First Analysis of Environment Design for Motion Planning with Contact

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***Abstract*—As the structure of the environment plays an important role for a motion planners success we introduce the environment design problem into the motion planning process. This problem requires the environment designer to plan for adding features to the environment to e.g. reduce uncertainty, shorten paths etc. without blocking the path to the goal. A contact based motion planner from our previous work serves as baseline algorithm. We demonstrate the advantages of environmental design in simulation through manual landmark insertion in identified map areas. As result of our proposed strategy to modify the environment, paths are found faster and with higher goal state and overall certainty as well as we achieve a better free-space map exploration rate.**

I. Introduction

Environment design planning is common practice and applied to multiple areas. Industrial automation is a good example for highly engineered environments through part feeders [2, 3, 4], fixtures [5] and conveyor belt systems [10]. And there are further real life examples of natural and less structured environments in which the environment contains consequences of thoughtful investigation and planning to provide ideal conditions for a particular task. We refer to them as Environmental Constraints (ECs) as defined by Eppner et al. [7]. Especially in environments designed for humans, we find manufactured ECs to fulfill diverse expectations on safety (safety rail), ease (coin slots), guidance (traffic signs), comfort (room divider), productivity (office compartmentation) and feedback (coloring of a pressed button). It is hardly surprising that in robotics where we mainly aim for safety and high precision we are in the need of similar environment features. To satisfy regulations on safety robots operate in cages or behind shatterproof glass, get equipped with more and more sensors or get softer and more compliant. If feasible, high precision can be achieved by improving sensorization or actuation. However, not always can we change those, as we can not change humans, and can alternatively facilitate the reduction of uncertainty by modifying the environment.

Environmental design can range from modifying to adding or removing parts in the environment up to the extreme of designing an environment from scratch. Various research areas investigated modifying ECs. A common issue of motion planning has been addressed in the literature under the question:

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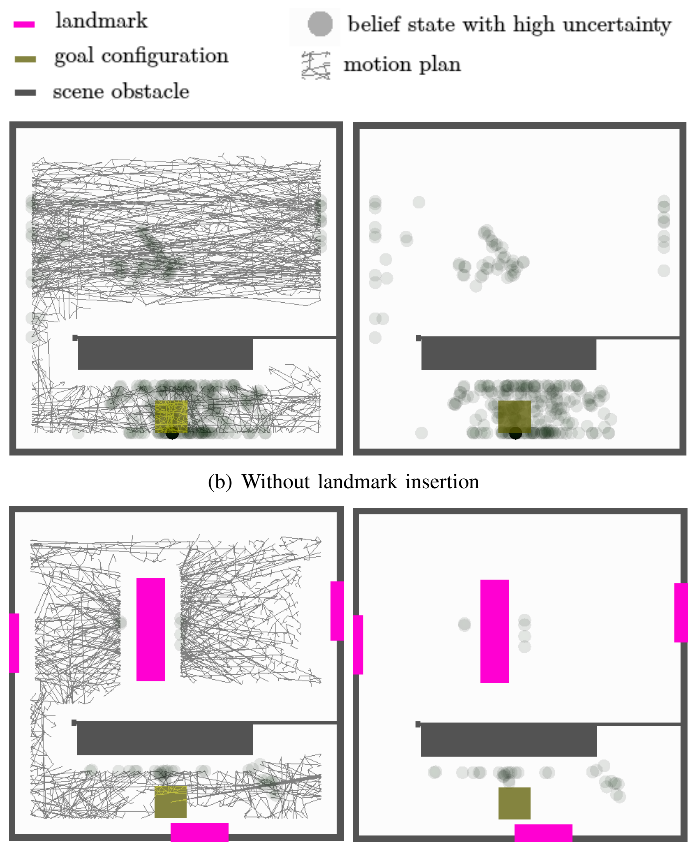


(b) Without landmark insertion

(c) With landmark insertion in uncertain map areas

Fig. 1. With the targeted landmark placement strategy proposed in this paper 1(c) we are able to reduce the uncertain map areas in size or eliminate them completely. Furthermore, the tree generated by the planner is much sparser since the solution is found quicker than without landmark insertion 1(b). The landmarks are placed based on the uncertainty map (grey blobs). The environment is colored in grey, the goal configuration in yellow and landmarks in pink.

