Soft Fixtures: Towards Practical Caging-Based Manipulation of Rigid and Deformable Objects

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***Abstract*—We present a sampling-based approach and initial experiments to reasoning about the manipulation of both rigid and a simplified class of deformable objects, modeled as articulated rigid bodies with gravitational and elastic potential energy in 3D. We extend earlier work generalizing the notion of caging to include energy function constraints to allow for a quasi-static analysis and the inclusion of elastic potential energy of deformable objects. While past works on caging have predominantly focused on provably correct algorithms applicable to restricted simple classes of rigid objects such as polygons in 2D or simple meshes in 3D, our approach only provides upper bounds to escape energies, but in return allows for the analysis of such soft fixtures in much higher-dimensional configuration spaces. In this workshop contribution, we present initial demonstrations of simulation scenarios indicating that our approach can be applied to the analysis of escape energy for quasi-static manipulation scenarios involving rigid and articulated objects. Simulation results indicate that a variation of a BIT*-based motion planner outperforms an incremental search-based RRT planner as a baseline for this application in particular.**

***Index Terms*—robotic manipulation, caging, sampling-based motion planning, potential energy**

I. Introduction and Related Work

The task of restraining an object, which is also referred to as fixturing, is one of the key functions of robotic grasping [1] and a key step towards robust dexterous manipulation. Enveloping grasps [2] effectively constrain objects by wrapping the fingers and palm around them, while fingertip grasps enable dexterous manipulation of objects with distal phalanges. While classical grasping approaches such as form and force closure [3] focus on the analysis of point-contacts with the goal of fully controlling the pose of a grasped object, these approaches, however, might suffer from grasp instability issues due to noise in perception and susceptibility to external disturbances. Caging provides an alternative approach to fixturing, where the object is not necessarily fully immobilized. The notion of caging was introduced by Kuperberg [4] as the problem of preventing a polygon from escaping arbitrarily far away using a set of fixed point-obstacles. More precisely, an object configuration is caged if its path-component in collision-free configuration space is bounded. Rimon et al. [5], [6] then applied the caging concept in the context of robotic grasping and introduced a theory for caging-based grasping of planar objects [7], [8] and presented methods of finding two-finger cage formations of planar polygons or 3D polyhedra

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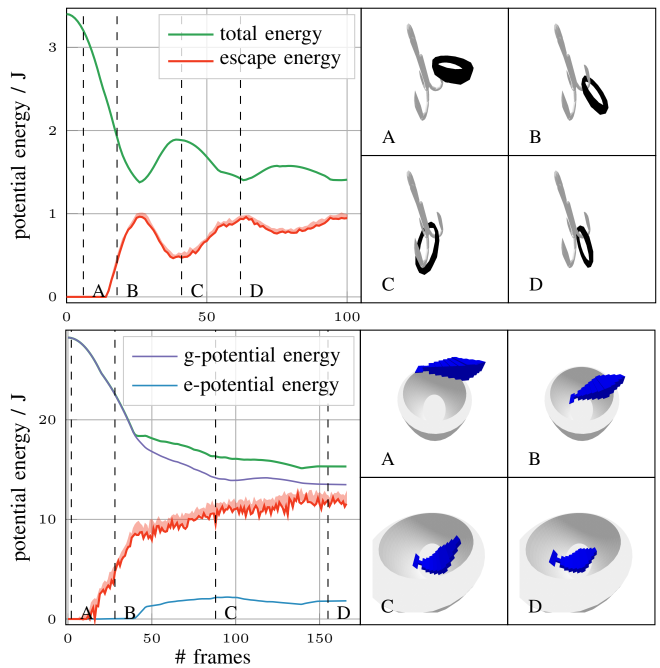

Fig. 1: Quasi-static soft fixture analysis of two simulated dynamic scenes of a rigid ring under gravity (top) and a deformable fish model falling into a bowl (bottom). We display total potential energy (green), gravitational potential energy (purple), elastic potential energy (blue), and estimated required soft fixture escape energy (red) for each frame. Escape energy is estimated using 5 independent runs of a 2-min execution of the BIT*-based escape energy approximation.

based on contact-space search. Rodriguez et al. [9] showed that caging grasps may be regarded as a viable means of achieving immobilizing grasps through finger closure. Based on the analysis of topological and geometric features, [10], [11] have applied caging grasps to certain classes of 3D rigid and deformable objects, but the proposed methods are only applicable to objects with specific features, such as holes or double forks. Energy-bounded caging of 2D objects was introduced by Mahler et al. [12], [13] and introduced additional constraints defined in terms of potential energy to the caging paradigm and relied on a cell-based decomposition of configuration space and the use of persistent homology.

