ \mathbf{q} + \dot{\mathbf{q}} \in \mathcal{C}, \quad \mathbf{q} \in \mathcal{C}, \quad \dot{\mathbf{q}} \in \mathbb{R}^p \]

is the configuration reached from \( \mathbf{q} \) after following constant velocity \( \dot{\mathbf{q}} \) during unit time.

Note that the definitions above stem from the Riemannian structure of the configuration space of the robot. The above sum corresponds to the exponential map. We do not have enough space in this paper to develop the theory in a more rigorous way. The reader can easily state that “following a constant velocity” makes sense for the four types of joints defined in Table I. We refer to [18] Chapter 5 for details about Riemannian geometry.

<table>
<thead>
<tr>
<th>Name</th>
<th>Dimension</th>
<th>Config Space</th>
<th>Velocity</th>
</tr>
</thead>
<tbody>
<tr>
<td>translation</td>
<td>1</td>
<td>( \mathbb{R} )</td>
<td>( \mathbb{R} )</td>
</tr>
<tr>
<td>bounded rotation</td>
<td>1</td>
<td>( \mathbb{R} )</td>
<td>( \mathbb{R} )</td>
</tr>
<tr>
<td>unbounded rotation</td>
<td>2</td>
<td>( \mathbb{S}^3 \subset \mathbb{R}^2 )</td>
<td>( \mathbb{R} )</td>
</tr>
<tr>
<td>( SO(3) )</td>
<td>4</td>
<td>( \mathbb{S}^3 \subset \mathbb{R}^4 )</td>
<td>( \mathbb{R}^3 )</td>
</tr>
</tbody>
</table>

TABLE I: Translation and rotation joint position are defined by 1 parameter corresponding respectively to the translation along an axis and a rotation angle around an axis. Unbounded rotation is defined by a point on the unit circle of the plane: 2 parameters corresponding to the cosine and the sine of the rotation angle. \( SO(3) \) is defined by a unit quaternion. The velocity of translation and unbounded rotation joints is the derivative of the configuration variable. The velocity of an unbounded rotation joint corresponds to the angular velocity. The velocity of a \( SO(3) \) joint is defined by the angular velocity vector \( \omega \in \mathbb{R}^3 \).

B. Straight interpolation

Let \( \mathbf{q}_1, \mathbf{q}_2 \in \mathcal{C} \) be two configurations. We define the straight interpolation between \( \mathbf{q}_1 \) and \( \mathbf{q}_2 \) as the curve in \( \mathcal{C} \) defined on interval \([0,1]\) by:

\[ t \rightarrow \mathbf{q}_1 + t(\mathbf{q}_2 - \mathbf{q}_1) \]

This interpolation corresponds to the linear interpolation for translation and bounded rotations, to the shortest arc on \( \mathbb{S}^1 \) for unbounded rotation and to the so called sleep interpolation for \( SO(3) \).

C. Problem definition

We consider as input a path composed of a concatenation of straight interpolations between \( wp + 2 \) configurations: \( (\mathbf{q}_0, \mathbf{q}_1, \ldots, \mathbf{q}_{wp+1}) \). This path is the output of a random sampling path planning algorithm between \( \mathbf{q}_0 \) and \( \mathbf{q}_{wp+1} \). We wish to find a sequence of waypoints \( \mathbf{q}_1, \ldots, \mathbf{q}_{wp} \) such that the new path \( (\mathbf{q}_0, \mathbf{q}_1, \ldots, \mathbf{q}_{wp+1}) \) is shorter and collision-free. Note that \( \mathbf{q}_0 \) and \( \mathbf{q}_{wp+1} \) are unchanged and that the workspace of the robot contains obstacles. We denote by \( x \) the optimization variable:

\[ x \triangleq (\mathbf{q}_1, \ldots, \mathbf{q}_{wp}) \]

