# Deformable Linear Object manipulation planning with contacts

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*Abstract*— **We consider the manipulation planning problem of a Deformable Linear Object (DLO) in free or contact space. We assume the DLO is handled by a gripper at one of its extremities and during the manipulating phase, the grasped end may change. The problem is solved by coupling dynamic simulation for the DLO and kinodynamic motion planning with contacts. We show the necessity of considering contacts for this type of problem with several simulation experiments by comparing with classical collision-free approaches.**

## I. INTRODUCTION

Motion planning plays an essential role in assembling and disassembling industrial cases. Approaches [15] have been proposed to the extension of this problem to robots manipulating movable rigid objects among rigid obstacles. Moreover, in the automotive or aeronautical industry, manipulating deformable parts is necessary. In this context, most of these consist in DLOs which are characterized by having one dimension much greater than the other two (cable, hose, pipe,...). In this paper, we consider the manipulation planning problem of a DLO in free or contact space. We assume the DLO is handled by a gripper at one of its extremities and the grasped end may change during the manipulating phase.

As DLO can be geometrically interpreted as an infinite-dimensional continuous curve, planning in the discretization of this curve may lead to high finite-dimensional configuration space. Furthermore, identifying the manifold of feasible configurations, i.e. which satisfy mechanical constraints, on this configuration space might not be straightforward.

Some work has been done using the reasonable assumption of considering only the collision free space of quasi-static configurations. These approaches are based on the numerical minimization of the total elastic energy for given gripper placements [8], [11], [17]. Recent results based on the local solution of a geometric optimal control problem enabled to define this configuration space [3], where it is shown this space defines a finite dimensional manifold that can be parameterized by a single chart. Based on these results, we presented how this parameterization can be efficiently used with sampling-based methods in collision-free space [13].

An approach to the manipulation planning considering dynamics of the DLO and contacts is to plan in the finite space of controls for a given number of grippers. In this case, the state transition function is assumed to be known and can be delegated, for example, to a simulator. For a physically realistic DLO model, these might use complex finite elements methods resulting in computationally expensive local planning schemes. For instance, the motion planning problem for deformable objects has been addressed in [12] which coupled a deformable dynamics model with a kinodynamic motion planning algorithm. However, the use of fully deformable environments prevents the robot to be stuck in local minima and bypasses the local control problem.

In [14], the manipulation planning problem of a DLO is adressed from a topological perspective by focusing on knot tying application with the help of many passive or active grippers.

More generally, the motion planning problem for deformable objects has already been investigated, especially in the case of simplified visually realistic deformation models. For example, [2] extendeded the Probabilistic Roadmap Methods (PRMs) [1] for deformable objects by reducing the deformation space to a one dimensional one. In [5], Gayle et al. used the Constraint Based Motion Planning framework to simulate a deformable robot along a guide path computed for a point-like robot. This work has then been extended to the specific class of DLOs in [6].

On the other side, great progress has been done in simulating deformable objects, for example eXtented Dynamics Engine (XDE) [10] is a physics simulation software environment fully developed by CEA-LIST for realtime application in haptic context.

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## II. OUR APPROACH

The problem addressed in this paper is to find a feasible solution to the manipulation planning problem for a DLO using dynamics and by allowing contacts. In this context, we rely on a realistic DLO dynamics simulation using the XDE engine and we must couple it with sampling-based motion planning methods such Rapidly-exploring Random Trees (RRTs).

The basic idea is to limit the number of calls to the simulator and to take advantage of provided information, such as contact forces. The algorithm must share the use of XDE for local step simulation with the roadmap extension of RRT. By allowing contacts between the deformable object and obstacles, we will show we increase the deformation space and we can efficiently handle constrained environments, i.e. having a very poor $\epsilon - goodness$ [7], and narrow passages by sliding along the contact space.

### A. The physical engine XDE

XDE offers a realistic multi-body dynamics simulation with various kinematics constraints (e.g. joints, kinematic loops) and with real-time performances. In addition to rigid bodies and kinematic chains, it can also handle deformable bodies such as DLOs, modeled as geometrically exact 3D beams. This model enables large displacements thanks to Reissner kinematics and uses geometrically exact finite elements.

Furthermore, XDE can also handle non-smooth contacts accurately with friction (e.g. using Coulomb law) with constraints based methods. This type of simulators is well suited for interactive applications but the simulation cost is typically very high making their integration with motion planning algorithms difficult.