In this work, we present initial progress on further extending the notion of caging to what we refer to as a **soft fixture**, where an object is constrained to a bounded path-component within a sublevel set of a suitable constraint function. We in particular explore constraints imposed by the sublevel set of a function defined in terms of potential energy for this purpose. Unlike computationally expensive volumetric approximations of configuration space such as 3D rigid body caging using the methods of [14], which currently cannot be applied in higher-dimensional configuration spaces or dynamic scenarios, we utilize a sampling-based approach that we show is applicable even to deformable objects approximately modeled as articulated objects. Three initial demonstrations of such soft-fixtures and their quasi-static analysis are implemented in our simulation experiments in particular[1].

II. Methodology

Articulated Objects with Gravitational and Elastic Energy: We denote by $\mathcal{C} \subset \mathrm{SE}(3) \times \mathbb{R}^{n_j}$ the configuration space of an object $\mathcal{O} \subset \mathbb{R}^3$ in 3D with $n_l = n_j + 1$ serial links connected by revolute joints (with each angle constrained to $[-a, a]$, with $a < \pi$ and a special case of $n_j = 0$ for rigid objects). We denote an element $\boldsymbol{\xi} \in \mathcal{C}$ by $\boldsymbol{\xi} = (\boldsymbol{r}, \boldsymbol{q}, \boldsymbol{\alpha})$, where $\boldsymbol{r}$, $\boldsymbol{q}$ are the position and orientation (a unit quaternion) of the center of mass of the object's base link respectively, and $\boldsymbol{\alpha} \in [-a, a]^{n_j} \subset \mathbb{R}^{n_j}$ is a vector of revolute joint angles. The collision space $\mathcal{S}$ indicates the collection of configurations for which $\mathcal{O}$ penetrates at least one of the rigid obstacles $\{\mathcal{J}_1, ..., \mathcal{J}_{n_o}\}$ placed in the workspace. The free configuration space is given by $\mathcal{F} = \mathcal{C} - \mathcal{S}$. We assume that torsion springs are attached at each of the revolute joints. Therefore, joint configurations other than $\boldsymbol{\alpha} = \mathbf{0}$ exhibit non-zero elastic potential energy. Combining this elastic potential energy [15] with the standard gravitational potential energy and defining points in collision space to have infinite energy, we consider the following energy function $E : \mathcal{C} \to \mathbb{R} \cup \{\infty\}$:

$$E(\boldsymbol{\xi}) = \begin{cases} \sum_{i=1}^{n_l} m_i g z_i(\boldsymbol{\xi}) + \sum_{h=1}^{n_j} \frac{1}{2} k_h \alpha_h^2, & \text{if } \boldsymbol{\xi} \in \mathcal{F} \\ \infty & \text{if } \boldsymbol{\xi} \in \mathcal{S} \end{cases}$$

Here, g denotes the gravitational acceleration constant, $z_i(\boldsymbol{\xi})$ the height of the center of mass of the i'th link in the world coordinates (gravity in $-z$ direction), k_h the stiffness coefficient of the h'th joint and α_h the h'th joint angle.

Caging and Soft Fixtures: For any continuous path $p : [0, 1] \to \mathcal{F}$, we define $V(p) = \max_{t \in [0,1]} E(p(t))$ to be the maximal potential energy encountered along p. We consider the object $\mathcal{O}$ in configuration $\boldsymbol{\xi}_s \in \mathcal{F}$ to be in a soft fixture configuration with respect to E if, for some $u \geq 0$, $\boldsymbol{\xi}_s$ lies in a bounded path component inside the sublevel set:

$$\mathcal{U}(\boldsymbol{\xi}_s, u) = \{\boldsymbol{\xi} \in \mathcal{C} : E(\boldsymbol{\xi}) \leq E(\boldsymbol{\xi}_s) + u\}$$

We call the supremum over all such $u \geq 0$ the escape energy of the fixture. This discussion is in essence a reformulation of the notion of an energy-bounded cage defined in 2D in [12], [13] to general energy functions and expresses the notion that the initial configuration $\boldsymbol{\xi}_s$ is constrained to a bounded path component subject to not raising potential energy by more than a certain threshold. With respect to our definition of energy function above, a soft fixture with infinite escape energy in particular corresponds to the classical concept of a cage, where $\boldsymbol{\xi}_s$ lies in a bounded path component of $\mathcal{F}$.

