Toward a kinetically-aware motion planning for robotic cutting on arbitrary surfaces

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***Abstract*— This paper proposes a method for constrained motion planning using vision and the kinematics of the arm, given a start and destination points. No prior knowledge of the surface shape, but observes it from a noisy point cloud is assumed. We address the multi-optimisation problem of finding trajectories which maximises the robot's manipulability throughout the motion while minimising surface-distance travelled between the points. We show how detours in the cut path can be leveraged, to increase the manipulability of the robot at all points along the path. We show how a sampling-based planner can be projected onto the Riemannian manifold of a curved surface, and extended to include a term which maximises manipulability. We present results on two different surfaces shapes. Our planner enables successful task completion while avoiding singularities and ensuring significantly greater manipulability when compared against a conventional RRT* planner.**

I. Introduction

Robotic cutting operations rise an interest problem of motion-planning for a serial arm. The robot must touch the cutting surface with the end-effector and apply forces to split into pieces the original object. The surface, where the interaction lies, can be regarded as a manifold upon which the tool must follow a trajectory between a point A and a point B, while a forces are applied throughout the motion.

Our work addresses the issues of application such as the cleanup of legacy nuclear waste [1], and emergency operations such as bomb-disposal, fire-fighting and disaster-response [2]. In these scenarios, the main concern is the cutting of containers for inspection. Therefore, an exact cutting path is not important as long as the robot successfully cut open the barrel. However, the hazardous environments where such applications are performed introduce significant perturbations that might compromise the task. Vision noise, uncertain properties on the material to cut, and robot model inaccuracies are only a few examples of problems to face during the operations. Many works research how to plan paths in either constrained and uncostrained scenarios [3], [4]. However, a little body of literature investigate the problem using the kinematic of the robot [5]. Tackling the uncertainties considering the kinematic allows the path to be more robust to unforeseen problems throughout the execution. By this means, we would like the robot to *have sufficient manipulability to provide capacity for responding compliantly to such perturbations*, while following a desired cutting path. We introduce a modified cost which is the sum of a "manipulability" cost along the path scaled by the number of the elements in the path and a cost of "distance" from the starting point.

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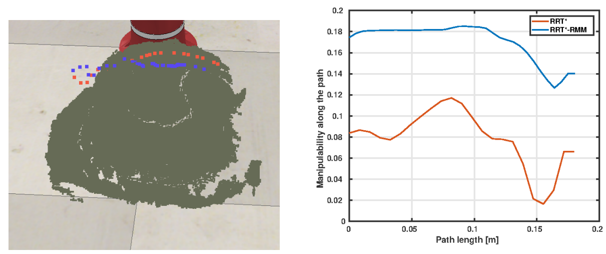

(a) (b)

Fig. 1. The image shows the results of RRT* (red) and RRT*-RMM (blue) on a helment. Fig.1(b) depicts the manipulability of the two paths. A little discrepancy between paths and pointcloud is due to visualisation purposes.

II. Problem formulation

We use RRT* to implement the proposed metric and generate a path from point A to point B. The cost function accounts for the manipulability of the robot throughout the motion and the distance upon the surface between A and B. Moreover, we incorporate *Riemannian manifold mapping* into our approach to generate samples that lie on the point cloud of the object. As such, our approach is called "RRT*-RMM" which stands for RRT* with added Riemannian Manifold mapping and added Manipulability cost.

Rapidly-exploring Random Tree:* Rapidly-exploring Random Tree (RRT) is arguably one of the most common sampling-based path planners, [4]. RRT samples points within a region of interest and adds them in a tree structure based on a distance metric. Every iteration, the algorithm generates a new point based on some motion constraints and, then, connects it to the closest node in the tree. RRT* is an extension to the classical RRT proposed in [6], which allows the re-evaluation of nodes already in the tree when a new point is available.

Manipulability: The manipulability of the robot measures the remaining capability of the robot of making a movement - or applying forces - given a specific configuration, $\boldsymbol{q} \in \mathbb{R}^n$ with n number of degrees of freedom (dof) of the robot. Constraining the joints' velocities to be unitary, we obtain

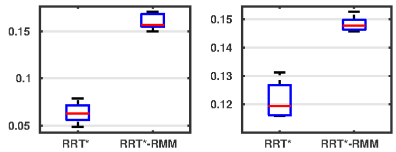

Fig. 2. Box plot of the manipulability values obtained by RRT* and RRT*-RMM for all four objects. Left) helment, Right) curved surface.