### B. Kinodynamic motion planning

Consider a DLO parameterized by $s \in [0,1]$, its configuration $q(s)$ can be represented by the mapping $q : [0,1] \rightarrow SE(3)$. The resulting configuration space $\mathcal{C}$ would be a sub-manifold of the infinite dimensional space $SE(3)^{\infty}$. As the DLO is discretized by XDE using FEM into $N-1$ elements (thus $N$ nodes), the actual configuration space will be a sub-manifold of $SE(3)^N$. We will note the state space of the DLO by $\mathcal{X}$, i.e. the set of all states defined by $x = \begin{pmatrix} q_1 & \dot{q}_1 & \dots & q_N & \dot{q}_N \end{pmatrix}^T$.

Recently, this manifold has been identified for quasi-static elastic rods without contacts [3]. However, to the best of our knowledge, we are still unable to extend this result to dynamic rods with contacts.

As shown in [9], RRTs can be extended to handle kinodynamics constraints of the system. Ideally, we need to keep the Voronoi-bias property for the state space. This would requires to provide three methods:

- **A state sampler for the DLO.** As we mentioned previously, we are still unable to identify the manifold of dynamic states with contacts for a physically realistic DLO. Consequently, it seems complicated to sample states for the DLO and more especially to perform uniform sampling on this manifold.
- **A local planner for moving between two states.** Given two states $x_{near}$ and $x_{rand}$, the aim of the local planner would be to give the sequence of control $\tilde{u}_{loc}$ for the system to go from $x_{near}$ to $x_{rand}$. In practice, it must be fast and able to reach the state $x_{rand}$ with a low error. However, in our case of dynamic DLO with contacts, we do not have a complete local planning method for finding a trajectory between two states.
- **A metric on the state space.** Although good metric between two configurations of a DLO could be obtained in many ways (e.g. considering swept volume), finding a good metric when working in a state space is generally more complex. This could be provided by the local planner using the cost to go between states as measure of energy for example.

In the opposite, a naive random control sampling would be to choose a control for a given gripper in the space of admissible wrenches. Then this control would be integrated for a given amount of time (typically also chosen randomly). However, such approach leads to an inefficient exploration of the state space as we would loose the Voronoi-bias property of the RRT. Indeed, as shown in [9], the resulting tree would actually have a strong bias toward already explored regions. The inefficiency of this approach has been experimentally verified in our case.

Instead of planning directly in this control space, we chose as an alternative to plan in the space of quasi-static configurations of the gripper. Under this assumption, the state sampling is straightforward (we sample a position and orientation in $SE(3)$) and the local planner can be achieved with a controller for the gripper. To this end, XDE provides smooth bodies interactions mechanisms as Proportional-Derivative coupling for a given body position. This can be applied to a system where the gripper, a rigid body, is grasping the cable. In our local planner, the controller minimizes the error between current position and velocity of the gripper and its desired position at null speed (see II-C).

To avoid confusion, we will note by $\mathcal{B}$ the space on which we perform sampling, i.e. the set of all states $b$, where

$$b = \begin{pmatrix} b_{pos} \\ b_s \end{pmatrix} \text{ with } \begin{cases} b_{pos} \in SE(3) \\ b_s \in \{0,1\} \end{cases}$$

Here $b_{pos}$ is the position of the gripper in the workspace and $b_s$ is the position of the gripper along the DLO. Note we restricted $b_s$ to be a discrete Degree of Freedom (DoF) for our needs, but this could be generalized to any position $s \in [0,1]$. The sampling space $\mathcal{B}$ is then 7-dimensional.

This approach can be seen as an compromise between the two previously mentioned and enables us to keep a good exploration of the state space.

### C. Motion planning framework

At the local planning level, the physics engine XDE can provide the state transition model $x_{k+1} = f(x_k, u_k)$ for a DLO at step $k$. The given control $u_k$ represents external forces and torques applied on a given gripper of the DLO. At the local planning level, XDE provides a simulator and a PD controller which computes for a given DLO state $x_{from}$ and a sampled gripper state $b \in \mathcal{B}$ the sequence of controls $\tilde{u}_{loc}$ to reach the resulting state $x_{to}$. Let $g_{pos} : \mathcal{X} \times \{0,1\} \rightarrow SE(3)$ be defined as

$$\begin{cases} q_1 \text{ if } b_s = 0 \\ q_N \text{ if } b_s = 1 \end{cases}$$

In other words, the mappings $g_{pos}$ represents the position of the desired gripper.

The desired position of the gripper $b_{pos}$ is related to the DLO state $x_{to}$ by

$$b_{pos} H_g = g(x_{to}, b_s)$$

where $H_g \in SE(3)$ is the position of DLO at $g(x_{to}, b_s)$ relatively to the gripper frame and is assumed known and fixed (see figure 1).

