Efficient Optimization for Autonomous Robotic Manipulation of Natural Objects

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Abstract

Manipulating natural objects of irregular shapes, such as rocks, is an essential capability of robots operating in outdoor environments. Physics-based simulators are commonly used to plan stable grasps for man-made objects. However, planning is an expensive process that is based on simulating hand and object trajectories in different configurations, and evaluating the outcome of each trajectory. This problem is particularly concerning when the objects are irregular or cluttered, because the space of feasible grasps is significantly smaller, and more configurations need to be evaluated before finding a good one. In this paper, we first present a learning technique for fast detection of an initial set of potentially stable grasps in a cluttered scene. The best detected grasps are further optimized by fine-tuning the configuration of the hand in simulation. To reduce the computational burden of this last operation, we model the outcomes of the grasps as a Gaussian Process, and use an entropy-search method in order to focus the optimization on regions where the best grasp is most likely to be. This approach is tested on the task of clearing piles of real, unknown, rock debris with an autonomous robot. Empirical results show a clear advantage of the proposed approach when the time window for decision is short.

Introduction

Humans learn how to grasp and manipulate all sorts of objects from a very early age. Yet, this seemingly trivial capability is still a major challenge when it comes to robots (Amor et al. 2013). The main reason behind the difficulty of grasping unknown objects is the need for a complex combination of perception, planning, motor skills and learning. Take for example the task of autonomously searching for an object hidden beneath a pile of debris (Figure 1). To perform this task, the robot needs to: (1) analyze visual information in order to determine a set of candidate actions, (2), plan each action and estimate its outcome, (3), execute the action with the highest expected outcome, and (4), eventually learn from this experience. In addition, the robot should avoid any damaging action, and perform the task under time constraints. Perception is the first step in the grasping process. The scene is usually segmented into continuous homogeneous regions that correspond to different sides, or *facets*, of the objects (Szeliski 2011). This step narrows down the number of useful actions to a few grasps per side of an object. Segmentation is difficult in the context of rubble removal because the objects are overlapping and unknown. Also, one cannot use prior models if the clutter contains natural objects or debris.

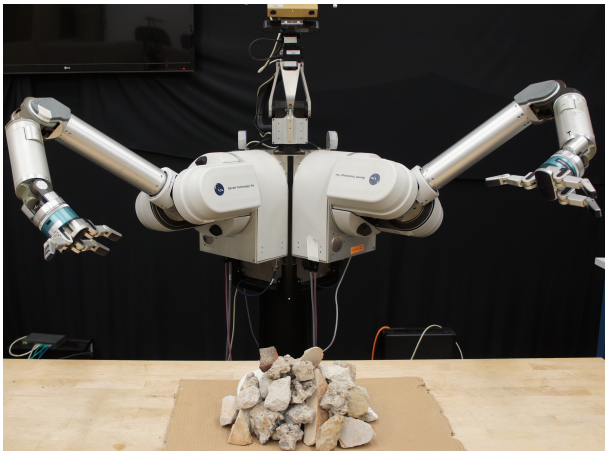


Figure 1: Two WAM arms equipped with two Barrett hands and a time-of-flight camera. The robot's task is to autonomously remove all the rocks in the pile.

To solve this problem, we use a fast template-matching method to detect successful grasps, without resorting to segmentation. A template is a patch in the depth image, containing the points that may collide with the hand. A large number of templates were collected and labeled. The outcome of a grasp is predicted by its k-nearest neighbor templates.

The best grasps detected by the template-matching technique are further optimized by varying the robotic hand's rotation and the angles of its fingers. Trajectories of the palm and the fingers are simulated with different configurations. To evaluate the quality of a configuration, we use a heuristic that measures the angles between each point of contact of the fingers and the palm's center of contact. The grasp with the highest quality in simulation is selected for execution.