1) Cost: let \( W \in \mathbb{R}^{wp \times wp} \) be a diagonal matrix of weights:

\[ W = \begin{pmatrix}
    w_1 I_{p_1} & 0 \\
    0 & w_2 I_{p_2} \\
    \vdots & \vdots \\
    0 & w_m I_{p_m}
\end{pmatrix} \]

where \( I_{p_i} \) is the identity matrix of size \( p_i \) and \( w_i \) is the weight associated to joint \( J_i \). We define the length of the straight interpolation between two configurations as:

\[ ||\mathbf{q}_2 - \mathbf{q}_1||_W \triangleq \sqrt{(\mathbf{q}_2 - \mathbf{q}_1)^T W^2 (\mathbf{q}_2 - \mathbf{q}_1)} \]

Weights are used to homogenize translations and rotations in the velocity vector. For rotations, the weight is equal to the maximal distance of the robot bodies moved by the joint to the center of the joint.

Given \( \mathbf{q}_0 \) and \( \mathbf{q}_{wp+1} \) fixed, the cost we want to minimize is defined by

\[ C(x) \triangleq \frac{1}{2} \sum_{i=1}^{wp+1} \lambda_i ||\mathbf{q}_i - \mathbf{q}_{i-1}||^2_W \]

where the \( \lambda_i \) coefficients benefit will be explained in the results section. For now we can assume that \( \forall i, \lambda_{i-1} = 1 \).

Note that \( C \) is not exactly the length of the path, but it can be established that minimal length paths also minimize \( C \). This latter cost is better conditioned for optimization purposes.
D. Resolution

We assume that the direct interpolation between the initial and final configurations contains collisions. Let \( H \) denote the constant Hessian of the cost function, an iteration is described as follow:

\[
\mathbf{p}_{i+1} = -H^{-1} \nabla c(x_i)^	op
\]

\[
x_{i+1} = x_i + \alpha_i \mathbf{p}_{i+1}
\]

where \( \alpha_i \) is a real valued parameter. Taking \( \alpha_i = 1 \) yields the unconstrained minimal cost path, i.e. all waypoints aligned on the straight line between \( q_0 \) and \( q_n+1 \). Since this solution is in collision, we set \( \alpha_i = \alpha \) where \( \alpha \) is a parameter that will be explained in the algorithm section.

We iterate step (1) until path \( x_{i+1} \) is in collision. When a collision is detected, we introduce a constraint and perform a new iteration from \( x_i \) as explained in the next section. We use a continuous collision checker inspired of [19] to validate our paths and to return the first colliding configuration along a path. This step corresponds to validatePath in Algorithm 1.

E. Constraints

Let \( T \) be a positive real number such that each path \( x_i \) is a mapping from interval \([0, T]\) into \( \mathcal{C}: x(0) = q_0, x(T) = q_{n+1} \) for all \( i \). Let us denote by \( t_{coll_i} \) the abscissa of the first collision detected on path \( x_{i+1} \), which previous iteration \( x_i \) was collision-free (see Figure 3). Thus in configuration \( x_{i+1}(t_{coll_i}) \) a collision has been detected. Two cases are possible:

1) the collision occurred between two bodies of the robot: \( B_1 \) and \( B_2 \), or

2) the collision occurred between a body of the robot \( B_1 \) and the environment.

In the rest of this section, we will only consider the first case. Reasoning about the second case is similar, except that the constraint is on the transformation of \( B_1 \) with respect to the environment.

Let \( M^* \in SE(3) \) denote the homogeneous transformation between frames of \( B_1 \) and \( B_2 \) in configuration \( x_i(t_{coll_i}) \). Let \( M \in SE(3) \) denote the same transformation in configuration \( x(t_{coll_i}) \) where \( x \) is any path in \( \mathcal{C}^{wp} \). Let \( R \in SO(3) \) (resp. \( R^* \)) and \( t \in \mathbb{R}^3 \) (resp. \( t^* \)) be the rotation and translation parts of \( M \) (resp. \( M^* \)). See also Figure 4 for notations.

