The Impact of Time Step Frequency on the Realism of Robotic Manipulation Simulation for Objects of Different Scales

Minh Q. Ta[1,§], Holly Dinkel[1,§], Hameed Abdul-Rashid[1], Yangfei Dai[1], Jessica Myers[1], Tan Chen[2], Junyi Geng[3], Timothy Bretl[1]

***Abstract*—This work evaluates the impact of time step frequency and component scale on robotic manipulation simulation accuracy. Increasing the time step frequency for small-scale objects is shown to improve simulation accuracy. This simulation, demonstrating pre-assembly part picking for two object geometries, serves as a starting point for discussing how to improve Sim2Real transfer in robotic assembly processes.**

***Keywords*—Robotic Manipulation, Grasping, Simulation, Smart Manufacturing, Sim2Real Transfer**

I. Introduction

Manipulation simulation is valuable input to the design of planning and control algorithms for real applications on robot hardware. Information about the behavior of objects in contact with each other, such as gripper fingers with a grasped component or the component with the environment, is important in the deployment of manufacturing and maintenance robots [1], [2]. In practice, the physics of contact in hardware experiments disagrees with the physics in simulation experiments which can exhibit jittering, bouncing, sticking, penetration, or other physical constraint violations. Contact inconsistency between simulation and reality is evident when the scale of the grasped object is considered as the only variable, shown in Figure 1. Reconciling physical behaviors in simulation with behaviors in the real world (Sim2Real), is paramount for broadening adoption of robotic systems for manufacturing [3], [4]. This work evaluates the impact of Time Step Frequency (TSF) and component scale on simulation accuracy. In general, simulating any object of small volume requires an increased time step frequency to achieve simulation accuracy. Simulation demonstration videos are shared publicly at https://t.ly/tSlqr.

II. Related Work

Manipulating objects of similar shapes depends on the geometry of contact: on their sizes, on their deformability, on contact constraints with the environment, and on contact constraints with the robot. Contact and collision reduction is one of the most expensive operations performed in simulation [5]–[10]. The traditional approach to computing physics

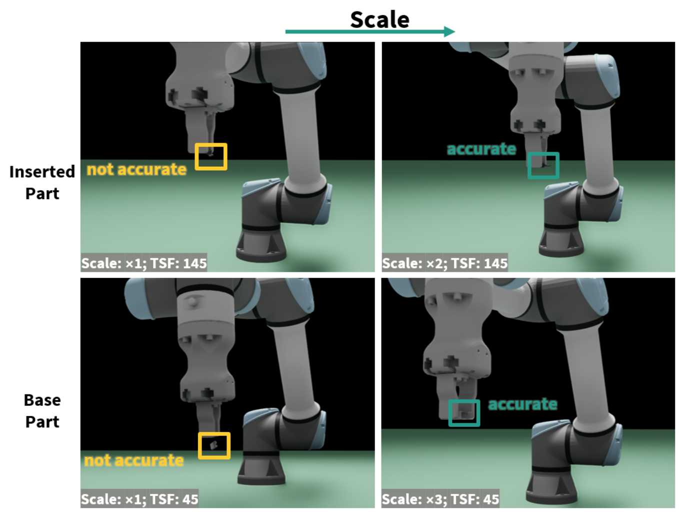

Fig. 1: Inaccurate contact simulation results in differences between simulation and reality. Accurate physics constraint resolution in simulation results in reasonable component manipulation.

with contact constraints is to take one large time step with n constraint solver iterations, solving one difficult problem accurately [11]. More recent, real-time, local solvers, including the Temporal Gauss-Seidel (TGS) and Projected Gauss-Seidel (PGS) solvers, compute n small time steps each with one constraint solver iteration, solving n simpler problems approximately. Selection of a real-time local solver using smaller time steps (a higher time step frequency) results in fast convergence and physical feasibility of contact simulation [12], [13]. A manipulation policy learned from a simulation with feasible physics is more transferable to a real system.