This last planning step turns out to be the most expensive operation because of the collision checking needed for each evaluation. Therefore, a near-optimal grasp should be found

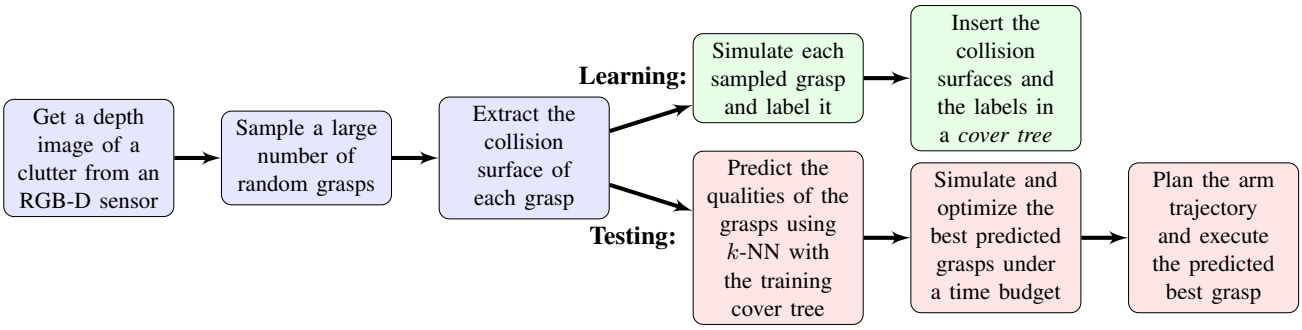


Figure 2: Overview of the approach. The learning and the testing mechanisms are both automated, with no human supervision.

with a minimum number of evaluations. We cast this problem in the *Bayesian optimization* framework (Jones, Schonlau, and Welch 1998; Lizotte 2008; Tesch, Schneider, and Choset 2013). Specifically, we model the grasp quality function as a Gaussian Process (GP) (Rasmussen and Williams 2005), and calculate a distribution on the best grasp. The grasps are evaluated in the order of their contributions to the entropy of this distribution, which is updated after each evaluation, until a time limit is reached. Figure 2 illustrates the pipeline of the proposed approach. There are two separate processes, learning and testing.

We use three-fingered robotic hands; two fingers are always maintained in parallel and point to the opposite direction of the thumb (Figure 1). We define a grasping configuration by $(\vec{a}, \theta, d, c)$, where $\vec{a}$ is the approach direction of the hand (the palm's normal vector), θ is the rotation angle of the hand, d is the initial distance between the tips of the fingers (the opening), and c is the contact point, obtained by projecting the palm's center on the clutter in the direction $\vec{a}$.

Feature extraction

A grasp quality measure is a function of different features of the hand, the object, and the surrounding clutter (Suárez, Roa, and Cornella 2006). These features include mechanical properties of objects, such as inertia matrices and friction factors. Due to the difficulty of inferring mechanical properties of unknown objects from visual input, we consider only geometric features. These features are obtained by projecting a three-dimensional model of the hand onto the point cloud, and retaining all the points that may collide with the hand when it is fully open (blue strips in Figure 3(a)). We call this set a *collision surface*.

The collision surface is transformed to a standard frame, relative to the hand. This frame is defined by setting c, the palm center projected on the cloud, as the origin, the thumb's direction as the x-axis and the approach direction as the z-axis. A collision surface can then be seen as a function $S : \mathcal{D} \rightarrow \mathbb{R}$, where $\mathcal{D} \subset \mathbb{R}^2$ and $S(x, y) = z$ for points (x, y, z) in the point cloud transformed to the hand frame. Domain $\mathcal{D}$ depends on the type of the hand (For instance, $\mathcal{D} = [-17.6, 17.6] \times [-3.75, 3.75]$ for a Barrett hand). To make this function well-defined, we keep only points with the maximum z-coordinate if there are multiple points with the same (x, y). We also discretize $\mathcal{D}$ into a regular grid, and define $S(x, y)$ as the average z-coordinate of the points in cell (x, y). For cells (x, y) with no points (due to occlusions for example), we set $S(x, y)$ to a default value, corresponding to the average of S in all cells that contain points. Figure 3(b) shows a collision surface represented as a function.

