Towards synthesizing grasps for 3D deformable objects with physics-based simulation

Tran Nguyen Le, Jens Lundell, Fares J.Abu-Dakka, and Ville Kyrki
Intelligent Robotics Group
Department of Electrical Engineering and Automation, School of Electrical Engineering, Aalto University, Finland

I. INTRODUCTION

Despite recent remarkable successes in robotic grasping, most works on grasp synthesis assume either implicitly or explicitly rigid objects [8, 11, 7]. Rigid objects simplify grasp planning to the choice of contact points along the object surface, but the assumption does not hold for many real objects. However, planning grasps on non-rigid objects is difficult because objects deform under interaction forces meaning that the 3-D contact locations also depend on the forces exerted on the object. Most existing works on planning grasps on deformable objects aim to minimize the deformation [18, 15, 2], while some works [6] actually take advantage of the deformation. Nevertheless, how object stiffness affects grasping and how to use the object deformation to generate grasps remains an open question. In this context, it is important to note that grasps generated by methods assuming rigid objects do not necessarily translate well to deformable objects and vice versa. Therefore, there is a need to study how to generate grasps that harness the target objects’ stiffness.

Of late, deep learning is the major driving force behind the progress in rigid object grasping. Many of these techniques share a similar pipeline, where a deep neural network is trained on a real or synthetic dataset to generate and evaluate grasp candidates given an input image. Rigid body simulators such as Graspit! [10] and OpenGRASP [4] have been used to generate thousands of grasp candidates to serve as training data for those methods. The large amount of training data helped those methods to achieve remarkable successes in terms of grasp success rate on rigid objects. Recently, to study how to manipulate cloth and rope-type objects, simulators such as PyBullet [1] and MuJoCo [16] have been used [17, 19, 9]. However, the use of these simulators for 3D solid deformable objects is still limited.

To address the aforementioned open issues, we envision an approach that generates grasps on a wider range of objects with varying stiffness by incorporating stiffness as an additional input to a state-of-the-art deep grasp planning pipeline (Fig. A.2). Our system generates grasp candidates and grasp qualities for every pixel given an input depth image and stiffness image. When combined with depth information, the model outputs can be reprojected into 3D space, allowing a robot to execute a generated grasp in the real world.

The approach is evaluated in simulation and shows an improvement in terms of grasp success rate for a wide range of objects with various shapes and varying stiffness. The approach is able to generate different grasping strategies for different stiffness values such as pinching for soft objects and caging for hard objects even though no pinch grasps were included in the training data.

II. GRASP GENERATION USING PHYSICS-BASED SIMULATION

A. Simulation platform choice

Simulating dynamics of deformable objects relies heavily on their geometric representations. Yin et al. [20] presents three primary deformable object modelling approaches, Mass-spring system (MSS), Position-based dynamics (PBD), and Finite element method (FEM), and their limitations. In this work, we use FEM because it is often used to model 3D objects such as food or tissues and, compared to other modeling approaches, offers a more physically accurate representation of a deformable object in a continuous domain.

Most robotic simulators do not support FEM except NVIDIA’s recent version of the Isaac Gym simulator [14], which supports soft body simulation through the NVIDIA Flex backend. Similar to SOFA [3], Isaac Gym includes co-rotational linear model for precision in modeling and simulating the object deformation under interaction. Furthermore, the Isaac simulator also provides the capability to integrate robot-related functions, making it easier to build robotic applications. NVIDIA also provides a grasping framework [13] to automatically perform and evaluate grasp tests on an arbitrary target object. We use this framework in our work to generate training data and test grasps.

B. Grasp generation network

To take object stiffness into account for generating grasps, we propose to use the Deep Neural Network (DNN) (Fig. A.2). The network is inspired by [11] but modified to take a stiffness image as an additional input channel. Each pixel in the stiffness image represents object stiffness. The proposed network is trained with supervised learning on a synthetic dataset. We generated our own dataset containing labeled grasps on soft and rigid objects using Isaac Gym as no such dataset existed from before.

C. Training data generation

Depth and stiffness input We captured depth images of target objects with a virtual camera set to view the scene from top-down. To model variable object stiffness, four values of Young’s modulus from $2\cdot10^9$ to $2\cdot10^3$ were used. The Young’s
modulus is normalized to [0,1] range and the corresponding stiffness value is assigned to every pixel in the stiffness image that the object occupies.

**Grasp candidates** Grasps are sampled with an antipodal grasp sampler to obtain approximately 200 grasp candidates for each target object. All grasp candidates that collide with the mesh are filtered out, a process that keeps about 25-40 grasps per object. The grasps are executed and evaluated using a Franka Emika Panda model in Isaac Gym. Positive grasps are then represented as rectangles in 2D image plane as shown in Fig. A.2.