III. Manipulation Simulation Experiments

This work evaluates the impact of time step frequency, the *Time Steps Per Second* simulation parameter, and component scale, measured in multiples of the original object volume and inertial properties, on manipulation simulation accuracy. The simulation environment is described in Section III-A and simulation results are discussed in Section III-B.

A. Simulation Environment

Manipulation simulation was performed in Isaac Sim [14]–[16]. The robot work cell in simulation included two Universal Robots UR5 manipulators, each with a Robotiq Hand-E Gripper. One manipulator was simulated performing pre-assembly part picking. The two robot movements included aligning the

[1]University of Illinois Urbana-Champaign. {minh,hdinkel2,hameeda2,yangfei4,jmmyers3,tbretl}@illinois.edu.
[2]Michigan Technological University, Houghton, MI, 49931. tanchen@mtu.edu.
[3]The Pennsylvania State University, University Park, PA, 16802. jgeng@psu.edu.
[§]Equal Contribution

×	Not accurate
✓	Accurate

Inserted Part Picking

Part Scale	Time Step Frequency (Time Steps Per Second)				
	120	130	145	165	180
×1	×	×	×	✓	✓
×2	×	×	✓	✓	✓
×3	×	✓	✓	✓	✓

Base Part Picking

Part Scale	Time Step Frequency (Time Steps Per Second)				
	45	60	70	80	90
×1	×	×	✓	✓	✓
×2	×	×	✓	✓	✓
×3	✓	✓	✓	✓	✓

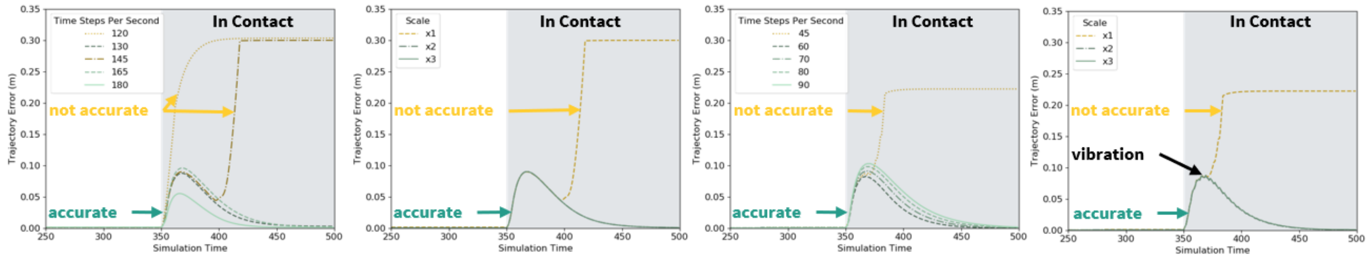

Fig. 2: (Top) The simulation accuracy of picking two electronic components varies based on their scales. Objects of smaller scale require a higher time step frequency to achieve simulation accuracy.

robot joints for grasping (non-contact) and grasping and lifting (in contact). Two components with different geometries were used in the picking task, an inserted part and a base part. Picking was performed using three different component scales, the original ($\times 1$), doubled ($\times 2$), and tripled ($\times 3$) scales. The volumes and contact surface areas of the original scales were measured in Meshlab from their associated mesh files and are shown in Table I [17]. The gripper finger contact surface area was considered to be the same as the object it grasps, so it is omitted from this table. The simulation parameters were set as *Enable GPU Dynamic = True*, *Solver Type = TGS*, *Collider Approximation = Convex Decomposition*, *Contact Offset* = 10^{-5}, *Dynamic Friction = 1*, *Static Friction = 1*, *Restitution = 0*, and all other parameters remained default. Simulations were performed on a computer with an i9 CPU, two GeForce RTX 4090 GPUs, and 64 GB RAM.