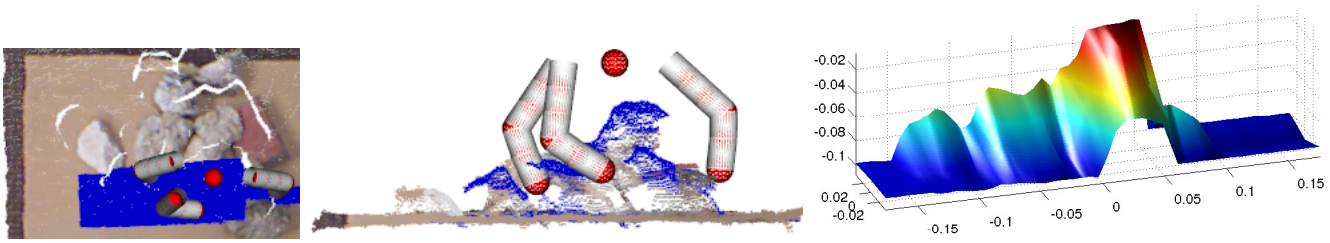
Planning

To simulate the trajectories of the robotic hand and fingers, we implemented a 3-D model of the Barrett hand using the Point Cloud Library (PCL) (Rusu and Cousins 2011). Time is discretized to short steps. The hand moves in direction $\vec{a}$ towards contact point c, with a constant velocity. Upon touching the surface, the fingers start closing. Collisions with the clutter are checked at every time-step. Any collision stops the motion of the palm, as well as the parts of the fingers involved in the collision.

To measure the quality of a grasp $(\vec{a}, \theta, d, c)$ at the final time-step of the simulated motion, we use a simple heuristic that we found useful in our experiments. For each finger i, we search for the point p_i^* on its surface that maximizes $h(p_i) = \frac{\vec{a}.(p_i - c)^T}{\|p_i - c\|_2}$. The grasp quality is given by $\sum_{i \in \{1,2,3\}} h(p_i^*)$. For example, a grasp is maximally stable when each finger circulates the object, i.e. $(p_i^* - c) \parallel \vec{a}$ and $h(p_i^*) = \vec{a}.\vec{a} = 1$. Another example is when finger i is blocked by clutter above of c and $h(p_i^*)$ becomes negative. Planning is performed by varying one or more of the initial parameters $(\vec{a}, \theta, d, c)$, and simulating the corresponding grasps. The grasp with the highest value is retained.

Learning the grasp quality

Planning in simulation is a reliable way to obtain stable grasps, but also time-consuming. This problem is even more concerning if we simulate the dynamics of irregular objects in clutter, using a physics-based engine. In order to minimize the number of evaluations, the planner should be given a number of good initial grasps to start from. We use a learning method to quickly detect these initial grasps. Our approach consists in randomly sampling a large number of grasp configurations $(\vec{a}, \theta, d, c)$, and predicting their qualities by matching their collision surfaces with the ones of already evaluated grasps. Specifically, we use the k-nearest neighbors (k-NN) regression. The distance between grasps i and j is defined as the distance between collision surfaces S_i



(a) Top and side views of a planned grasping action in a clutter of rocks (b) corresponding collision surface

Figure 3: An example of a simulated grasping action of a rock in clutter, and the corresponding contextual features

and S_j , given by $\sum_{(x,y)\in\mathcal{D}} \big(S_i(x,y) - S_j(x,y)\big)^2$. We use the *cover tree* algorithm (Beygelzimer, Kakade, and Langford 2006) for efficient batch requests. The grasping examples are automatically collected from different depth images of clutters, and evaluated in simulation, using the heuristic quality measure. A large set of examples can be generated this way, which cannot be done manually.

Grasp optimization with Entropy Search

The predicted best grasp by learning is not the best grasp, simply because it is chosen from a finite set of randomly generated grasps, and also because of the regression error. However, the actual best grasp is likely to be in the vicinity of the one predicted by learning. Therefore, we use the output of k-NN to select an initial starting point for the planner.

The planner searches for a locally optimal grasp around the starting point. The objective function to maximize maps the parameters $(\vec{a}, \theta, d, c)$ of a grasp to a quality value. The quality value can be obtained only after simulating the grasping action with the given parameters. This is clearly a black-box optimization problem (Jones, Schonlau, and Welch 1998). The objective function is unknown, and there is a computational cost for evaluating it in a given point.

