Evaluating and Optimizing Adaptive Grippers for Difficult Objects

1st Kevin Hu
Department of Computer Science
University of California - Berkeley
Berkeley, US
kevin.hu(at)berkeley.edu

2nd Doug Pan
Department of Computer Science
University of California - Berkeley
Berkeley, US
doug.s.pan(at)berkeley.edu

3rd Leonard Wei
Department of Computer Science
University of California - Berkeley
Berkeley, US
lwei(at)berkeley.edu

***Abstract*—Adaptive grippers are useful for robotic applications because they augment parallel grippers by adding the ability to perform an encompassing grasp. However, designing an effective adaptive gripper is difficult and time-consuming since both the parallel grasp and the encompassing grasp must be simultaneously considered during design. This paper explores the adaptive gripper design space for difficult to grasp objects from the Evolved Grasping Analysis Dataset (EGAD), and utilizes differential evolution to automatically select adaptive gripper design parameters that perform better than a baseline adaptive gripper in simulation.**

***Index Terms*—grasping, adaptive grippers, optimization, differential evolution, grasp policies**

I. Introduction and Motivation

A. Motivation

Parallel jaw grippers are widely used in industry because of their low complexity, long lifetime, and ability to precisely manipulate objects [1]. As a result of this ubiquity, the scientific community uses parallel jaw grippers extensively in research, and over the past decades, developed various analytical [2] and data-driven [3] approaches to plan and evaluate grasps with the goal of improving manufacturing production lines and warehouse logistics operations.

While significant progress has been made, autonomous grasp planning remains a complex topic with rich areas of research in both physical modeling of phenomena like contact friction, slip, compliance and object movement [2] as well as overcoming uncertainty in sensing and actuation.

In class, we implemented a basic grasp planning workflow, as shown in the figure 1, and saw that this process struggled with generating grasp plans that would successfully pick up an object. One significant constraint was the fixed gripper geometry that had an arbitrarily selected maximum jaw size. This reflects the problem encountered in warehouse logistics where robotic hardware is selected beforehand, and must be capable of picking objects - many of which is hasn't seen before.

However, there is another approach. In manufacturing, the object to be grasped is often known beforehand, and grippers are custom-designed in order to maximize the chances of a successful grasp. Automatic design of grippers would reduce the lead time and cost of developing high throughput manufacturing processes.

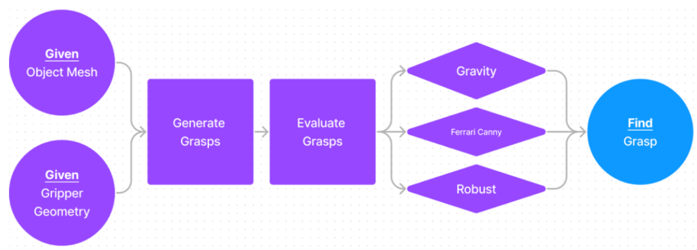

Fig. 1. The goal of grasp planning workflow is to output a stable grasp given an object mesh and gripper geometry. The process we implemented consisted of generating and evaluating grasp candidates, which are gripper orientations executable by the manipulator. The top grasp candidates are output as stable grasps.

Therefore, in this paper, we developed a design, evaluation and optimization process for complex grippers, and demonstrate the output of this process on adaptive grippers. Adaptive grippers are underactuated grippers capable of parallel jaw grasping and encompassing grasps, and are good candidates for optimization because of clear design parameters that can be quickly evaluated.

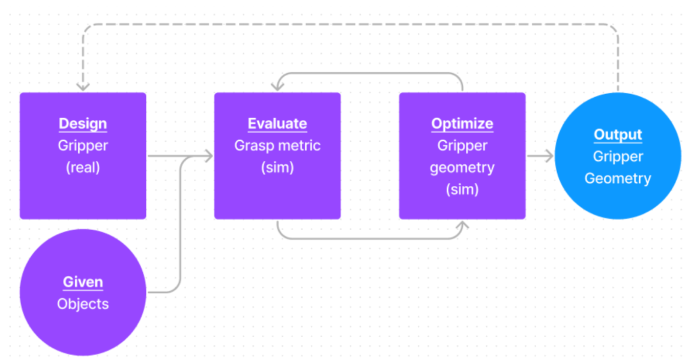

Fig. 2. Our goal was to demonstrate how the design of a gripper type could be automated. In this process, we design a baseline gripper, evaluate its performance on a set of objects, and optimize gripper geometry in an iterative manner, ultimately outputting updated gripper geometry capable of better grasps.

