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

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***Abstract*—This work evaluates the impact of time step frequency and component scale on robotic manipulation simulation stability. Increasing the time step frequency for small-scale objects is shown to improve simulation stability. 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. Reconciling physical behaviors in simulation with behaviors in the real world (Sim2Real), such as the example in Figure 1, is paramount for broadening adoption of robotic systems for manufacturing [3], [4]. This work evaluates the impact of time step frequency and component scale on simulation stability. In general, simulating any object of small volume requires an increased time step frequency to achieve simulation stability. Simulation demonstration videos are shared publicly at https://t.ly/tSlqr.

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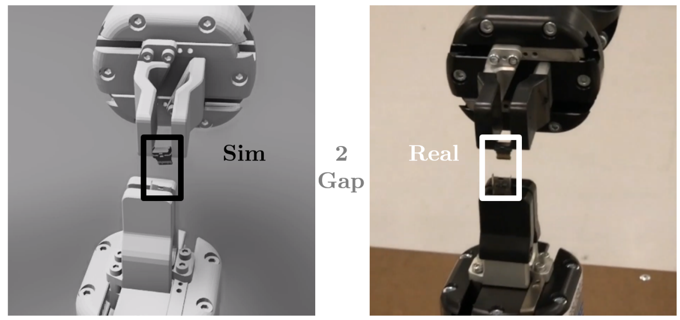

Fig. 1: Robotic manipulation of two electronic components in an assembly process diverges in simulation (left) from reality (right).

II. Related Work

Manipulation of objects of similar geometry depend on the geometry of contact: on their sizes, on contact constraints with the environment, and on their contact 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 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 significantly faster convergence and physical feasibility of contact simulation [12], [13].

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 stability. 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 the Isaac Sim environment [14]–[16]. The robot work cell in simulation included two Universal Robots UR5e manipulators, each equipped with a Robotiq Hand-E Gripper. One of these manipulators was simulated performing a pre-assembly part picking task. The two robot movements in the picking task

Inserted Part Picking

Part Scale	Time Step Frequency (*Time Steps Per Second*)				
	60	120	150	180	240
x1	×	×	×	✓	✓
x2	×	×	✓	✓	✓
x3	×	✓	✓	✓	✓

Key	
×	Unstable
✓	Stable

Base Part Picking

Part Scale	Time Step Frequency (*Time Steps Per Second*)				
	40	50	60	75	90
x1	×	×	✓	✓	✓
x2	×	×	✓	✓	✓
x3	✓	✓	✓	✓	✓

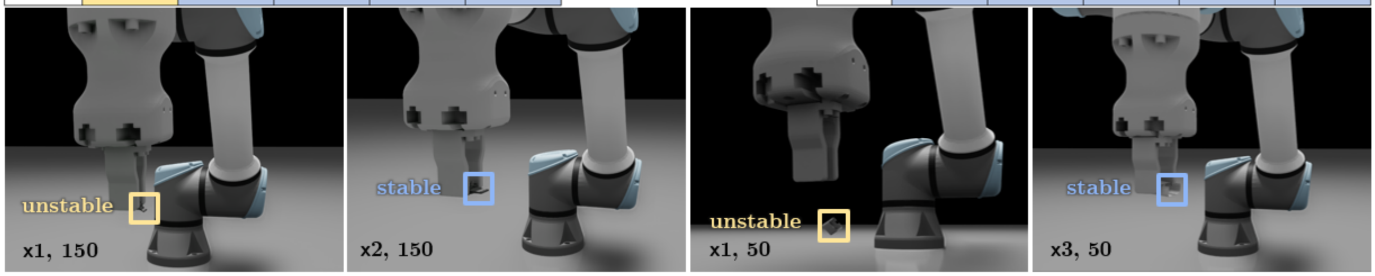

Fig. 2: (Top) The simulation stability of picking two electronic components varies based on their scales. Objects of smaller scale require a higher time step frequency to achieve simulation stability. (Bottom) Unstable contact simulation results in differences between simulation and reality. Stable physics constraint resolution in simulation results in reasonable component manipulation.

included aligning the robot arm 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.

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	-

The simulation parameters were set as *Enable GPU Dynamic = True*, *Solver Type = TGS*, *Collider Approximation = Convex Decomposition*, *Contact Offset = 0.00001*, *Dynamic Friction = 1.0*, *Static Friction = 1.0*, *Restitution = 0.0*, and the other parameters were kept as default. All simulations were performed on a computer with an Intel i9 CPU, two NVIDIA GeForce RTX 4090 GPUs, and 64 GB RAM.

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. Results show increasing the time step frequency is important when dealing with objects of small-scale to improve the stability and accuracy of the manipulation simulation.

The trade-off between simulation stability and computational effort when choosing a time step frequency is well known. A higher time step frequency improves the accuracy of collision detection, the physical behavior of objects, and constraint solving, enabling more stable resolution of contacts and constraints. However, an increased time step frequency increases computational cost and reduces the simulation speed. The results of this study are a reminder of this trade-off, which becomes more pronounced when simulating the manipulation of small-scale objects.

One question the results in Figure 2 raise is whether the relationship between time step frequency, scale, and simulation stability 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 higher time step frequency for stability, suggesting small-scale manipulation generally requires finer temporal resolution.

Robot Scale	Time Step Frequency				
	150	180	200	220	240
x0.5	×	✓	✓	✓	✓
x1	×	×	×	✓	✓

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

IV. Conclusions and Future Work

This work used a part picking task to demonstrate the impact of time step frequency and component scale on manipulation simulation stability. Experiments show the selection of an appropriate number of time steps per second is essential for realistic physics, however it is one of many tunable parameters. Future work could study how combinations of these parameters interact 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 used in this study, 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 stability-performance tradeoff [18].

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