We formulate this problem in the Bayesian optimization framework (Lizotte 2008). For clarity, we use general notations. $x \in \mathbb{R}^n$ denotes the parameters $(\vec{a}, \theta, d, c)$ of a grasp, and $f(x) \in \mathbb{R}$ denotes its value according to the simulator. We search for $x^* = \arg\max_{x\in\mathbb{R}^n} f(x)$. Function f is generally non-convex and piecewise differentiable. Moreover, it is often difficult to obtain accurate estimates of the derivatives of f, because of the noise, and also because additional evaluations of f are needed to estimate ∇f. Nevertheless, a grasp is often surrounded by grasps of nearly equal qualities. Therefore, the objective function f can be learned locally.

The learning of quality function f is an on-line process that happens within a planning cycle. The planner chooses a grasp to evaluate, inquires the simulator about its quality, and learns more about f from this example. The learned model of f is used to efficiently choose the next grasp to evaluate. This process is repeated until the planning time limit is reached, and the best grasp is executed by the robot.

This learning problem is different from the previous one, solved with k-NN, because it is local and temporary. Here, we are interested in predicting the values of grasps using examples, provided by the simulator, from the same small region of the same scene. k-NN, on the other hand, was used to generalize examples to new scenes. For this reason, the features used in k-NN contain contextual information in the form of collision surfaces, while one can simply use the parameters $(\vec{a}, \theta, d, c)$ as features if the grasps are all in the same scene. This learning is also temporary because the scene changes after the robot executes an action.

We use a formulation of Bayesian optimization originally presented in (Hennig and Schuler 2012). Our belief about the objective function f is a probability measure $p(f)$ over the space of all functions $f : \mathbb{R}^n \to \mathbb{R}$. This measure implicitly defines another measure P_{max} on the location of the the optimal grasp x^*,

$$P_{max}(x) \triangleq P\big(x = \arg\max_{\tilde{x}\in\mathbb{R}^n} f(\tilde{x})\big)$$
$$= \int_{f:\mathbb{R}^n\to\mathbb{R}} p(f)\Pi_{\tilde{x}\in\mathbb{R}^n-\{x\}}\Theta\big(f(x) - f(\tilde{x})\big)\mathrm{d}f,$$

where Θ is the Heaviside step function. The product function Π over $\mathbb{R}^n$ is well-defined because $\Theta\big(f(x) - f(\tilde{x})\big) \in \{0, 1\}$. The belief p over f is updated from a sequence of evaluations $\{\big(x_t, f(x_t)\big)\}$ by using Bayes' Rule. Consequently, P_{max} is also updated from the evaluations. The problem now is to find a short sequence of evaluations $\{\big(x_t, f(x_t)\big)\}$ that decreases the entropy of P_{max}.

To solve this problem, we use a Gaussian Process (GP) to represent p. We briefly present here the GP regression, and refer the reader to (Rasmussen and Williams 2005) for more details. Let k be a kernel function, $k : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$, for measuring the similarity between two points in $\mathbb{R}^n$. Let $X_t = \big(x_1, x_2 \ldots, x_t\big)$ be a sequence of evaluation points, and let $Y_t = \big(y_1, y_2 \ldots, y_t\big)$ be the corresponding values, where $y_i = f(x_i) + \epsilon_i$ and $\epsilon_i \sim \mathcal{N}(0, \sigma^2)$ is an independent white noise. The kernel Gram matrix K_{X_t,X_t} is a $t \times t$ positive-definite matrix, defined as $K_{X_t,X_t}(i,j) = k(x_i, x_j)$, for $i, j \in \{1, \ldots, t\}$. Given X_t and Y_t, the posterior distribution on the values of f in any set of points $\tilde{X} = \big(\tilde{x}_1, \tilde{x}_2 \ldots, \tilde{x}_m\big)$ is a Gaussian with mean vector $\mu_{\tilde{X}}$ and covariance matrix $\Sigma_{\tilde{X},\tilde{X}}$ given by

$$\mu_{\tilde{X}} = K_{\tilde{X},X_t}\big(I + \sigma^2 K_{X_t,X_t}\big)^{-1} Y_t^T,$$
$$\Sigma_{\tilde{X},\tilde{X}} = K_{\tilde{X},\tilde{X}} - K_{\tilde{X},X_t}\big(I + \sigma^2 K_{X_t,X_t}\big)^{-1} K_{X_t,\tilde{X}}, \quad (1)$$