$|\dot{\boldsymbol{q}}| = \dot{\boldsymbol{r}}^{\boldsymbol{T}}\boldsymbol{\Gamma}^{\dagger}\dot{\boldsymbol{r}} = \mathbf{1}$, where $\boldsymbol{r}$ is robot description in the Cartesian space, $\boldsymbol{J}$ is the Jacobian of the robot, and † is the pseudoinverse (or inverse if $\boldsymbol{J}$ is square) of the Jacobian. The matrix $\boldsymbol{\Gamma}$ embeds the information about the manipulability of the robot as a function of a configuration $\boldsymbol{q}$. The conventional approach to measure the manipulability, [7], is defined as the square root of the determinant of $\boldsymbol{\Gamma}$.

Riemannian Manifold: Computing distances between points is not straightforward on curved surfaces. A Riemannian Manifold is a smooth manifold equipped with an inner product on the tangent space of each point $\boldsymbol{p}$ onto the manifold, which changes smoothly from point to point and its vector spaces are differentiable. The spaces endowed with a Riemanian manifold can map the points on the manifold with a tangential plane using two maps called logaritmic $L = \log_p(\Delta)$, and exponential map $\Delta = \exp_p(L)$, with L onto the tangent plane and Δ onto the manifold.

Proposed method RRT-RMM:* Our algorithm performs a multi-optimisation between length and manipulability throughout the path as per Eq. (1).

$$C(\boldsymbol{p}) = (1-\alpha)C_d(\boldsymbol{p}, \boldsymbol{p_S}) + \alpha C_{\boldsymbol{M}}(\boldsymbol{q}_p) \qquad (1)$$

where C_d is the distance cost for reaching $\boldsymbol{p}$ from $\boldsymbol{p_S}$ (starting point) and $C_{\boldsymbol{M}}$ is cost for the manipulability along the path with last configuration $\boldsymbol{q}_p$ (it is computed with Inverse Kinematic by $\boldsymbol{p}$). The manipulability cost is computed over the path, we sum the manipulability index presented by Yoshikawa [7] from the starting point to the current one and we weigh the sum with the number of step in the path. We implement the cost into the sample based RRT* framework. We want the path to lie on a surface, which is given using a point cloud and we sample points from it to build the tree. Points sampled onto the tangent space of $\boldsymbol{p}$ onto the manifold can be projected onto the original manifold thanks to the exponential map.

III. Experimental results

We test our approach on two different surface shapes a helmet and curved object. In our experiment, we use a simulated 7-dof Sawyer robot and we task the algorithm to find paths onto the objects with the best compromise between overall manipulability and length. Fig.1(a) shows the result for the experiment on the helmet. The graph in 1(b) shows the manipulability attained with our method in comparison with a naive RRT* which looks for the shortest path between the points A and B. Because the RRT* is a sample-based approach, we need to run many times the same algorithm to check whether the results are consistent over iterations or just by serendipity. We collect the results for 100 iterations of the algorithms for the four objects and we show the outcome in Fig.**??** and Fig. 3. As we expected, the RRT*-RMM takes a departure from the shortest path and requires to travel a long distance to connect the points, on the contrary RRT* performs better in term of length. As per the manipulability cost, the RRT*-RMM drastically improves the manipulability along the path in a very consistent manner no matter the objects. Moreover, the boxplot shows a reduced variance over the trials for the RRT*-RMM in comparison with the RRT*. This is due to the knowledge that RRT*-RMM has and RRT* has not.

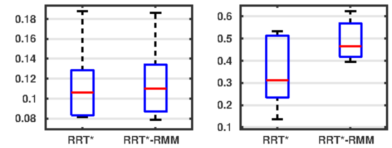

Fig. 3. This figure shows the path length found for the same objects. Left) helmet, Right) curved surface.

IV. Conclusion

This paper addresses the problem of the motion planning from vision, which enables a robot to perform a cutting task under uncertainties thanks to the kinematic-awareness. We find robot trajectories which maximise the robot's manipulability throughout the motion. The obtained path is the result of a compromise between travelling distance and manipulability throughout the motion of the robot. Also, we use the Riemannian manifold concept to project random samples onto the surface and vice versa. Thus, a pointcloud of the surface is sufficient for the algorithm (no need of a 3D model of the object). This work has application in industrial problems of robotic rough cutting. RRT*-RMM attains an increased manipulation capability at the cost of an increased path length, however, in the cutting problem of interest, avoiding kinematic issues, *i.e.*, singularity, is acceptable.

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