

Visual Extraction Effort Estimation for Grasp Selection Among Unstructured Massive Objects

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Abstract—This paper describes an approach for visual estimation of the minimum magnitude grasping wrench necessary to extract massive objects from an unstructured pile, subject to limitations of a given end effector. This is enabled through representation of the net wrench restraining each component of the pile, comprised of the weight of an item and contact forces applied by adjacent objects, as a ‘wrench space stiction manifold’. The model acts upon depth information of object candidates, furnished by exteroception and any desired segmentation algorithm, in this implementation using a RealSense RGBD camera. Properties such as volume and mass are estimated from the point cloud, and a geometric adjacency graph used to infer incident wrenches upon each object. An extension of classical force closure analysis is then applied to these parameters, producing a notion of the ‘stiction’ force restraining each object as a function of direction. Candidate extraction object/force-vector pairs may then be selected from the pile that are within the system’s capability.

1. Introduction

Grasp selection in unstructured environments has proven a challenging task, and is complicated further when lacking *a priori* knowledge of manipuland shape and mass properties. Prior art has sought to address the problems of object agnostic grasp synthesis [1] [2] [3], grasping of known and unknown objects amongst clutter [4] [5], as well as lifting of massive objects with wrench constrained end effectors or actuators [6].

This work seeks to address the intersection of these, in particular the disassembly of unstructured piles of massive objects (e.g. Figure 1 right), where lifting one object may induce lifting or pulling other objects, which in turn increases the required grasp wrench, and may exceed the capabilities of the manipulation system, as occurred in Figure 1 left.

While indiscriminate, randomized grasp and lift motions can be coupled with proprioceptive wrench guarding to eventually find a viable removal candidate (if one exists),

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Figure 1. Left: Army Research Lab’s ‘RoMan’ mobile manipulation platform with broken proximal joint on Robotiq 3-finger Gripper. Right: Example debris pile of massive objects, where lifting two or more items exceeds manipulator payload limits.

the aim of this task is to decompose the object pile time efficiently. This necessitates leveraging exteroception to infer the composition and structure of the pile, allowing the system to more rapidly identify grasps that comply with the force and torque limits of the manipulation system.

The approach is now being applied to the task of clearing debris piles from urban environments, with object masses in the range of 1-20kg, and grasp synthesis achieved through fitting geometric prototypes [7].

2. Wrench Space Stiction Manifold

Each candidate manipuland within a static, unstructured pile is subject to its own weight, and the contact forces imparted upon it by adjacent objects. In order for an item to be extracted from the pile, the static equilibrium of the structure around the item must be broken by exceeding the net of those forces via a grasp wrench applied by a given manipulator. This is termed the ‘stiction’ wrench that restrains the item, the magnitude of which varies as a function of direction due to the pose of normal and frictional contact forces.

A segmentation algorithm is used to produce singulated object candidates and a best guess of inter-object contacts through geometric adjacency (this implementation employing Locally Convex Connected Patches [8]). For each singulated object, an estimate of the volume is developed by suitable means and used to infer mass from a prediction of possible densities within the task environment. The geometric adjacency graph from exteroception is then employed to predict the inter-object wrenches present within the structure. For this early work, contact normals are assumed to be co-linear with the vector between the centers of mass