where $K_{\tilde{X},X_t}(i,j) = k(\tilde{x}_i, x_j)$, $K_{\tilde{X},\tilde{X}}(i,j) = k(\tilde{x}_i, \tilde{x}_j)$, $K_{X_t,\tilde{X}}(i,j) = k(x_i, \tilde{x}_j)$, and I is an identity matrix. A vec-

tor of values of f at points $\tilde{X}$ can be sampled by drawing a vector $\psi \sim \prod \mathcal{N}(0,1)$ of independent, one-dimensional, standard Gaussian random values. The sampled f vector is

$$\tilde{Y} = \mu_{\tilde{X}} + C\big(\Sigma_{\tilde{X},\tilde{X}}\big)\psi^T, \quad (2)$$

where $C\big(\Sigma_{\tilde{X},\tilde{X}}\big)$ is the Cholsky upper matrix of $\Sigma_{\tilde{X},\tilde{X}}$.

The distribution P_{max} does not have a closed-form expression. Therefore, we discretize the domain of f, and use Monte Carlo (MC) for estimating P_{max} from samples of f.

Specifically, $X_t = \big(x_1, x_2 \ldots, x_t\big)$ is the sequence of grasps that have been simulated and evaluated at time t, and Y_t is the sequence of their values. We need now to choose x_{t+1}, the next grasp to evaluate, from a finite list of candidates $\tilde{X} = \big(\tilde{x}_1, \tilde{x}_2 \ldots, \tilde{x}_m\big)$. We calculate the mean vector and the covariance matrix of all the grasps (X_t and $\tilde{X}$) (Equation 1), and we sample vectors of f values in both X_t and $\tilde{X}$ (Equation 2). $P_{max}(x)$ is estimated by counting the fraction of sampled f vectors where x has the highest value, i.e. $f(x) > f(x'), \forall x' \in X_t \cup \tilde{X} - \{x\}$. Note that the covariance of all the grasps does not depend on the output values Y_t, therefore, it is calculated only once, at the beginning.

The Monte Carlo Entropy Search method (Hennig and Schuler 2012) chooses the next evaluation point x_{t+1} by estimating the information gain of every candidate x as follows: (1) Sample several values $y = f(x) + \epsilon$ according to the GP obtained from current data (X_t, Y_t). (2) For each sampled value y, calculate the posterior GP with data (X_t, Y_t) and (x, y), and estimate the new P_{max} by MC sampling. The candidate that leads to the lowest entropy of P_{max}, on average, is the next point x_{t+1}.

The MC Entropy Search method was not efficient for our purpose because of the two nested loops of MC sampling. We propose here a simpler and more efficient alternative for selecting the evaluation points with only one loop of sampling. At each step t, we estimate P_{max}, the distribution over the best grasp, by sampling several quality functions f according to the GP obtained from accumulated data (X_t, Y_t). We choose the point x that has the highest contribution to the current entropy of P_{max}, i.e. the highest term $-P_{max}(x) \log\big(P_{max}(x)\big)$, as the next grasp to evaluate. We refer to this method as the Greedy Entropy Search method.

Experiments

Extensive experiments were performed to evaluate each component of the proposed approach. Final experiments, on autonomous clearing of rock piles, were aimed at evaluating the full system. The only few human interventions were the ones needed for setting objects in the operational space and field of view of the robot. All the results reported here were obtained by using a single-core CPU implementation. For transparency, unedited videos of all the experiments have been uploaded to http://goo.gl/73Q10S .