We denote by \( F \) the mapping from \( \mathcal{C}^{wp} \) to \( \mathbb{R}^6 \) defined by

\[
F(x) = \left( \frac{R^*(t^* - t)}{\log(R^* R^*)} \right)
\]

\( \log(R^* R^*) \) represents here a vector \( v \) of \( \mathbb{R}^3 \) such that \( R^* R^* = e^v \). Note that \( F \) vanishes for any path \( x \) such that in configuration \( x(t_{coll_i}) \) the relative position of \( B_2 \) w.r.t. \( B_1 \) is equal to \( M^* \). Let \( r \) denote the radius of the bounding sphere of \( B_2 \) centered at the origin of \( B_2 \) local frame. Let us denote by \( d \) the minimal distance between \( B_1 \) and \( B_2 \) in configuration \( x_i(t_{coll_i}) \). We have the following property.

**Property 1:** Let \( x \in \mathcal{C}^{wp} \) be a path and let us denote by \( t \) and \( v \) respectively the 3 first coordinates and the 3 last coordinates of \( F(x) \). If

\[
\|t\| + r\|v\| \leq d
\]

then in configuration \( x(t_{coll_i}) \) \( B_1 \) and \( B_2 \) are collision-free. The proof is straightforward: expressed in reference frame of \( B_1 \), the motion of \( B_2 \) between configurations \( x(t_{coll_i}) \) and \( x_i(t_{coll_i}) \) is a translation of vector \( t \) followed by a rotation of angle \( \|v\| \). No point of \( B_2 \) has moved by more than \( \|t\| + r\|v\| \). Therefore no collision is possible.

When a collision is detected at \( t_{coll_i} \) along path \( x_{i+1} \), we wish to add constraint

\[
F(x) = 0
\]

However, as this constraint is non-linear, we linearize it around \( x_i \):

\[
\frac{\partial F}{\partial x}(x_i)(x - x_i) = 0
\]

for any later iteration \( x_j \), \( j \geq i+1 \).

We refer to [20] for solving constrained quadratic programs (QP). This corresponds to computeIterate in Algorithm 1.

F. Relinearization of constraints

As constraint (3) is not exactly enforced, but linearized, a new collision may appear at \( t_{coll_i} \) on a later iteration between \( B_1 \) and \( B_2 \). To avoid this undesired effect, we check the values of all the constraints at each iteration. The constraints
that fail to satisfy Property 1 are relinearized around the latest valid path \( x_k, k > i + 1 \), as follows:

\[
\frac{\partial F}{\partial x}(x_k)(x - x_k) = -F(x_k)
\]

This step is performed by solveConstraints in Algorithm 1.

**G. Algorithm**

In this part we describe the path-optimizer Algorithm 1 according to the previous step definitions. The main difficulty here is to handle the scalar parameter \( \alpha \) determining how much of the computed step \( p \) will be traveled through, and also to return a collision-free path. Typically, we chose \( \alpha_{init} = 0.2 \) to process small steps. \( \alpha_{init} = 0.5 \) is more encountered in the optimization literature, procuring larger steps but with more risks of collision.

**Algorithm 1** Gradient-based path-optimization.

```plaintext
1: procedure OPTIMIZE(x0)
2: \( \alpha \leftarrow \alpha_{init}; \epsilon \leftarrow 10^{-3} \)
3: minReached \leftarrow false
4: validConstraints \leftarrow true
5: while (not(noCollision and minReached)) do
6: \( p \leftarrow \text{computeIterate}() \)
7: minReached = (||p|| < \epsilon or \( \alpha = 1 \))
8: \( x_1 \leftarrow x_0 + \alpha p \)
9: if (\( \alpha \neq 1 \)) then
10: if (not(solveConstraints(x_1))) then
11: \( \alpha \leftarrow \alpha * 0.5 \)
12: validConstraints \leftarrow false
13: else
14: validConstraints \leftarrow true
15: if (not(validatePath(x_1))) then
16: noCollision \leftarrow false
17: if (\( \alpha \neq 1 \)) then
18: addCollisionConstraints()
19: \( \alpha \leftarrow 1 \)
20: else
21: if (validConstraints) then
22: \( \alpha \leftarrow \alpha_{init} \)
23: else
24: \( x_0 \leftarrow x_1 \)
25: noCollision \leftarrow true
26: \( \alpha \leftarrow 0.5 * (1 + \alpha) \)
27: return x0
end procedure
```