**Quality metrics** None of the standard grasp quality metrics are applicable for both rigid and deformable objects. As a quality metric we use a shake task which measures how easily an object is displaced in hand under various accelerations. The metric is provided by the Isaac Gym framework. A higher metric indicates that a grasp is better because it withstand higher accelerations.

**Training dataset** As a training dataset, we use a total of 30 objects on which we generate and label grasp candidates. The objects include 13 primitive objects provided in Isaac Gym, 5 objects from YCB dataset, and 12 objects with adversarial geometry from the EGAD! dataset [12]. With the varying stiffness, the training set contains a total of 120 objects. To counteract the small size of the training set, we further augment the dataset with random crops, zooms, and rotations to create a set of 5400 depth and stiffness images and 27000 labeled grasps map images.

III. RESULTS

We evaluated the quality of the proposed grasp generation in simulation on objects with varying stiffness. We tested the approach on 7 common objects shown in Fig. A.4. We evaluated the top-5 generated grasps using the shake test on each object for each of the four stiffnesses, resulting in 20 grasps per object. To demonstrate the importance of stiffness input, we compared the generated grasps against grasps generated with a similar approach without stiffness information.

Over all stiffnesses, the average grasp success rate is 30% higher with the proposed approach that takes stiffness input into account compared to the baseline where stiffness input is ignored. This result stems from the fact that the performance of the baseline approach deteriorates significantly when changing from high value to low value of the Young’s modulus. For instance, the relative performance drop for the baseline approach from $2 \cdot 10^7$ to $2 \cdot 10^5$ is 10% and to $2 \cdot 10^4$ the drop is 30%. This is much higher compared to the 0% and 12% drop using our approach. As the baseline approach does not consider stiffness input, that method generates the same grasps for a target object regardless its stiffness. These generated grasps may successfully grasp the objects, however, during the shake task, the objects usually slip away from the gripper due to their deformation. Therefore, by taking the stiffness input into account, the proposed network is able to learn to avoid areas with high probability of slippage, resulting in higher grasp success rate.

![Fig. 1: Grasp success rate of 7 common objects with four values of Young’s modulus. Plain columns present the result of the model that takes stiffness input into account and striped columns present that of the model that use only depth image as input.](image)

Another interesting finding is that our approach can generate different grasp types such as pinch or cage grasps depending on the stiffness, even though there were no pinch grasps in the training dataset. This behavior is shown on object 5 in Fig. A.5. Specifically, the sponge with a low Young’s modulus admits pinching behavior where the grasp press on the object and pinch, while the hard sponge only admits caging grasps. One possible reason behind this behavior is that the proposed network learned that the grasp quality is high almost everywhere on soft objects thanks to their deformation. Similar behaviour was also reported in [5] on a few objects. It is worth pointing out that our approach produces the same behavior as in [5] but on a completely synthetic dataset containing order of magnitudes less data. Furthermore, our proposed approach provides more meaningful insights in terms of the relationship between object deformation and grasps.

IV. CONCLUSION

Grasping deformable objects is not well researched due to complexity in the modelling and simulating the dynamic behavior of such objects. However, with the rapid development of physics-based simulators that support soft bodies, the research gap between rigid and deformable objects is getting smaller. To leverage the capability of such simulators and to challenge the assumption that has guided robotic grasping research so far, i.e., object rigidity, we proposed a deep-learning based approach that generates stiffness dependent grasps. Our network is trained on purely synthetic data generated from a physics-based simulator. The same simulator is also used to evaluate the trained network. The results show improvement in terms of grasp ranking and grasp success rate. Furthermore, our network can adapt the grasps based on the stiffness. We are currently validating the proposed approach on a larger test dataset in simulation and on a physical robot.
REFERENCES

[1] Erwin Coumans and Yunfei Bai. Pybullet, a python module for physics simulation for games, robotics and machine learning. http://pybullet.org, 2016–2021.

[2] A. Delgado, C. A. Jara, D. Mira, and F. Torres. Tactile-based grasping strategy for deformable objects’ manipulation and deformability estimation. In 2015 12th International Conference on Informatics in Control, Automation and Robotics (ICINCO), volume 02, pages 369–374, 2015.

[3] François Faure, Christian Duriez, Hervé Delingette, Jérémie Allard, Benjamin Gilles, Stéphanie Marchesseau, Hugo Talbot, Hadrien Courtecuisse, Guillaume Bouquet, Igor Peterlik, and Stéphane Cotin. SOFA: A Multi-Model Framework for Interactive Physical Simulation. In Yohan Payan, editor, Soft Tissue Biomechanical Modeling for Computer Assisted Surgery, volume 11 of Studies in Mechanobiology, Tissue Engineering and Biomaterials, pages 283–321. Springer, June 2012.