Planning

The geometric planner plays a major role in the quality of the executed actions. To assess its performance separately from the learning and the Bayesian optimization components, we tested it on the task of autonomously clearing clutters of man-made unknown objects. An example of the piles used in the experiments is shown in Figure 4. We used the approach of (Katz et al. 2013) in order to segment the clutter into facets (curved 3-D rectangles) defined by their centers and principal and secondary axis. For each facet, we simulate the grasping actions centered on it, while setting the hand's direction to the surface normal and the hand's orientation to the principal or secondary axis of the facet. For each orientation of the hand, we simulate trajectories with different initial distances between the tips of the fingers, ranging from the length (or width) of the facet plus 0.5 cm to 20 cm, using steps of 0.5 cm. The grasp with the highest heuristic value, as explained in the section on planning, is selected for execution. The CHOMP algorithm (Ratliff et al. 2009) is then used to generate arm trajectories, and a library of compliant hand motions with force-feedback is used to execute the grasping action (Kazemi et al. 2012).

	objects	actions	failures	success
Pile 1	10	10	0	100%
Pile 2	10	10	2	80%
Pile 3	10	9	0	100%
Pile 4	10	12	2	83%
Pile 5	10	9	0	100%
Total	50	50	4	**92%**

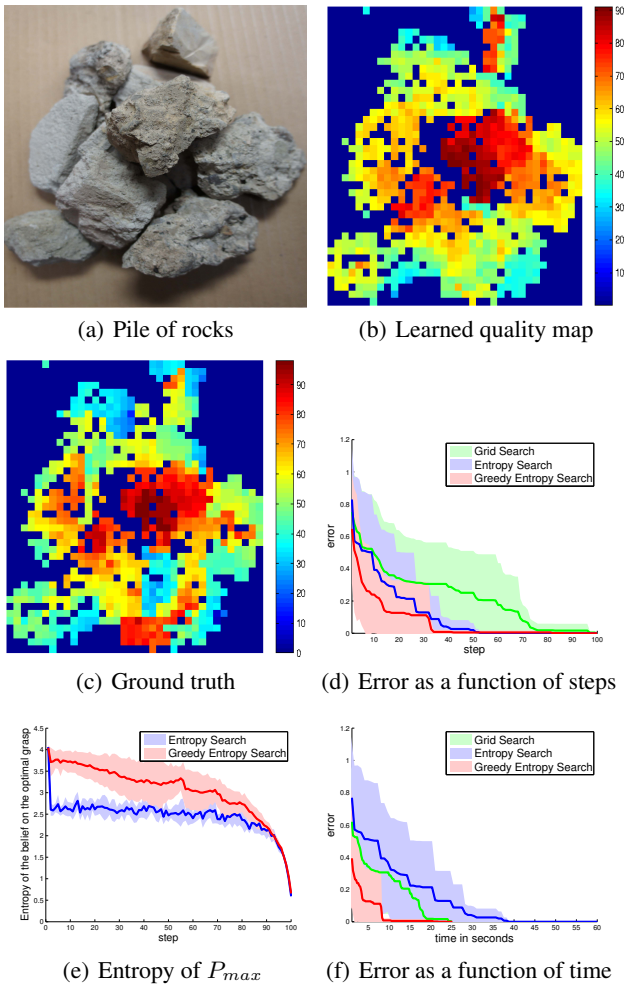
Figure 4: Regular objects used to assess the grasp planner. The table indicates the number of objects in each experiment, the number of grasping actions needed to remove all the objects, the number of failed grasps, and the success rate.

Figure 4 shows the results of experiments with five random piles of ten objects. The robot managed to clear each pile in twelve actions at most. In some piles, less than ten actions were needed because the robot grasped more than one object at once. The overall success rate of the attempted grasps is 92%, which is a significantly higher than the result reported in (Katz et al. 2013). The same segmentation technique was used in that work along with an SVM for classifying grasps, and the authors reported a success rate of 53%.

Learning

To evaluate the k-NN method, using the collision surfaces as features, we designed an automated mechanism for collecting a large number of examples. The examples were obtained from depth images of 16 piles of man-made and natural objects. In each pile, $2,000$ random grasping actions were sampled and evaluated by the planner. It is important to mention here that the distances between the fingers were not randomly sampled in the examples. The distances were always optimized by the planner because this information is not included in the collision surfaces. The features and the labels of the examples were organized in a cover tree.