II. Related Work

A. Adaptive Grippers

Adaptive grippers are capable of both parallel (or pinch) grasping and encompassing (or power) grasping. One way of creating low-complexity adaptive grippers with high repeatability is the underactuated mechanism patented by RobotIQ[6].

As shown in Figure 3, this mechanism is mechanically simple with clear design parameters that are derived from the various linkage lengths (fingertip length, distal and proximal phalanx length, and palm width). This gripper was selected because it is easier to design, evaluate and optimize in comparison to soft grippers and vaccuum grippers that have many more degrees of freedom [7].

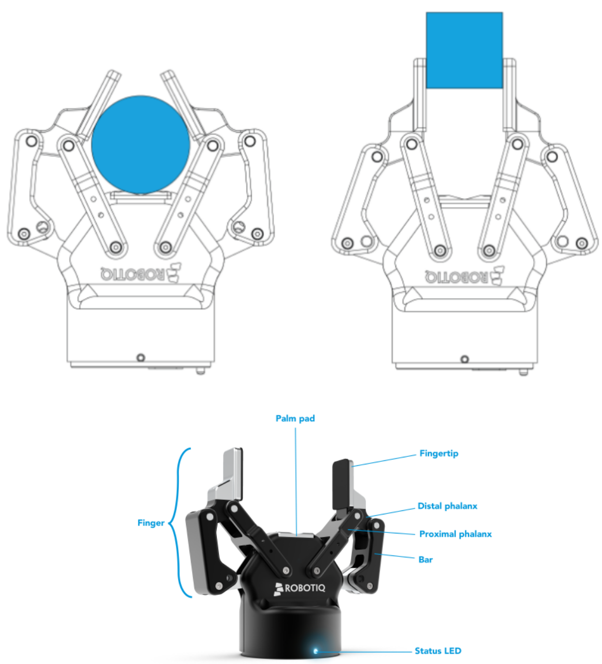

Fig. 3. The Robotiq 2-Finger Adaptive Gripper. The top row shows the different possible rips. Whether the fingers close to produce an encompassing or parallel grasp is decided at the gripper level and depends on the objects geometry and relative psoition of the object with respect to the gripper. In other words, picking the same object could result in either an encompassing or fingertip grasp based on object position and geometry. A parallel grasp is only performed when the object touches the upper section of the distal phalanx and an encompassing grasp is performed when the object touches the lower distal phalanx first. The bottom image shows the parts of the adaptive gripper.

B. Optimization

Optimization - To optimize over the space of feasible adaptive grippers for the one best-suited for the given task, we formulate a straightforward optimization problem, where θ are the gripper parameters, O is the set of objects we would like to grasp, and Q is some quality metric:

$$max_{\theta} \sum_{o \in O} Q(\theta, o)$$

Global optimization methods are needed, as this is a non-convex problem with many local minima. For this project, we chose to use Differential Evolution (DE) [13] to find a good solution. An outline of the algorithm is shown in Figure 4, but generally, this approach involves:

1) Selecting and scoring a population of candidate grippers
2) Mutating / crossing-over parameters randomly for each member of the population
3) Selecting the population for the next iteration by choosing the top-scoring designs

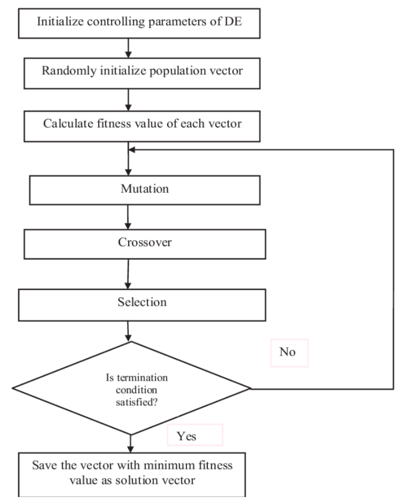

Fig. 4. Flow chart of the DE process. We use the gravity metric as the fitness function and run the DE algorithm for 175 iterations with a crossover rate of 0.7 and a mutation rate randomly chosen $\in [0.5, 1.0]$. Experiments show that the best candidate score is reached within 50 iterations, but that convergence is not achieved until iteration 175. It's possible that tuning some of the DE parameters would increase our search space and allow us to find a more global optimum, at the cost of slower convergence.