TABLE I: Scale Comparison of Manipulation Components

Component	Inserted Part	Base Part	Gripper Finger
Volume (mm^3)	178.17	224.29	13650
Contact Area (mm^2)	20.28	38.48	-

B. Simulation Results and Discussion

The experimental results for picking the two components at different scales and time step frequencies are shown in Figure 2. Trajectory error was measured for each scale against a reference trajectory at the same scale with 360 time steps per second. Increasing the time step frequency is important when dealing with objects of small-scale to improve the accuracy of the manipulation simulation.

The trade-off between simulation accuracy and computational performance when choosing a time step frequency is well known. A higher time step frequency improves the accuracy of constraint solving, enabling more accurate resolution of contacts. However, an increased time step frequency increases computational cost and reduces the simulation speed. The results of this study, included in Table II, are a reminder of this trade-off, which becomes more pronounced when simulating the manipulation of small-scale objects.

TABLE II: Simulated Picking of Inserted Part Runtime (s)

Time Steps Per Second				
120	130	145	165	180
10.5 ± 0.2	12.9 ± 0.0	14.8 ± 0.0	14.6 ± 0.0	18.5 ± 0.0

One question the results in Figure 2 raise is whether the relationship between time step frequency, scale, and simulation accuracy holds when the robot and object are closer in relative size. An additional study which halved ($\times 0.5$) the robot scale for manipulation of an original scale inserted part shows the simulation still requires a high TSF for accuracy, suggesting small-scale manipulation generally requires finer temporal resolution.

Robot Scale	Time Step Frequency					
	130	145	150	165	180	200
×1	×	×	✓	✓	✓	✓
×0.5	×	×	×	×	✓	✓

Fig. 3: Increasing step frequency improves manipulation simulation accuracy for inserted part picking when the robot scale is halved.

IV. Conclusions and Future Work

This work demonstrate the impact of time step frequency and component scale on manipulation simulation accuracy for part picking. Experiments show the selection of an appropriate number of time steps per second is essential for realistic physics, however it is one of many parameters. Future work could study the interaction of parameter combinations to further close the Sim2Real gap. The two electronic components used in this study are symmetric about one axis, however geometric symmetry may not be assumed for many types of assembly processes. For the inserted part, the center of mass is centered below its two assembly contact edges. Accounting for object geometric and inertial properties during simulation configuration can further improve Sim2Real transfer. The results from this work suggest adaptive time stepping, either through simulating different objects with different time step frequencies or adaptively sub-stepping the simulation, could balance the accuracy-performance tradeoff [18].

V. Acknowledgments

The authors thank the members of the UIUC-FIT CoBot Factory Project and the teams developing the open-source software used in this project. M.T., H.A.-R., Y.D., J.M., T.C., J.G., and T.B. were supported by the Foxconn Interconnect Technology (FIT) and the Center for Networked Intelligent Components and Environments (C-NICE) at the University of Illinois Urbana-Champaign. H.D. was supported by the Graduate Assistance in Areas of National Need award P200A180050-19. H.D. and J.M. are supported by the NASA Space Technology Graduate Research Opportunity awards 80NSSC21K1292 and 80NSSC23K1191, respectively.

References

[1] T. Chen, Z. Huang, J. Motes, J. Geng, Q. M. Ta, H. Dinkel, H. Abdul-Rashid, J. Myers, Y.-J. Mun, W.-C. Lin, Y.-Y. Yang, S. Liu, M. Morales, N. M. Amato, K. Driggs-Campbell, and T. Bretl, "Insights from an Industrial Collaborative Assembly Project: Lessons in Research and Collaboration," in *Workshop on Collaborative Robots and Work of the Future*, 2022.

[2] R. Tedrake and the Drake Development Team", "Drake: Model-Based Design and Verification for Robotics," [Online] Available: https://drake.mit.edu, 2019.

[3] E. Heiden, D. Millard, E. Coumans, and G. S. Sukhatme, "Augmenting Differentiable Simulators with Neural Networks to Close the Sim2Real Gap," *arXiv preprint arXiv:2007.06045*, 2020.

[4] E. Heiden, D. Millard, E. Coumans, Y. Sheng, and G. S. Sukhatme, "NeuralSim: Augmenting Differentiable Simulators with Neural Networks," in *IEEE Int. Conf. Robot. Autom. (ICRA)*. IEEE, 2021, pp. 9474–9481.