"What to do when no plan can be found?" [8] and it got answered by multiple papers with Minimal Constraint Removal (MCR) [9], which proposes to remove the fewest geometric constraints such that the planner can find a path from the start to the goal. In a biological context Denarie et al. [6] formulated the simultanous design and path planning problem (SDAP) based on the Transition-based Rapidly-exploring random tree (T-RRT). They explored all possible environment designs and their cost-functions and aim to solve for the best path-design pair. In swarm theory Becker et al. insert obstacle mazes into an environment to transform an unsorted swarm of particles into a target configuration [1]. To our knowledge, the idea of adding to a motion planner that exploits contact deliberately placed ECs which serve as landmarks to ensure uncertainty reduction in a particular dimension is not discussed in any prior work.

Why do we refer to them as landmarks, are they not simply additional obstacles that the planner has to cope with? Well, inserting an obstacle into the map of a motion planner that needs contacts to reduce state uncertainties is like throwing a sugar cube into a bacteria culture. The objective of this paper is to illustrate the benefits of targeted obstacle placement and to get you instead of questioning the success, start wondering how much and in which form and distribution the sugar should be added. So back to our landmark problem we want to guide you to the following questions:

How many landmarks are helpful to add, and when is it too many? Where should the landmark be placed? What shape should a landmark have?

II. ENVIRONMENT DESIGN PROBLEM

We make a first analysis of the Environment Design Problem in context of a motion planning algorithm that exploits contact. A motion planner that is aware of its weak spots in the environment such as impasses, detours or high state uncertainties could suggest environment modifications such as closing impasses, removing walls for direct paths or adding features to reduce uncertainties. The Environment Design Problem can be arbitrarily complex. The spectrum of environment design ranges from not changing to fully changing the environment. However, neither extreme is favorable. If we are not modifying the environment we can not optimize it for planning. On the other hand, engineering the optimal motion planner environment by iterating over all possible scene designs is not efficient. Therefore the target of our work lies within this spectrum but with the focus on the lower end as we are seeking for minimal invasive solutions.

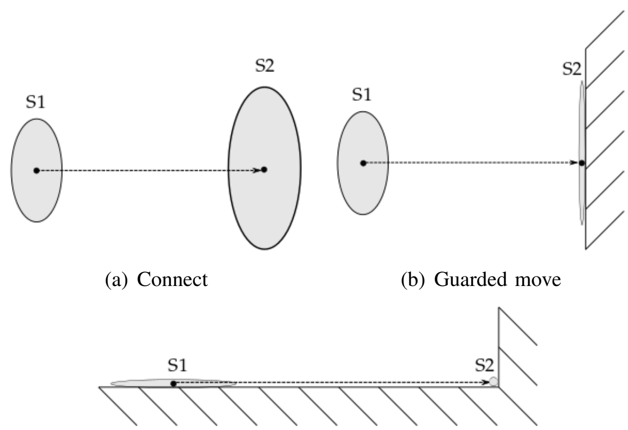
We define the overall Environment Design Problem as the search for the minimal set of landmarks $\mathcal{L} = \{l_1, \ldots l_N\}$ such that their removal or placement to a scene optimizes planning either in speed, quality or quantity of solutions. In this abstract however we concentrate on adding landmarks to limit the design space and therefore we seek for the minimum set of $\mathcal{L}$.

III. ENVIRONMENT DESIGN FOR MOTION PLANNING WITH CONTACT

We are investigating the environment design in the context of a planner that models the state uncertainties as particle sets such as the one proposed by Philips-Grafflin et al. [11] which showed that contact can be used in the RRT to reduce uncertainty. Moreover, our previous work (CERRT, by Sieverling et al. [12]) demonstrated that integrating contact exploiting actions in the planner increases the robustness. Sensors such as simple force-torque sensors turn surfaces, walls and edges into landmarks that guide the robot through the map and ensure the robot to reach its task constraints with high certainty. However, in large maps or in maps of insufficient or unfavorable EC availability additional contacts are needed to prevent the motion planner from dropping the states of low certainty. In the context of our previous work and motivated by our daily life EC experience we consider the environment as a fully controllable variable that can be designed arbitrarily, by adding constraints while aiming for a minimally invasive solution that optimizes a given environment for planning with low uncertainties.