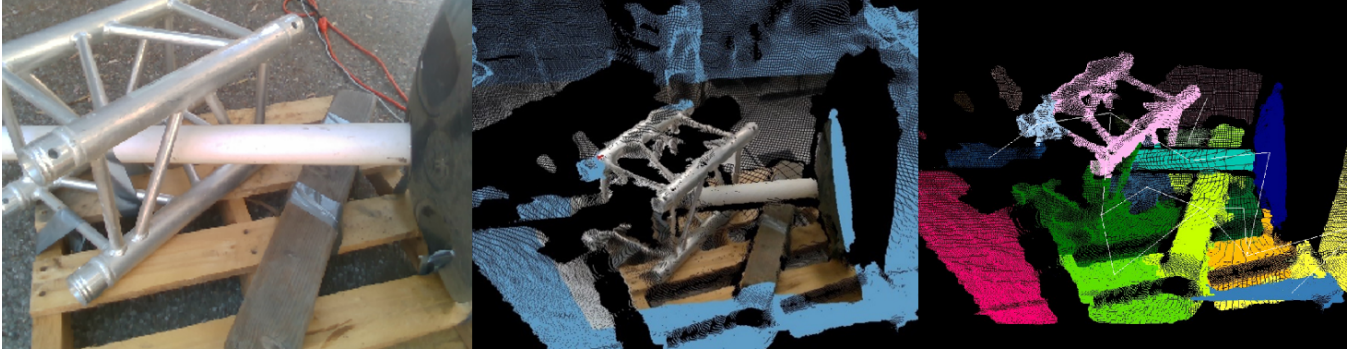


Figure 2. Left: RGB image of example debris pile containing Aluminum truss segment, safety barrier, 4x4 wood, and pallet. Center: Point cloud captured with RealSense D435. Right: Singulated object candidates with geometric adjacency from Locally Convex Connected Patches algorithm. [8]

(COM) of object pairs, though this could be improved by leveraging geometric context from the pointcloud.

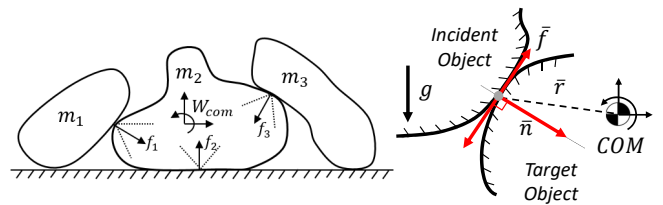
The graph describing object contacts is directed, as only objects below the line of gravity with respect to their pair must overcome the contact wrench to break stiction (e.g. object 2 in Figure 3a), whereas the reverse is not as the contact is simply broken (e.g. objects 1 & 3). Each wrench imparted by an incident object upon a target object is described in the COM frame of the target (Figure 3b). The point of contact between the objects is described by the vector \bar{r} , and through this point the normal and frictional contact forces act, represented by \bar{n} and \bar{f} respectively.

The frictional force is described with the Coulomb friction model and may lie anywhere in the orthogonal space of the normal vector, $\bar{f} \in \mathbb{R}^3$ s.t. $\bar{f} \cdot \bar{n} = 0, |\bar{f}| \leq \mu|\bar{n}|$. As the forces supporting an object may be statically indeterminate, this initial Newtonian analysis assumes the maximum friction force to provide an upper bound on the expected extraction effort. The sum of estimated object weight and all incident contact wrenches is then calculated across directions in wrench space to produce a ‘wrench space stiction manifold’, a closed set of the COM wrenches that will not overcome static friction.

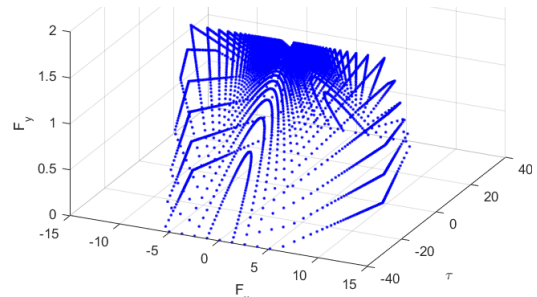
The minimum distance of this manifold from the origin represents the smallest wrench that could be applied to dislodge the given object from the pile. After evaluating this manifold for each object, candidate grasp points may be selected so as to have highest expectation of being within the systems’ capabilities, allowing expeditious disassembly of the pile.

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(a) Incident wrenches of two contacting objects about a central target object (b) Single inter-object wrench definition in COM frame



(c) F_y^+ half-space wrench stiction manifold for central object when all contact normals are coincident with COM

Figure 3. Example object support configuration in \mathbb{R}^2

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