As shown in figure 1, the PD controller minimizes the error between the current gripper position $p$ and velocity $v$ and the desired gripper position $b_{pos}$ described by $b_s$ at null speed.

From the global view and as shown in figure 2, the output to the manipulation planning problem is the trajectory $\pi_{sol}$ :

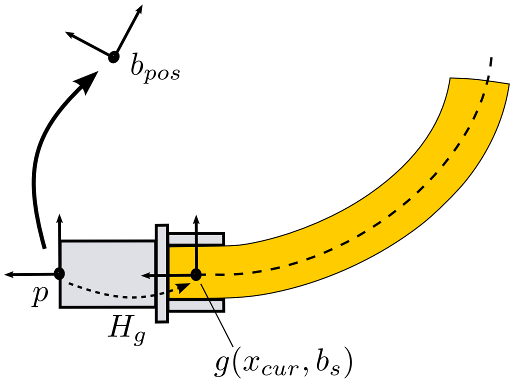


Fig. 1. Illustration of the PD coupling between the gripper (in grey) current position $p$ and its desired position $b_{pos}$. The current actuated end of the DLO (in yellow) given by $b_s$ can be expressed from $p$ using the known and fixed transformation $H_g$. Note the positions of the DLO are given along its centerline.

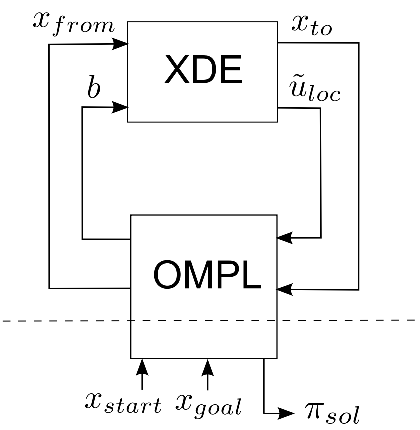


Fig. 2. Overview of the motion planning framework. Upper (resp. lower) part represents the local (resp. global) planning level.

$[0, T] \rightarrow U \times \{0, 1\}$ of duration $T$. This trajectory brings the initial DLO state $x_{start}$ to the desired state $x_{goal}$.

As the system is underactuated, we more exactly consider a goal region $X_{goal} \subset \mathcal{X}$ rather than a goal state. In our case of study of disassembly studies, this actually makes sense as the start state is well defined and the goal is typically a roughly defined state, or more formally a subset of the state space. The case of assembly studies is the symmetric problem with a start region and a well defined goal state and can addressed in the same way by processing backwards.

This local approach can be coupled with any Motion Planning library and we chose OMPL [16] in our implementation.

### D. Detailed planning algorithm

The algorithm presented in Algorithm 1 gives a general view of the kinodynamic manipulation planning algorithm we implemented.

The pseudo-metric used in the NEAREST function returns the distance in $SE(3)$ between the gripper setpoint given by $b_{pos}$ and the corresponding position on the DLO $g(x_{near}, b_s)$.

The PD controller for the gripper terminates if the goal $b_{pos}$ is reached at null speed (i.e. if the error is below a threshold) or after a given amount of simulated time, avoiding the system to be stuck in local minima.

**Algorithm 1** Kinodynamic RRT for a DLO ($x_{start}$, $X_{goal}$)

```
Initialize the tree 𝒯 with x_start
while ¬ solved and iter < N_max do
    b ← random gripper state ∈ ℬ or goal position
    x_near ← NEAREST(𝒯, b)
    Set gripper at position b_s
    Initialize controller for gripper with goal b_pos
    while not controller done do
        Step simulator for Δt
    end while
    Add current state x_cur to 𝒯
    Add edge (x_near, x_cur, ũ_loc)
end while
```

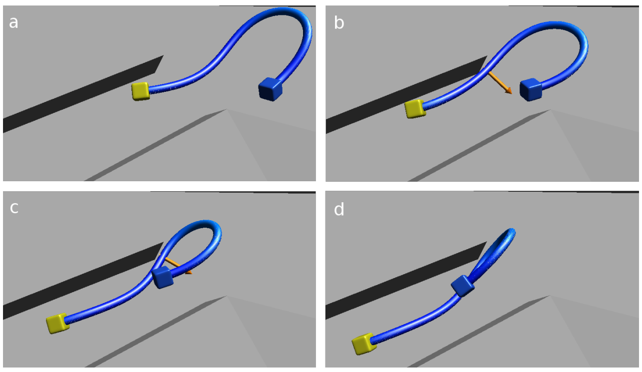


Fig. 3. Local planning sliding motion of the DLO (in blue) along an obstacle. Normal forces are shown as orange arrows. The yellow extremity represents the actuated one for this motion, i.e. where the gripper is.