A. Contact-Exploiting RRT (CERRT)

The concept behind the Contact-Exploiting RRT (CERRT) is that free-space motion, *connect* steps, on which the classical RRT depends are very costly when considering uncertainty. In CERRT each state of the RRT tree is modeled as a set of particles $\mathcal{Q} = \{q_1, \ldots q_N\}$ which can be simplified with an ellipsoid shape defined by the covariance matrix Σ. While free-space motions increase the state uncertainty, contact with the environment decreases it. CERRT defines three additional actions (see Fig. 2) that make use of this fact under the assumption that contact sensing is reliable and contact information is available to the planner at any time. The three actions: *guarded-move*, *slide* and *guarded-slide* can be sequenced with connect actions to ensure the exploitation of contacts to reduce uncertainty.



(a) Connect (b) Guarded move

(c) Guarded slide

Fig. 2. $S1$ indicates the uncertainty ellipsoid before and $S2$ after a CERRT action is applied. Whereas *connect* increases the uncertainty a *guarded move* and *guarded slide* decrease the uncertainty in each case in the motion direction. The *slide* action itself is not shown explicitly but implicitly illustrated in the guarded slide - while in contact with the surface the uncertainty in the opposite direction to the moving direction is not increasing. (figures adjusted from [12])

B. State Uncertainty Map

CERRT is aware of the uncertainty at each state that is inserted in the tree, but the overall uncertainty distribution of the states is not considered during the planning process. To detect areas in which high uncertainties appear during the planning we extended the CERRT algorithm with a state uncertainty map. In an offline process we build the CERRT tree and construct a state uncertainty map where the uncertainty at each state is the trace of the covariance matrix $tr(\Sigma)$ which represents the state uncertainty ellipsoid. The uncertainty map can be seen as mirror of the explored scene and is therefore dependent on a particular start and end configuration.

The right column of Fig. 1 shows the uncertainty map - only states with $tr(\Sigma) > 0.1$ are plotted to emphasize the uncertain areas.

C. Modifying the Environment

We want to place landmarks such that the planner is able to receive feedback frequently while exploring the map. Therefore we have to address the three initial questions that we raised regarding landmark placement, shape and quantity.

As we are aiming to reduce uncertainties in the contact motion planning process we base our landmark placement on the map of uncertainty described in the previous section. Whereas hitting the wall decreases the uncertainty only in one of the dimensions, hitting a corner or edge decreases the uncertainty in both dimensions. We identify regions of high uncertainty, and cluster the particle sets accordingly: $c = \{\mathcal{Q}_1, \dots \mathcal{Q}_N\}, \quad c \in \mathbf{c}$. In each cluster region we place a landmark with varying size proportional to the size of the uncertain area. Since in CERRT corners and edges result in the most effective uncertainty reduction we use box shaped landmarks, such that a landmark $l_i(dim_{a,b,c}, T) \in \mathcal{L}$ is fully defined by its dimensions $dim_{a,b,c}$ and pose T. However, only if an uncertain area is surrounded by free space we place a landmark in the center of the uncertain cluster. For clusters that align with an EC we have to ensure that we are not blocking passages to the goal by decreasing the passage width or generating additional narrow passages. Furthermore the direction of the landmark placement matters as we are considering uncertainty in both dimensions. In the experiment shown in Fig. 3, in the unmodified environment, most of the paths end up with a high uncertainty ellipsoid which simply does not allow for entrance to the narrow passage in which the goal configuration is located. In this case adding landmarks to the uncertain areas reduces the overall uncertainty and decreases the runtime. However, placing the obstacle such as it closes the impasse which is not relevant to the planner leads to even better results. This information however, is not encapsulated in the uncertainty map and needs further investigation.

Experiments in which we investigated if it is rather favourable to add multiple objects into an uncertain area than simply one object did not lead to clear results yet.