We tested the learning method on five piles of unknown objects. Figure 5(a) shows one of the piles. Figure 5(b) illustrates the quality map learned with k-NN. Each point corresponds to a center of a grasping action. For clarity, the direction of the robotic hand is set to the support surface



(a) Pile of rocks (b) Learned quality map

(c) Ground truth (d) Error as a function of steps

(e) Entropy of P_{max} (f) Error as a function of time

Figure 5: Example of the rock piles used for empirical tests.

normal, and the rotation is the top-bottom axis in the figure. The color indicates the predicted quality of the grasp; red indicates the best grasping centers and blue indicates the worst centers, which are the support surface. The predicted quality is correlated with the height of the point, but also with the shape of the clutter around it. For instance, isolated rocks have higher values. Figure 5(c) shows the ground-truth quality map, generated by simulating each grasp and evaluating it. The substantial similarities between the predictions of k-NN and the true values show the advantage of using a large number of examples with the collision surfaces as features.

	Planner	**k-NN**	**data st.d.**	**RMSE**	**r. o.**
Pile a	240 sec	2.71 sec	0.0058	0.0035	42%
Pile b	160 sec	2.45 sec	0.0041	0.0028	67%
Pile c	190 sec	2.32 sec	0.0074	0.0049	31%
Pile d	210 sec	2.95 sec	0.0050	0.0036	29%
Pile e	290 sec	3.57 sec	0.0075	0.0048	17%

Table 1: k-NN regression results

More importantly, the quality map in Figure 5(b) was generated in just 2.45 seconds. During this short period of time, the features of $2,000$ grasps were extracted and their values predicted by k-NN. It took the planner more than 160 seconds to simulate and evaluate the same grasps in order to generate Figure 5(c). Table 1 illustrates this advantage of k-NN, along with its root mean squared error (RMSE), and the standard deviation of the actual values. Since our goal is not to predict the values of the grasps but to rank them accurately, we report the *rate of overlapping* (r. o.), which is the fraction of the top 5% grasps according to k-NN that also appear in the top 5% grasps according to the planner.

Anytime optimization with Entropy Search

The next experiments are aimed at evaluating the performance of the Greedy Entropy Search (ES) algorithm, and comparing it to the Monte Carlo ES (Hennig and Schuler 2012) and to Grid Search.

The predicted best grasping action using k-NN is not, in general, an optimal action. This is due to prediction errors, and also to the fact that the action space is continuous, and the samples cover only a small countable subspace. We keep only the ten best points in Figure 5(b), and search for the actual optimal grasp in a list of candidates corresponding to different hand rotations around each point. We consider 100 regular rotations from 0 to 2π. The values of these rotations can be obtained from the simulator at a computational price.

The Grid Search method starts with the initial rotation and systematically evaluate each candidate grasp in the order of their rotations. This approach may sound naïve, but it is justified by the fact that the initial rotation is already predicted by k-NN as a good one. The two ES algorithms choose to evaluate grasp rotations according to their expected information gain. The Greedy ES method that we proposed is computationally more efficient than the non-greedy one.

Figure 5(d) shows the absolute difference between the optimal value and the value of the predicted optimal grasp as a function of the number of evaluated grasps. The results are averaged over ten different starting points. Both ES methods converged faster than Grid Search. Figure 5(e) shows the entropy of the distribution over the optimal grasp as a function of the number of evaluations. As expected, the entropy drops faster with the non-greedy ES.

Figure 5(f) illustrates the most important result of this experiment. It shows that although the Greedy ES technique needs more time than the Grid Search in order to select the next grasp to evaluate, it is still more efficient. These results also show that the advantage of the non-greedy ES is unclear.

Autonomous clearing of rock clutters

In the final experiments, we compare the Greedy Entropy Search method to the Grid Search on the challenging task of clearing piles of rocks. The setup is similar to the one used for regular objects, except that we use k-NN for selecting an initial grasp to optimize with the geometric planner, instead of segmenting the rocks into facets. We performed two series of experiments. In the first experiments, we limit the time of the perception module to only one second per executed action. The execution of the actions by the robot requires more time at the moment, for safety reasons. In the second

	time limit	objects	actions	failures	success
Pile 1	1 sec	11	26	15	42%
Pile 2	1 sec	11	25	14	44%
Pile 3	1 sec	11	18	9	50%
Pile 4	1 sec	11	30	19	37%
Pile 5	1 sec	11	45	34	24%
Avg.	1 sec	11	29	18	**39±10 %**
Pile 1	5 sec	11	13	2	85%
Pile 2	5 sec	12	13	2	85%
Pile 3	5 sec	12	14	3	79%
Pile 4	5 sec	11	18	7	61%
Pile 5	5 sec	11	19	8	58%
Avg.	5 sec	11	15	4	**74±13 %**