[4] Beatriz León, Stefan Ulbrich, Rosen Diankov, Gustavo Puche, Markus Przybylski, Antonio Morales, Tamim Asfour, Sami Moisio, Jeannette Bohg, James Kuffner, and Rüdiger Dillmann. OpenGRASP: A Toolkit for Robot Grasping Simulation. In Noriaki Ando, Stephen Balakirsky, Thomas Hemker, Monica Reggiani, and Oskar von Stryk, editors, Simulation, Modeling, and Programming for Autonomous Robots, pages 109–120, Berlin, Heidelberg, 2010. Springer Berlin Heidelberg. ISBN 978-3-642-17319-6.

[5] Sergey Levine, Peter Pastor, Alex Krizhevsky, Julian Ibarz, and Deirdre Quillen. Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection. The International Journal of Robotics Research, 37(4-5):421–436, 2018.

[6] Huan Lin, Feng Guo, Feifei Wang, and Yan-Bin Jia. Picking up a soft 3D object by “feeling” the grip. The International Journal of Robotics Research, 34(11):1361–1384, 2015.

[7] Jens Lundell, Francesco Verdoja, and Ville Kyrki. Robust Grasp Planning Over Uncertain Shape Completions. In 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pages 1526–1532, 2019. doi: 10.1109/IROS40897.2019.8967816.

[8] Jeffrey Mahler, Jacky Liang, Sherdil Niyaz, Michael Laskey, Richard Doun, Xinyu Liu, Juan Aparicio Ojea, and Ken Goldberg. Dex-Net 2.0: Deep Learning to Plan Robust Grasps with Synthetic Point Clouds and Analytic Grasp Metrics. 2017.

[9] Jan Matas, Stephen James, and Andrew J. Davison. Sim-to-realm reinforcement learning for deformable object manipulation. In 2nd Annual Conference on Robot Learning, CoRL 2018, Zürich, Switzerland, 29-31 October 2018, Proceedings, volume 87 of Proceedings of Machine Learning Research, pages 734–743. PMLR, 2018. URL http://proceedings.mlr.press/v87/matas18a.html

[10] A.T. Miller and P.K. Allen. Graspit! A versatile simulator for robotic grasping. IEEE Robotics Automation Magazine, 11(4):110–122, 2004.

[11] Douglas Morrison, Peter Corke, and Jürgen Leitner. Closing the Loop for Robotic Grasping: A Real-time, Generative Grasp Synthesis Approach. In Proc. of Robotics: Science and Systems (RSS), 2018.

[12] NVIDIA. Deformable object grasping framework. https://github.com/NVlabs/deformable_object_grasping. 2020.

[13] NVIDIA. ISAAC gym. https://developer.nvidia.com/isaac-gym. 2020.

[14] Zherong Pan, Xifeng Gao, and Dinesh Manocha. Grasping Fragile Objects Using A Stress-Minimization Metric. In 2020 IEEE International Conference on Robotics and Automation (ICRA), pages 517–523, 2020.

[15] Emanuel Todorov, Tom Erez, and Yuval Tassa. MuJoCo: A physics engine for model-based control. In 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems, pages 5026–5033, 2012.

[16] Yilin Wu, Wilson Yan, Thanard Kurutach, Lerrel Pinto, and Pieter Abbeel. Learning to Manipulate Deformable Objects without Demonstrations. In Proceedings of Robotics: Science and Systems, Corvalis, Oregon, USA, July 2020. doi: 10.15607/RSS.2020.XVI.065.

[17] Jingyi Xu, Michael Danielczuk, Jeffrey Ichnowski, Jeffrey Mahler, Eckhard Steinbach, and Ken Goldberg. Minimal Work: A Grasp Quality Metric for Deformable Hollow Objects. In 2020 IEEE International Conference on Robotics and Automation (ICRA), pages 1546–1552, 2020.

[18] Wilson Yan, Ashwin Vangipuram, Pieter Abbeel, and Lerrel Pinto. Learning predictive representations for deformable objects using contrastive estimation. CoRR, abs/2003.05436, 2020. URL https://arxiv.org/abs/2003.05436.

[19] Hang Yin, Anastasia Varava, and Danica Kragic. Modeling, learning, perception, and control methods for deformable object manipulation. Science Robotics, (64), 2021.

APPENDIX
Fig. A.2: The proposed pipeline where stiffness information is incorporated.

Fig. A.4: Seven common numbered objects used in the experiment. All objects are single-material objects except for object 7, where the stiffness of its red part can be varied.

Fig. A.5: In the case of soft sponge (a), the proposed method learned that the grasp quality is high across the whole objects thanks to their deformation, which in turn, enables pinch grasp. While in the case of hard sponge (b), the high quality grasp tends to be generated at the center of the object, and the grasp width is almost as big as the object in order to successfully cage the object.