[1]A video is available here: https://youtu.be/tnYr7MSPMTw

Estimation of Escape Energy Upper Bounds: Note that as long as the object $\mathcal{O}$ is in a configuration $\boldsymbol{\xi}_g$ that is sufficiently far away from obstacles there always exist trivial trajectories that escape arbitrarily far away from the $\boldsymbol{\xi}_g$ without ever raising potential energy. E.g. by moving a finite amount away from potential obstacles in the plane orthogonal to the gravity direction and then following the direction of gravity as far as desired. Our strategy for estimating soft fixture escape energy is to search for escape paths $p \subset \mathcal{U}(\boldsymbol{\xi}_s, u)$ starting at an initial configuration $\boldsymbol{\xi}_s$ and connecting to some goal configuration $\boldsymbol{\xi}_g$ with lower energy $E(\boldsymbol{\xi}_g) < E(\boldsymbol{\xi}_s)$ and sufficiently far away from obstacles to demonstrate an escape path at a given threshold u, thus providing an upper bound to escape energy. As a baseline, we can run an RRT [16] planner constrained to $\mathcal{U}(\boldsymbol{\xi}_s, u)$ starting at $\boldsymbol{\xi}_s$ and attempt to reach a goal configuration $\boldsymbol{\xi}_g$ sufficiently far away from obstacles. In experiments, we consider a ball $\mathcal{B}$ containing the obstacles in workspace and consider a path in $\mathcal{U}(\boldsymbol{\xi}_s, u)$ to have escaped sufficiently far from an initial configuration $\boldsymbol{\xi}_s$ with position component $\boldsymbol{r}_s \in \mathcal{B}$ if a configuration $\boldsymbol{\xi}_g = (\boldsymbol{r}_g, \boldsymbol{q}_g, \boldsymbol{\alpha}_g)$ is reached with position $\boldsymbol{r}_g$ corresponding to the "bottom" lowest position of that ball in gravity direction, an arbitrary rotation $\boldsymbol{q}_g$ and an equilibrium $\boldsymbol{\alpha}_g = 0$, to demonstrate that $\boldsymbol{\xi}_s \in \mathcal{U}(\boldsymbol{\xi}_s, u)$ does not lie in a bounded path component.

To approximate escape energy upper bounds of $\boldsymbol{\xi}_g$, we tested a very simple incremental search approach – in spirit similar to the bisection method of [17], who applied this to a 2D partial caging. In each iteration i, we run an RRT motion planner with a finite time budget to search for a trajectory fully contained in $\mathcal{U}(\boldsymbol{\xi}_s, u^i)$, starting at $\boldsymbol{\xi}_s$ and connecting to $\boldsymbol{\xi}_g$, starting with $u^0 \gg 0$. We then retrieve a feasible path p^i if it is found which establishes an upper bound $u^{i+1} = \max\{V(p^i) - E(\boldsymbol{\xi}_s), 0\}$ for escape energy and the search restarts in the smaller sublevel set $\mathcal{U}(\boldsymbol{\xi}, u^{i+1})$ and any found path successively attempts to establish a tighter upper bound for escape energy. The loop terminates when $u^i \approx 0$, or a maximum iteration limit or a time limit is reached for the execution of the motion planner, thus establishing an upper bound for escape energy.

Inspired by Batch Informed Trees (BIT*) [18], a planning algorithm that balances the benefits of graph-search and sampling-based techniques and efficiently approximates the high dimensional space, we furthermore considered a search for minimum escape energy trajectories using BIT*. The search in BIT* is prioritized by potential solution quality, as in A*, and is asymptotically optimal, as in RRT* [19]. We propose a modification of BIT* by introducing a configuration-cost function that aims to prioritize states with lower potential energy. This results in a type of cost-space path planning that computes low-cost paths with respect to a cost function defined on the path space p [20]. We define the state cost function $c(\boldsymbol{\xi}_n)$ of a new sample $\boldsymbol{\xi}_n \in \mathcal{F}$ in a batch if it connects to a current vertex $\boldsymbol{\xi}_i \in \mathcal{F}$ already in the graph as $c(\boldsymbol{\xi}_n) = \max\{c(\boldsymbol{\xi}_i), E(\boldsymbol{\xi}_n) - E(\boldsymbol{\xi}_s)\}$ with $c(\boldsymbol{\xi}_s) = 0$. This cost function is intended to steer the exploration to expand new vertices and rewire edges according to their potential energy-based cost-to-come $V(p)$ ($p(0) = \boldsymbol{\xi}_s, p(1) = \boldsymbol{\xi}_n$) with the aim of pruning branches of the search tree that are unlikely to lead to an escape path p with minimal $V(p)$.

III. Evaluation

We present an evaluation of the proposed BIT*-based approach relative to the incremental search-based baseline for quasi-static soft fixture analysis. Two dynamic scenarios are presented in Figure 1: (1) a ring caught by a fish hook, (2) a fish modeled as an articulated object with elastic potential energy falling in a bowl. A third scenario of a starfish (modeled as a rigid object) captured by a Robotiq 3-finger gripper [21] can be found in the supplementary video. We used the Open Motion Planning Library (OMPL) [22] with its Python binding for the implementation of the motion planners and Pybullet [23] is used for collision detection and forward simulation of bodies under gravity. All experiments are performed on an Intel Core i9-12900H up to 5.0GHz processor with 14 cores. On average, approximately 1000 samples are processed per second by the BIT*-based planner.