(a) k-NN and **Grid Search**

	time limit	objects	actions	failures	success
Pile 1	1 sec	11	22	11	50%
Pile 2	1 sec	11	14	4	71%
Pile 3	1 sec	11	24	13	46%
Pile 4	1 sec	11	18	7	61%
Pile 5	1 sec	11	22	11	50%
Avg.	1 sec	11	20	9	**56±10 %**
Pile 1	5 sec	11	23	12	48%
Pile 2	5 sec	12	16	5	69%
Pile 3	5 sec	12	14	3	79%
Pile 4	5 sec	11	16	6	63%
Pile 5	5 sec	11	16	5	69%
Avg.	5 sec	11	17	6	**66±11 %**

(b) k-NN and **Greedy Entropy Search**

Figure 6: Results of the experiments on clearing piles of rocks. Both search methods use k-NN to find good starting points.

experiments, we increase the time budget to five seconds. In all experiments, the optimization is stopped after reaching the time limit, and the predicted best grasp is executed.

The results of these experiments are shown in Figure 6. In the one-second time limit experiments, the grasps predicted by the Greedy ES had an average success rate of **56%**, compared to **39%** with the Grid Search. When we increased the time limit to five seconds, we noticed that the Grid Search performed slightly better than the Greedy ES (74% vs. 66%). In fact, given enough time, Grid Search evaluates all the candidate grasps and always finds the best one, while the Greedy ES method evaluates less grasps because a portion of the time is used to choose which grasp to evaluate. The advantage of efficient search methods, such as the proposed Greedy ES technique, is more pronounced when the grasp planner requires more time, which is the case of dynamics planners like GraspIt (Miller and Allen 2004).

Related work

We encourage the reader to consult an extensive recent review in (Bohg et al. 2013) on data-driven grasping. Until the last decade, the majority of the robotic grasping techniques required accurate and complete 3-D models of objects in order to measure stability by using analytical methods (Bicchi and Kumar 2000). However, building accurate models of new objects is difficult and requires scanning the objects. Statistical learning of grasping actions is an alternative approach that have received increased attention in the recent years. For instance, SVMs were used to predict the stability of grasps from sequences of haptic feedback (Bekiroglu et al. 2011). It was also shown that a simple logistic function can be learned to predict the position of stable grasping points in a 2-D image (Saxena, Wong, and Ng 2008). A more recent work used deep learning for the same purpose (Lenz, Lee, and Saxena 2013). Note that these methods were tested only on regular objects. It is quite difficult to obtain good grasps for natural objects in clutter, e.g. Figure 5(a), without using depth features. The features used in (Herzog et al. 2012) for template matching are closely related to the collision surfaces presented in this paper. A key difference is that we do not separate an object from its surrounding clutter. Thus, we do not need to segment the scene. The general approach of using a planner to automatically collect examples was first suggested in (Pelossof et al.), an SVM was trained using examples obtained from the GraspIt simulator.

The works of (Villemonteix, Vazquez, and Walter 2009) and, particularly, (Hennig and Schuler 2012) provided the general framework of optimization by entropy search, from which we derived our greedy search method. Note also that GPs were used to efficiently optimize the parameters of a snake robot's controller (Tesch, Schneider, and Choset 2011a; 2011b; 2013), the parameters were evaluated in the order of their *expected improvement*, which is different from entropy minimization. In (Kroemer et al. 2010), the grasping outcome was also represented as a GP, and the Upper Confidence Bound heuristic was used for exploring the actions.

Conclusion

We presented a simple learning technique for detecting useful grasping actions in a clutter of unknown natural objects. The parameters of the detected actions are fine-tuned by a geometric planner. The planning process is necessary in cluttered scenes, but also time-expensive. To reduce the computational cost, the planner learns on-line the outcomes of the simulated actions and evaluate them in the order of their information gain. Experiments show that this technique is efficient when the robot has a small window of time for action.

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