III. Methods

A. Goal

Our goal was to evaluate the baseline performance of an adaptive gripper in real life on difficult objects (defined as those with poor Ferrari Canny scores for a parallel grip) , and to compare performance of subsequent optimized adaptive grippers against this baseline. We were able to compare simulation performance. Real life comparison is saved as future work.

B. High level approach

Our process to achieve this goal was divided into three steps.

1) **Select a set of difficult to grasp objects** In order to evaluate performance, we selected two difficult to grasp objects from the Evolved Grasping Analysis Dataset (EGAD) evaluation model set[8]. E1 and F1 were selected because of their low shape complexity, but high grasp difficulty. Shape complexity is calculated as the entropy of the probability density function of the angular deficit of each vertex. Grasp difficulty is measured by the 75th percentile grasp quality of the computed Ferrari-Canny quality metric for each object.

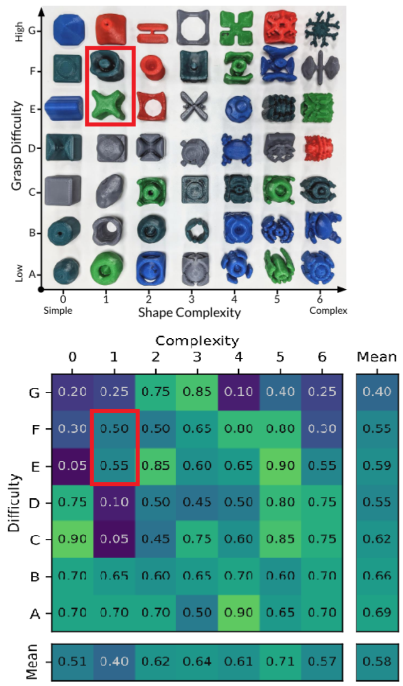

Fig. 5. Left hand side: The 49 evaluation objects chosen from the 2000 EGAD objects. The objects provide a range of objects from simple to complex geometry (left to right) and easy to difficult graspability (bottom to top). Right hand side: Average grasp success rate for each object using GG-CNN as described in[8]. Note the very low success rates for objects in the upper left hand corner.

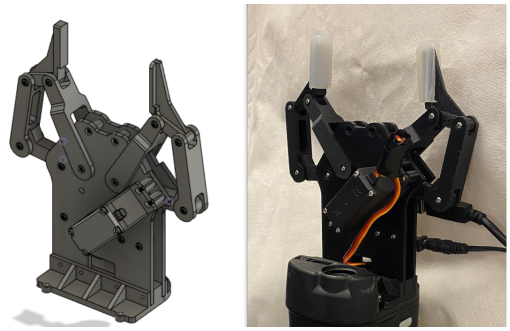

Fig. 6. Left hand side: 3D CAD model of the adaptive gripper. Right hand side: Printed version of the adaptive gripper as installed on a Baxter robot platform.

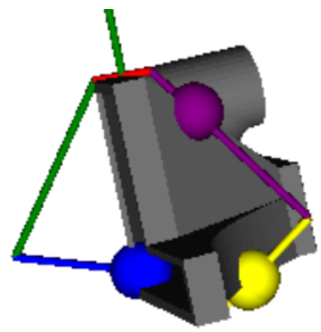

Fig. 7. Design parameters indicated with the colored lines. Palm length is red. Proximal lengths are green and purple. Tip lengths are blue and yellow. We also assume that the gripper behaves symmetrically when executing the encompassing grip.

2) **Design and fabricate an adaptive gripper** Because we wanted to test baseline performance in real life, we also designed and fabricated our own adaptive gripper that mimicked the geometry of the Robotiq 2F-85. This gripper has a 85mm opening and is designed to install onto the Baxter arm. It is actuated by a Towerpro MG996R Servo and controlled via serial commands from a host computer. During testing, we validated that this gripper was capable of performing both parallel and encompassing grasps just like the Robotiq 2F-85. This gripper is the baseline adaptive gripper that we compare all future optimizations to.
3) **Evaluate and Optimize adaptive gripper for the difficult objects** In order to demonstrate the feasibility of this automatic design process, we selected the computationally simple gravity metric as our objective function and optimized the adaptive gripper for three design parameters across three scenarios. The first scenario was an adaptive gripper specifically optimized for EGAD object E1; the second scenario was for EGAD object F1; the third scenario considered both E1 and F1 in the optimization. Optimization results were mixed and further discussed in the Results section.