Qualitative Evaluation of Approximated Escape Energy: The evaluation scenarios present examples of dynamic soft fixtures in the course of hooking an object, catching it with a bowl and a transition from soft fixture to caging for the starfish example. We simulate the objects' trajectories under gravity and potential energy using Pybullet (see the video and Fig.1). In Pybullet, the objects freely fall under gravity and are caught by fixed obstacles (bowl, hook, gripper) afterwards. The object configurations $\boldsymbol{\xi}_i$ ($i = 0, 1, ...$) for each frame are recorded in this process and we analyze each such configuration in a quasi-static manner using our BIT*-based approach to approximate the required escape energy – kinetic energy is ignored in the analysis, but present in the Pybullet simulation. We run 5 independent runs of a 2-min execution of the BIT*-based escape energy approximation for this purpose.

In the ring-hook example (Figure 1 top), a rigid ring with 1 N gravitational force falls (subfigure A) and is caught by the fixed fish hook (B). We observe that its escape energy is initially zero as a sidewards translation and ring rotation around the center of mass provides an escape path that does not raise potential energy in the initial frames. After that, it enters a soft fixture (e.g. energy-bounded cage under gravity here) with estimated required escape energy reaching about 1 J as the hook's center of gravity falls deep below the tip of the hook. As the ring is suspended from the hook, it swings back and forth (C, D) due to kinetic energy present in the simulation - this results in an oscillation in our quasi-static escape energy analysis with a local minimum around C and local maximum around D as energy is stored in kinetic and potential energy during this swinging which is coming to rest over time resulting in a stabilizing non-zero escape energy.

In the previous example, we consider rigid objects such as the hook as a special case of articulated objects with zero elastic potential energy and $n_l = 1, n_j = 0$. Next, we consider a simple articulated fish model approximation with $n_l = 12, n_j = 11$, see the bottom part of Fig.1. As the fish falls (A) it initially can be pulled arbitrarily far away from its current configuration without raising potential energy, however, it then hits the rim of the bowl and pivots around the contact point (B). Around this time, the required escape energy starts to rise and the elastic potential energy is non-zero due to the deformation caused by the collision with the rim and the pull of gravity. The fish slides down slowly (C, D) along the inner wall of the bowl, and its curvature and elastic potential energy are constrained by the curvature of the bowl. We also observe that a configuration with maximum energy along an optimal escape path appears to lie in the vicinity of (1) the tip of the fish hook with the ring dangling from it, and (2) the rim of the bowl with the fish body slightly bent downward respectively.

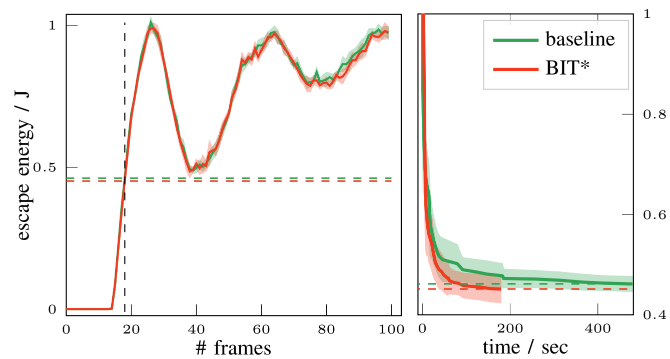

Fig. 2: Comparison of the BIT* and baseline for approximating escape energy for each frame of the ring-hook scenario (Figure 1 top) shows near identical numerical values. The calculated escape energy (as approximated using the BIT*-based and incremental planner) for each frame i (left) is nearly identical for both methods. Convergence of the algorithms over time (right) at frame 18 (corresponding to the vertical dashed line, and a ring configuration $\boldsymbol{\xi}_{18}$ corresponding to B in the top of Figure 1) indicates superior performance by BIT*. Escape energy is estimated using 6 independent runs of a 3-min execution of the BIT*-based approach, and an 8-min incremental search as the baseline. The horizontal dashed lines (red and green) indicate the terminal approximation value of escape energy by running BIT* and the baseline, respectively.

Accuracy and Efficiency Compared to Baseline: We empirically verify the accuracy and efficiency of our proposed BIT*-based approach in Figure 2. While BIT* appears to result in a very similar accuracy as compared to the baseline over 100 frames, we observe improved convergence of BIT* as shown in the left part of that figure for frame 18.

IV. Conclusion

We have demonstrated escape energy approximation of soft fixtures with complex gravitational and elastic potential energy constraints can in principle be studied using the proposed methods, but further investigation is required and these methods still need to be validated in real-world experimentation. We believe the initial results presented in this workshop contribution provide a starting point for discussion and further experimental validation of these ideas that we intend to submit to an upcoming conference.

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