Each time a collision-constraint is added, the solution of the current QP is tested (i.e. \( \alpha = 1 \)). If this path is collision-free, the algorithm returns it as the solution (lines 7-25). Otherwise, smaller steps are iteratively applied and tested toward the minimum (lines 21-22), and constraints are added each time a collision is found (line 18).

If the constraint relinearization fails to validate Property 1, \( \alpha \) is halved and the algorithm restarts from the latest valid path (lines 10-12).

**IV. RESULTS**

This part gathers optimization results performed on the planning software Humanoid Path Planner [21]. The initial trajectory is obtained with two kind of probabilistic planners: Visibility-PRM [22] and RRT-connect [23].

**A. From 2D basic examples...**

Figure 5 shows several iterations of our optimizer on 2D cases. Since in this special case, transformation constraints are equivalent to compulsory configurations to pass through, we can verify that our optimized path is applying all computed constraints. We can also understand which collisions have led to the constraints.

Besides, these examples give a better understanding of how the tuning of \( \alpha \) has to balance lot of iterations and relevant collision-constraint addition. For example, if we alter a lot the initial path with a large gradient step and compute the corresponding collisions, constraints will be chosen on a very-not optimal path and will not be pertinent w.r.t. the obstacles we wanted to avoid.

Figure 5 illustrates a path example that random shortcut will not manage to optimize in an affordable time, because of probabilistically failing to sample configurations in the box. Our gradient-based algorithm succeeds to optimize the path contained in the box, with the following cost coefficients

\[
\lambda_{i-1} = \frac{1}{\sqrt{(q_i - q_{i-10})^2 + 2W^2(q_i - q_{i-10})}}
\]
aiming at keeping the same ratio between path segment lengths at minimum as at initial path, represented by
the waypoints \( (q_{10})_{1\leq n+1} \). Without these coefficients, the path
that minimizes the cost corresponds to a straight line with
the waypoints equidistantly allocated, which is not adapted
for the Figure 6 type of problems with a local passage very
constrained by obstacles. Note that this cost is also working
with all other examples presented in this paper.

B. To 3D complex problems

We also experiment our algorithm on more complex
robots, with transformation collision-constraints. Unless an-
other value is given, \( c_{\text{max}} \) is set to 0.2.

In the included video, we present four situations where
our algorithm has been tested and compared to random
shortcut [24] (Algorithm 2). The termination condition of
random shortcut allows it to try shortening the path until 5
iterations of non-improvement are reached (corresponding
to \( \text{maxNbFailures} \) in Algorithm 2).

On the 5-DOF double-arm problem, one arm has to get
around an obstacle while the other is relatively far from
obstacles. As expected, the initial path given by RRT-connect
activates both arms to solve the problem. Contrary to random
shortcut, our optimizer manages to cancel the rotation of
the free-arm while optimizing the first arm motion. Initial path
length 5.17 has been decreased to 4.55 by random shortcut
and to 3.20 by the gradient-based optimizer.

For the following example with a 6-axis manipulator arm
in a cluttered environment, path reduction only manages
to reduce some but not all detours. This behavior can be
explained by a path over-constraining due to the important
proximity of the robot to the obstacles during the whole
path, and because there are not so many DOF to play on
to easily avoid collisions and return a small-cost solution.
We advance this explanation because on the two following
high-DOF examples of the video (and Figure 1), results are
better in terms of path length and quality.