We go into some more detail for the optimization below.

C. Optimization

As previously mentioned, we applied DE to maximize the sum of some quality heuristic for all objects. Here, we simply chose to use gravity resistance, for its ease of implementation and computational simplicity. For each set of candidate gripper parameters, we judge its quality by computing the gravity resistance metric for its best grasp on each object:

$$Q(\theta, o) = \max_{\phi} \textbf{gravityresistance}(\theta, \phi, o)$$

This is solved with a sample-based approach. Specifically, we sample 500 valid encompassing grasps, and return the one with the best score. To sample and score grasps for the adaptive gripper, we:

1) Select a random point on the object mesh, and a random angle theta
2) Initialize an open adaptive gripper with its base's center in contact with the selected point, and its orientation determined by theta and the face normal at that point
3) Close the gripper around the mesh by iteratively increasing joint angles and checking for contact with the mesh and self-collisions
4) Using the discovered contact points (excluding contact points with the base of the gripper) to compute gravity resistance

With only 500 grasp samples, we observed that our quality heuristic had high variance, so as a workaround, we returned the mean of the top 5 scores. This allowed for more stable quality measurements and faster convergence.

Since we restricted our optimized grippers to be symmetric, we restricted our candidate parameters to 3 bounded values ($\theta \in \mathbb{R}^3, \theta_i \in (0, 0.1]$), which contained what we believed to be a "reasonable" upper bound on the size of each linkage length (10cm). This allowed us to restrict the search space further and improve the speed at which the optimizer converged to some solution.

IV. Results

Our reported consist of quantitative and qualitative simulation results. Quantitative results compare gravity metrics for the Baxter parallel jaw gripper, our baseline adaptive gripper, and an optimized adaptive gripper. Qualitative results are realized 3D models of the adaptive gripper with optimized link lengths.

A. Quantitative simulation results

There were two surprising results from the comparison of metrics. The first was that optimization only improved the gravity metric marginally. The second was that for some of the difficult to grasp objects, there were only minor differences between the parallel jaw gripper and the adaptive gripper. This forces us to reconsider the benefits of an additional grasping mode, or to consider whether the gravity metric is an effective cost function for the optimization process.

Table 1 summarizes our results. To compensate for the high variance in the results we observed, the table shows both the best result and the average of the top 5 results for each difficult to grasp object.

TABLE I

	Parallel Jaw	Baseline Adaptive	Optimized Adaptive
Best E1	3.51	2.59	2.45
Top 5 E1	3.90	2.86	2.52
Best F1	2.21	2.25	2.25
Top 5 F1	2.22	2.44	2.32

B. Qualitative simulation results

We also evaluated the optimization output in a qualitative manner, by creating 3D CAD models of an adaptive gripper based on the optimization output. Using these results, we discovered that the gripper model used for optimization was flawed and overly simplistic. The optimized parameters resulted in gripper geometries that are highly specialized for specific encompassing grasps and would be incapable of most parallel jaw grasps due to a design that prevents the jaws from ever touching.

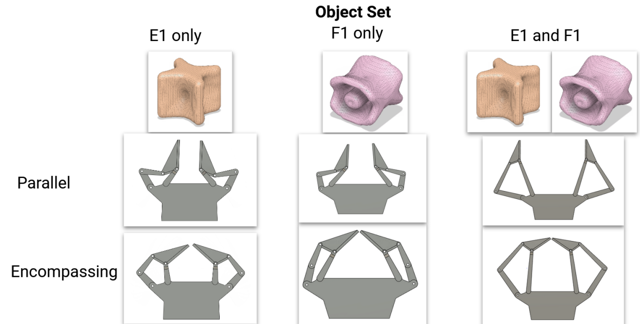

Fig. 8. Design parameters indicated with the colored lines. Palm length is red. Proximal lengths are green and purple. Tip lengths are blue and yellow. We also assume that the gripper behaves symmetrically when executing the encompassing grip.

V. Conclusion

A. Summary

Parallel grippers are ubiquitous in industry because of their low complexity, long life, and acceptable performance for most tasks. In applications such as manufacturing where there is low object variance and the need for high grasp success rates, automated gripper design may reduce lead time and costs.

In this paper, we demonstrated a computer-aided process to optimize adaptive gripper design for difficult to grasp objects and show that the optimized gripper has better simulated performance, and implemented a planner on the Baxter robotics platform to evaluate real-life performance.