D. Environment Design Problem

We now can formulate our goals of Sec. II in context of CERRT as the following minimization problems regarding uncertainty, invasiveness and map exploration rate.

$$min \left\{ \sum_{j=1}^{|\mathbf{c}|} \sum_{i=1}^{|\mathbf{Q}|} tr(\Sigma_{\mathcal{Q}_i c_j}) \right\} \tag{1}$$

$$min \left\{ \sum_{i=1}^{|\mathbf{Q}_{goal}|} tr(\Sigma_{\mathcal{Q}_{goal_i}}) \right\} \tag{2}$$

We define $\mathbf{Q}$ as the set of all beliefs $\mathcal{Q}$ explored by CERRT and with $\mathbf{Q}_{goal}$ the set of all beliefs with $\mu < \epsilon_{goal}$, where ϵ_{goal} is the allowed distance to the goal configuration, such that $\mathbf{Q}_{goal} \subset \mathbf{Q}$. Both equations (1), (2) formulate minimization problems which target the reduction of the CERRT exploration uncertainty in the map. Here it should be noted that Eq. (1) can follow the same objectives as Eq. (2), but (1) $\neq$ (2).

$$min \{|\mathcal{L}|\} \tag{3}$$

$$min \left\{ \sum_{i=1}^{|\mathcal{L}|} V_{l_i} \right\} \tag{4}$$

$$min \left\{ \frac{\mathcal{C}_{\text{free}_\mathcal{L}}}{\mathcal{C}_{\text{expl}_\mathcal{L}}} \cdot \frac{\mathcal{C}_{\text{expl}}}{\mathcal{C}_{\text{free}}} \right\} \tag{5}$$

The above equations (3), (4), (5) formulate that we seek for the least invasive set $\mathcal{L}$. We define the map free configuration space as $\mathcal{C}_{\text{free}} = \mathcal{C}_{\text{map}} - \mathcal{C}_{\text{obstacles}}$ and with $\mathcal{C}_{\text{expl}}$ the configuration space in which CERRT explores beliefs. The volume of a landmark box is defined with $V_l = a \cdot b \cdot c$. Therefore we minimize over landmark (3) quantity; (4) volume; and (5) the increment of the unreachable area after placement of $\mathcal{L}$.

$$min \left\{ \frac{\mathcal{C}_{\text{free}}}{\mathcal{C}_{\text{expl}}} \right\} \tag{6}$$

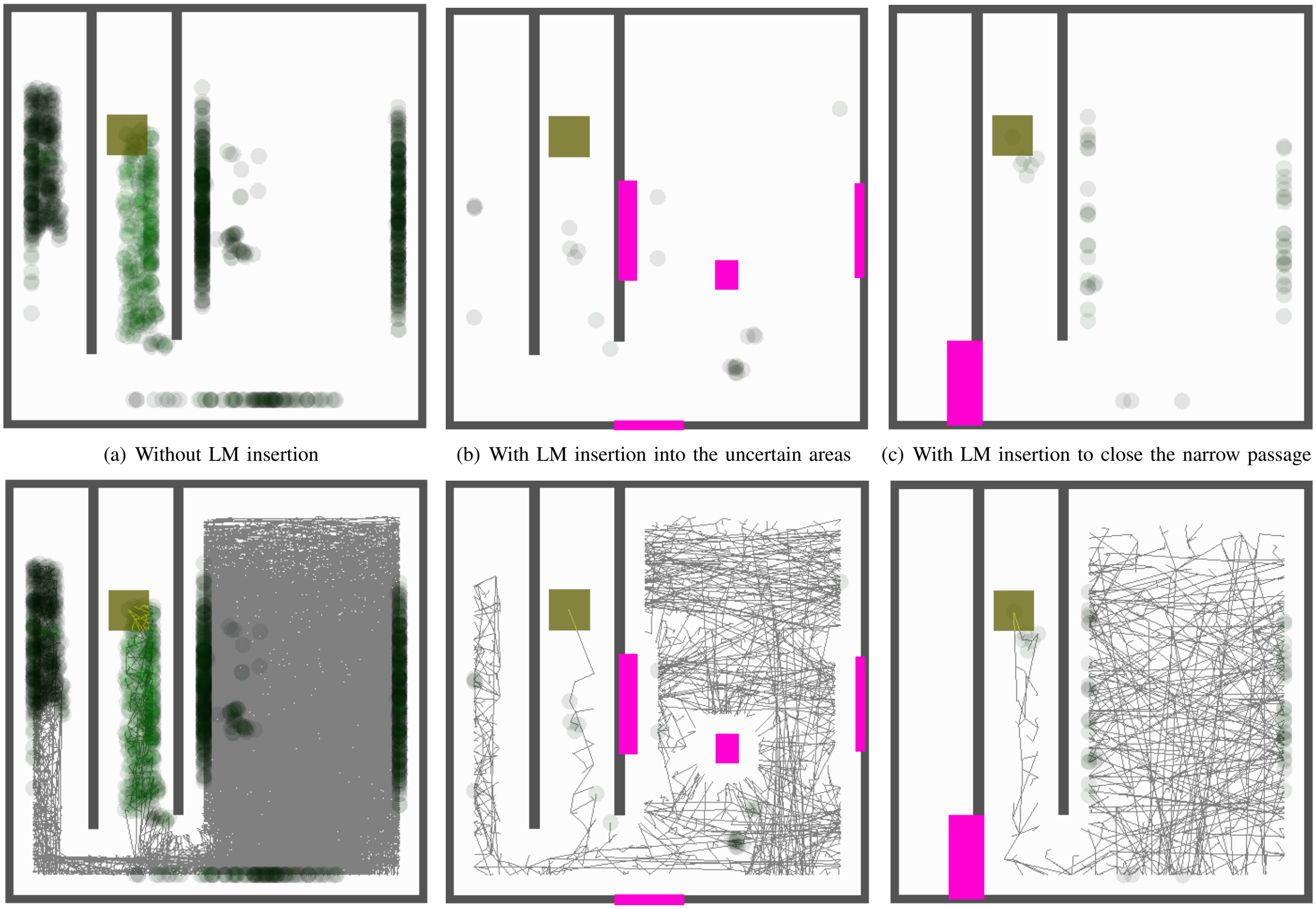
Minimizing the unexplored areas in Eq. (6) is only reasonable if we combine it with the search for the least invasive solution.