### E. Planning with contacts

At each simulation step, the PD controller computes the corresponding wrench and applies it on the gripper. As the gripper moves, the DLO follows and may slides along obstacles (see figure 3).

As most of the motion planning problem formulation states the configurations must lies in set of collision free configurations $\mathcal{C}_{free}$, it is well known that the exploration of classical sampling-based algorithms is very sensitive to the $\epsilon - goodness$ of the considered space. Although requiring only collision-free configurations can be an expectation, we believe it is most commonly used as planning with the contact-space is still a challenging problem. However, taking advantage of the contact can also guide the exploration by allowing the tree to slide along the contact space.

Some work already underlined the importance of environmental constraints for other related problems such robotic grasping [4].

Even if it may seems obvious, we emphasize that without contacts some manipulation planning scenarios for a DLO cannot be solved. Indeed, as contacts add constraints to DLO dynamics, it actually increases its deformation space

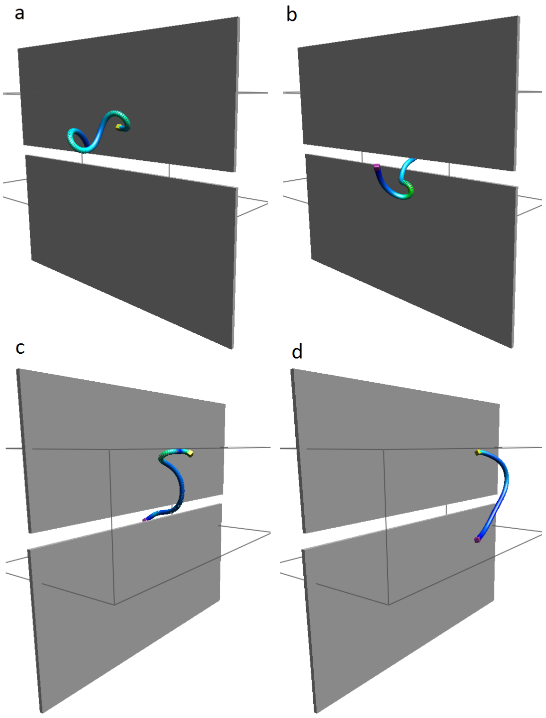


Fig. 4. Solution path for the "crack" toy scenario. The DLO starts from the front side of the crack (a and b) and goes to the back side (c and d).

by allowing new states that could not be reached without contacts.

We will show in the results that allowing the contact space substantially changes the efficiency of our algorithm.

## III. RESULTS

In this section, we will present some simulation experiments of DLO manipulation and will show how the use of contacts can dramatically improves the planning time.

We show the effectiveness of our approach on four scenarios:

- The **backward** scenario (figure 6). On this toy scenario where the main difficulty consists in reversing the DLO orientation between start ang goal orientations. In this case, an approach where first planning for the DLO head would fail.
- The **crack** scenario (figure 4). A toy scenario consisting in an two empty spaces connected by a crack through a wall, presenting a typical narrow passage for a DLO.
- The **hole** scenario (figure 5). A similar toy scenario, but here the two empty spaces are connected by a hole through a wall, making a longer and thus generally harder narrow passage for a DLO.
- The **engine** scenario shown (figure 7) corresponding to a concrete industrial disassembly study for the cable. The model consists in 132K faces and 65K vertices. This is a typically highly constrained scenario, presenting many narrow passages.

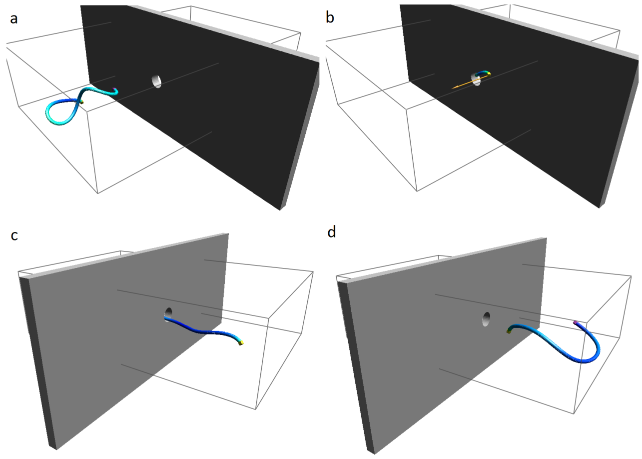


Fig. 5. Solution path for the "hole" toy scenario. As in for the "crack" scenario, the DLO starts from the front side of the hole (a and b) and goes to the back side (c and d).