B. Reflection

During this experiment, we ran into several difficulties.

1) **Computational bottlenecks** Optimization processes take significant computational resources. In this experiment, we started with additional design parameters and more sophisticated grasp metrics. However, the more complex optimization problem would have taken several days to output results. For the purposes of the course, we simplified the model and the metric and even then each optimization process took over 24 hours. Getting additional computational resources would have helped us maintain our original optimization formulation.
2) **Oversimplistic model** As a result of the computational constraints, we simplified the model. However, we did not realize how much we have oversimplified until we observed the results. Our assumptions about gripper kinematics and gripper symmetry resulted in gripper designs that would perform poorly. The grasps that they were intended to execute would have needed components that can pass through one another - a physical impossibility.

C. Future Work

Extensive real life testing is required for both the baseline and optimized adaptive grippers in order to evaluate optimization quality. Creating a parametric adaptive gripper CAD model would allow for quick design iterations, and use of a

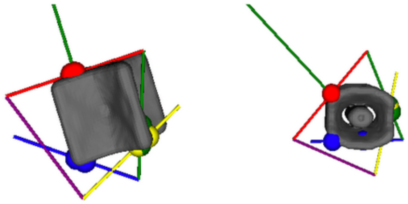

Fig. 9. Infeasible grasps from the optimized gripper geometry. Note how the gripper intersects itself. This is a direct result of an oversimplified gripper model, and results in gripper geometry that would not result in better grasps.

reset mechanism as devised in [9] would aid in automated grasp success evaluation.

Additional work would also include extending the design, evaluation and optimization process to other design parameters and gripper kinds. Design parameters we considered, but declined to explore due to the rapid complexity of the design space include the number of fingers, finger orientation, and number of joints of finger.

Finally, evaluating other grasp metrics, including learned metrics such as Grasp Quality Convolutional Neural Networks (GQ-CNN) , and using more complex kinematic models of the gripper might output higher quality and more accurate results.

References

[1] A. Bicchi and A. Marigo, “Dexterous grippers: Putting nonholonomy to work for fine manipulation,” The International Journal of Robotics Research, vol. 21, no. 5-6, pp. 427–442, 2002.

[2] A Goins, R. Carpenter, ”Evaluating the Efficacy of Grasp Metrics for Utilization in a Gaussian Process-Based Grasp Predictor,”

[3] J. Mahler, J. Liang, S. Niyaz, M. Laskey, K. Goldberg, ”Dex-Net 2.0: Deep Learning to Plan Robust Grasps with Synthetic Point Clouds and Analytic Grasp Metrics”

[4] E. Chinellato, R. B. Fisher, A. Morales, and A. P. Del Pobil, Ranking planar grasp configurations for a three-finger hand,” Proceedings - IEEE International Conference on Robotics and Automation, vol. 1, pp. 1133 – 1138, 2003.

[5] A. Morales, E. Chinelalto, P. Sanz, A. Del Pobil, and A. H. Fagg, “Learning to predict grasp reliability for a multifinger robot hand by using visual features,” Proceedings of the Eighth IASTED International Conference on Artificial Intelligence and Soft Computing, pp. 249 – 254, 2004.

[6] Demers, S (2012) Gripper having a two degree of freedom underactuated mechanical finger for encompassing and pinch grasping (US Patent US20140265401A1) U.S. Patent and Trademark Office

[7] S. Terrile, M. Arguelles, A. Barrientos (2021) Comparison of Different Technologies for Soft Robotics Grippers

[8] D. Morrison, P. Corke, J. Leitner (2020) EGAD! an Evolved Grasping Analysis Dataset for diversity and reproducibility in robotic manipulation

[9] M. Guo, D. Gealy, J. Liang, J. Mahler, A. Goncalves, S. McKinley, K. Golberg Design of Parallel-Jaw Gripper Tip Surfaces for Robust Grasping

[10] B. Lionel , T Schlicht, A Statistical Review of Industrial Grippers

[11] Z Samadikhoshkho, K Zareinia, F Janabi-Sharifi, A Brief Review on Robotic Grippers Classifications

[12] M Roa, R Suarez Grasp quality measures: review and performance

[13] Price, Kenneth V. ”Differential evolution.” In Handbook of optimization, pp. 187-214. Springer, Berlin, Heidelberg, 2013.