IV. EXPERIMENTS

Our expectations on the experiments discussed in this section are that with the targeted landmark placement into uncertain areas we achieve robuster motion plans. We were able to show that the landmarks reduce uncertainty which leads to sparser trees due to less computation time and higher goal state certainty.

We considered two different scenes. In the scene of Fig.1 a small overhang allows to reduce uncertainty right before entering the narrow passage, whereas the scene of Fig.3 contains two narrow passages without this beneficial EC. The scene presented in Fig. 1 we consider to be a good baseline, since the environment contains no extreme challenges for the planner other than distance.

We run the CERRT algorithm and while building the tree, the uncertainty map is constructed. The thresholded uncertainty map ($tr(\Sigma) > 0.1$) reveals the uncertain areas in which we manually place box-shaped landmarks scaled according to the size of an uncertain area. We place a box shaped robot



(a) Without LM insertion

(b) With LM insertion into the uncertain areas

(c) With LM insertion to close the narrow passage

(d) Motion plan overlayed with (a).

(e) Motion plan overlayed with (b)

(f) Motion plan overlayed with (c)

Fig. 3. CERRT needs around 4 minutes to find the entrance of the narrow passage that leads to the goal and approx. 18 minutes to actually reach the goal (left column). After multiple landmark insertion (middle column), into the uncertain areas, the planner reaches the goal in around ∼10 min and after single landmark insertion (right column), targeted to close the narrow passage, in less than a minute.

(yellow box) into arbitrarily but fixed places. In the figures the box is indicating the goal robot configuration. We assumed zero initial uncertainty of the robot state and if the robot moves through the map a high linear motion error $\sigma_v = 0.2$. This motion uncertainty corresponds to 0.2 rad error increment on 1 rad distance. The CERRT planners action selection (Fig. 2) was regulated through $\gamma = 0.5$ so that it equally favors exploiting and avoiding the environment. We chose a high goal error threshold $\epsilon_{goal} = 0.8$ in the case of the narrow passage experiment (Fig. 3) and a low $\epsilon_{goal} = 0.05$ in the initial example of (Fig. 1).

For 5 iterations of the narrow passage problem (Fig. 3) the CERRT algorithm without landmark insertion finds the entrance to the narrow passage after ~ 4 min and needs in total an average time of ~ 18.5 min to find a solution. Inserting multiple landmarks into the identified uncertain areas, leads to a runtime of ~ 9.9 min. The planner needs only ~ 0.65 min in the single landmark insertion experiment that closes the narrow passage identified as impasse.