[5] T. Erez, Y. Tassa, and E. Todorov, "Simulation Tools for Model-Based Robotics: Comparison of Bullet, Havok, MuJoCo, ODE and PhysX," in *IEEE Int. Conf. Robot. Autom. (ICRA)*, 2015, pp. 4397–4404.

[6] S. Bouaziz, S. Martin, T. Liu, L. Kavan, and M. Pauly, "Projective Dynamics: Fusing Constraint Projections for Fast Simulation," in *Seminal Graphics Papers: Pushing the Boundaries*, 2023, vol. 2, pp. 787–797.

[7] F. Xiang, Y. Qin, K. Mo, Y. Xia, H. Zhu, F. Liu, M. Liu, H. Jiang, Y. Yuan, H. Wang *et al.*, "Sapien: A Simulated Part-Based Interactive Environment," in *IEEE/CVF Int. Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2020, pp. 11 097–11 107.

[8] K. Werling, D. Omens, J. Lee, I. Exarchos, and C. K. Liu, "Fast and Feature-Complete Differentiable Physics for Articulated Rigid Bodies with Contact," *Robot. Sci. Syst. (RSS)*, 2021.

[9] Y. Narang, K. Storey, I. Akinola, M. Macklin, P. Reist, L. Wawrzyniak, Y. Guo, A. Moravanszky, G. State, M. Lu *et al.*, "Factory: Fast Contact for Robotic Assembly," *Robot. Sci. Syst. (RSS)*, 2022.

[10] M. Mittal, C. Yu, Q. Yu, J. Liu, N. Rudin, D. Hoeller, J. L. Yuan, R. Singh, Y. Guo, H. Mazhar *et al.*, "Orbit: A Unified Simulation Framework for Interactive Robot Learning Environments," *IEEE Robot. Autom. Lett.*, 2023.

[11] D. Baraff and A. Witkin, "Large Steps in Cloth Simulation," in *Seminal Graphics Papers: Pushing the Boundaries*, 2023, vol. 2, pp. 767–778.

[12] M. Macklin, M. Müller, N. Chentanez, and T.-Y. Kim, "Unified Particle Physics for Real-Time Applications," *ACM Trans. Graph. (TOG)*, vol. 33, no. 4, pp. 1–12, 2014.

[13] M. Macklin, K. Storey, M. Lu, P. Terdiman, N. Chentanez, S. Jeschke, and M. Müller, "Small Steps in Physics Simulation," in *ACM SIGGRAPH/Eurographics Symp. Comput. Animat.*, 2019, pp. 1–7.

[14] J. Liang, V. Makoviychuk, A. Handa, N. Chentanez, M. Macklin, and D. Fox, "GPU-Accelerated Robotic Simulation for Distributed Reinforcement Learning," in *Int. Conf. Robot Learn. (CoRL)*, 2018, pp. 270–282.

[15] V. Makoviychuk, L. Wawrzyniak, Y. Guo, M. Lu, K. Storey, M. Macklin, D. Hoeller, N. Rudin, A. Allshire, A. Handa *et al.*, "Isaac Gym: High Performance GPU-Based Physics Simulation for Robot Learning," *arXiv preprint arXiv:2108.10470*, 2021.

[16] NVidia, "Isaac Sim - Robotics Simulation and Synthetic Data Generation," [Online] Available: https://developer.nvidia.com/isaac-sim, 2023.

[17] P. Cignoni, M. Callieri, M. Corsini, M. Dellepiane, F. Ganovelli, G. Ranzuglia *et al.*, "Meshlab: An Open-Source Mesh Processing Tool," in *Eurographics Italian Chapter Conference*, vol. 2008. Salerno, Italy, 2008, pp. 129–136.

[18] G. Söderlind, "Automatic Control and Adaptive Time-Stepping," *Numer. Algorithms*, vol. 31, pp. 281–310, 2002.