In the example presented Figure 1 and in the video, the
mobile 40-DOF PR2 simply has to cross its arms from the
left arm up position to the right arm up one. Lengths of
the initial path, the random shortcut optimized path and the
gradient-based optimized path are respectively 14.5, 6.34 and
3.62. The RRT-connect planner returns detours and activates
non-useful DOF such as the head, the torso lift and the
translation on the ground. Once again, random shortcut will
hardly optimize the mobile base translation of the robot
and other unnecessary DOF such as the head, the torso lift and the
translation on the ground. Once again, random shortcut will

B. To 3D complex problems

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and other unnecessary DOF such as the head, the torso lift and the

```
Algorithm 2 Random shortcut as adapted from [8] Section 6.4.1. steeringMethod returns the linear interpolation
between two configurations. \( x_p \) denotes path \( x \) restricted to interval \( I \).
\( \text{maxNbFailures} \) is a parameter that affects time of computation and quality of the result.

1: procedure RANDOMSHORTCUT(x)
2:   nbFailures ← 0
3:   while nbFailures < maxNbFailures do
4:     failure ← true
5:     if \( T < \text{upper bound of } x \text{ definition interval} \) then
6:       \( l_p0 \) ← steeringMethod(\( x(0), x(t_1) \))
7:       \( l_p1 \) ← steeringMethod(\( x(t_1), x(t_2) \))
8:       \( l_p2 \) ← steeringMethod(\( x(t_2), x(T) \))
9:       newPath ← empty path defined on \([0, 0]\)
10: if \( l_p0 \) is collision-free then
11:     newPath ← \( l_p0 \); failure ← false
12: else
13:     newPath ← \( x(t_1) \)
14:     if \( l_p1 \) is collision-free then
15:       newPath ← concatenate(newPath, \( l_p1 \))
16:     failure ← false
17:     else
18:       newPath ← concatenate(newPath, \( x(t_1, t_2) \))
19:     if \( l_p2 \) is collision-free then
20:       newPath ← concatenate(newPath, \( l_p2 \))
21:     failure ← false
22:     else
23:       newPath ← concatenate(newPath, \( x(t_2, T) \))
24:     if failure then nbFailures ← nbFailures + 1
25:   end procedure
```
Thus the problem addressed in Figure 2 is solved considering the optimization of path lengths for mobile manipulation tasks. However, the extinction of the mobile base motion in the gradient-based optimizer is advanced in the right column of Table II. Thus our method presents similar computation times and achieves better results.

V. CONCLUSIONS

We managed to settle a path optimization for decoupled-DOF robots such as mobile manipulators. Our algorithm uses standard numerical tools as collision checking and QP resolution, and correlates them in a simple but effective way, playing on the scalar iteration parameter. Therefore, our method only require few distances computation, so geometry pre-processing or offline optimization are not necessary to remain time competitive. We demonstrate that the optimizer is time-competitive comparing to random shortcut and proposes better quality paths for high-DOF robots, removing unnecessary DOF motions. Our optimizer also manages to reduce a local detour in a long path while random shortcut methods will mostly fail.

The experimental results show that transformation constraints may in some cases be overconstraining. We also tried distance constraints without much success due to the non-continuous differentiability of distance. In a future work, we will study other one-dimensional constraints in order to achieve better results.

REFERENCES


<table>
<thead>
<tr>
<th></th>
<th>Computation time</th>
<th>Path length</th>
<th>Traveled distance by the base</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial</td>
<td>13.7</td>
<td>10.9</td>
<td></td>
</tr>
<tr>
<td>Gradient-based</td>
<td>781ms</td>
<td>3.69</td>
<td>10⁻⁶</td>
</tr>
<tr>
<td>Random shortcut</td>
<td>823ms</td>
<td>3.82</td>
<td>2.94</td>
</tr>
</tbody>
</table>

Table II: Results for 30 runs of the PR2-crossing-arms example. For each run, a solution path is planned by Visibility-PRM as initial guess for each optimizer. α_out is set to 0.2. The right column represents the distance that is traveled by the robot mobile base during the path.