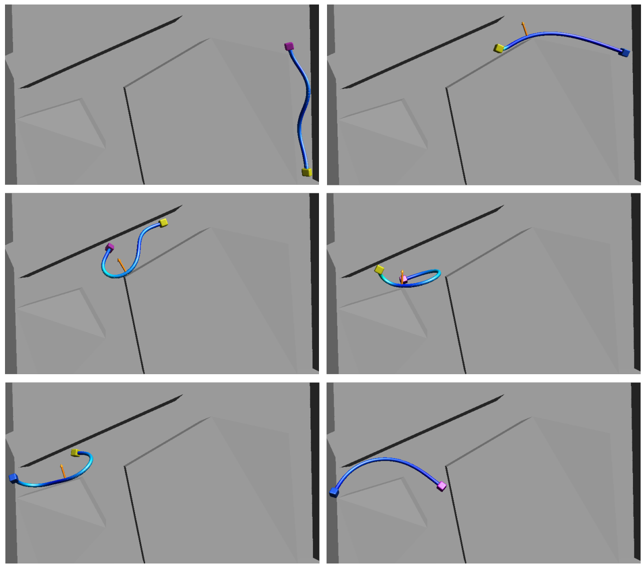

Fig. 6. Solution path for the "backward" toy scenario. Note the head (in magenta) position of the DLO on both start (a) and goal (f) states.

Each scenario has been run 50 times with a limit in time of 30 minutes and in memory of 4GB. All the benchmarks were run on a PC with 16GB of main memory and using one core of an Intel Core i7-2720QM processor running at 2.2GHz.

Results the manipulation planning of the DLO with contacts are shown in table I. Resolution time and number of generated states are given with as an average and a standard deviation.

- The sensitivity to the $\epsilon - goodness$ of the state space if low comparatively to collision free approaches. The interested reader may refer to [13] where a more classical collision free approach has been applied on some similar scenarios.
- The number of generated nodes in the roadmap is relatively low, implying a good exploration rate of the

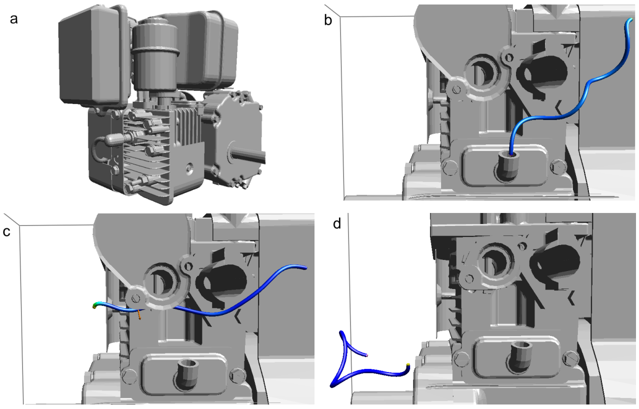


Fig. 7. The "engine" model (a) and a solution path (from b to d) where b (resp. d) shows the start (resp. goal) state. Note that on solution paths figures (b to d), the model view has been clipped for clarity.

TABLE I
PLANNING WITH CONTACTS RESULTS

| Scenario | Success rate | Resolution time (in seconds) | Number of generated states |
|---|---|---|---|
| crack | 100% | $35.7 \pm 26.5$ | $106 \pm 78$ |
| hole | 100% | $93.1 \pm 142.2$ | $147 \pm 226$ |
| backward | 100% | $97.6 \pm 296.9$ | $211 \pm 635$ |
| engine | 92% | $251.2 \pm 276.1$ | $39 \pm 43$ |

algorithm.

As a comparison, we implemented a variant of the presented algorithm that does not allow contacts. When staying in the collision free space, none of the scenario could be solved. The exploration rate is much more slower as the number of generated nodes at the timeout is generally up to tens of thousands. This is mainly due to the fact that generated states close to the contact space are more likely to fail exploring the free space.

## IV. CONCLUSION

In this paper, we proposed a motion planning method that solves the manipulation planning problem, i.e. finds sequence of manipulation controls, for a Deformable Linear Object. The proposed planner builds a roadmap in the state space and uses contact motions to handle efficiently highly constrained spaces. Results show allowing states in contact improves significantly the planning time and can be necessary for the completeness of some scenarios, as it increases the deformation space of the DLO. We underlie the importance of considering the contact space in the motion planning problem, especially for systems such as deformable bodies.

In future work, we plan to take advantage of contact forces provided by the simulator to guide the motion planning algorithm.

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