The results can be explained by recalling the CERRT actions. In CERRT a corner decreases uncertainty in two dimensions, therefore adding the single landmark that stops the algorithm from exploring the impasse is decreasing the state uncertainty straight before entering the narrow passage. This enables the ellipsoid to easily fit into the narrow passage, whereas multiple states get dropped by CERRT without this uncertainty reduction in the unmodified environment. Similarly to this reasoning, the same benefits increase the planner efficiency in terms of speed and uncertainty reduction within the multiple landmark insertion experiment.

V. Conclusion and Future Work

The purpose of this paper is to draw attention to the opportunities that lie in environment design for motion planning. We focused on motion planning with contact and illustrated the concepts based on a state uncertainty map of the scene and manual landmark insertion. Through targeted landmark insertion in the uncertain areas we could show that the uncertainty in the CERRT planning process can be kept low. Our next steps are to automate this process of uncertainty area detection and landmark placement to achieve a general solution for arbitrary start and goal states, therefore we are aiming for an analytical approach which allows us to estimate the uncertain areas automatically. Furthermore, our experiments on the ideal landmark placement, shape and quantity are preliminary and we are going to further investigate their effect on the planning results.

In this work we exclusively considered adding ECs (landmarks) to the map, however there are of course additional features an environment design planner could aim for. Removing ECs could be equally beneficial in multiple cases as addressed with the MCR problem. In the context of CERRT we could imagine MCR for freeing up space to avoid detours, removing walls that block paths to the goal or shape narrow passages. In a parallel work we are extending the CERRT planner with reactivity for ambiguous states. However, from an offline planning perspective we consider ambiguity as unfavourable and started also to investigate how we can change the environment to eliminate ambiguities.

References

[1] Aaron Becker, Erik D. Demaine, Sándor P. Fekete, Golnaz Habibi, and James McLurkin. *Reconfiguring Massive Particle Swarms with Limited, Global Control*, pages 51–66. Springer, 2014.

[2] G. Boothroyd and A.H. Redford. *Mechanized Assembly: Fundamentals of Parts Feeding, Orientation, and Mechanized Assembly*. McGraw-Hill, 1968.

[3] G. Boothroyd, C. Poli, and L.E.. Murch. *Handbook of feeding and orienting techniques for small parts*. Dept. of Mechanical Engineering, University of Massachusetts, 1989.

[4] Geoffrey Boothroyd. *Assembly Automation and Product Design, Second Edition (Manufacturing Engineering and Materials Processing)*. CRC Press, Inc., Boca Raton, FL, USA, 2005.

[5] I. Boyle, Y. M. Rong, and David C. Brown. A review and analysis of current computer-aided fixture design approaches. *Robotics and Computer Integrated Manufacturing*, 27(1):1–12, February 2011.

[6] Laurent Denarie, Kevin Molloy, Marc Vaisset, Thierry Siméon, and Juan Cortés. Combining System Design and Path Planning. In *Workshop on the Algorithmic Foundations of Robotics (WAFR)*, 2016.

[7] Clemens Eppner, Raphael Deimel, José Álvarez-Ruiz, Marianne Maertens, and Oliver Brock. Exploitation of environmental constraints in human and robotic grasping. *The International Journal of Robotics Research*, 34(7):1021–1038, 2015.

[8] Moritz Göbelbecker, Thomas Keller, Patrick Eyerich, Michael Brenner, and Bernhard Nebel. Coming up with good excuses: What to do when no plan can be found. In *Proceedings of the 20th International Conference on Automated Planning and Scheduling (ICAPS)*. AAAI Press, 2010.

[9] Kris Hauser. The minimum constraint removal problem with three robotics applications. In *Workshop on the Algorithmic Foundations of Robotics (WAFR)*, 2013.

[10] Gabriel Lodewijks, Wenfeng Li, Yusong Pang, and Xiaoli Jiang. An application of the IoT in belt conveyor systems. In *International Conference on Internet and Distributed Computing Systems*, pages 340–351. Springer, 2016.

[11] Calder Phillips-Grafflin and Dmitry Berenson. Planning and resilient execution of policies for manipulation in contact with actuation uncertainty. In *Workshop on the Algorithmic Foundations of Robotics (WAFR)*, 2017.

[12] Arne Sieverling, Clemens Eppner, and Oliver Brock. Interleaving motion in contact and in free space for planning under uncertainty. In *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) - (under review)*, 2017.