FONTYS UNIVERSITY OF APPLIED SCIENCES | VBTI

Project Plan

Digital Twin Simulation Framework for Robotics

A framework for reconstructing real-world environments into physically-based simulations to enable scalable data generation and continuous learning for robotics applications.

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1. Introduction

Project Description

A framework for reconstructing real-world environments into physically-based simulations to enable scalable data generation and continuous learning for robotics applications.

Problem Statement

Industry Perspective

Deploying robotic solutions at client sites currently requires significant on-site time. Engineers must visit the client location to collect data using a physical robot, return to the office to train models, and then verify results in a simplified in-house setup that does not accurately represent the client's environment. This process is time-consuming, costly, and limits iteration speed. Any mismatch between the testing environment and the real deployment scene leads to unpredictable performance at deployment, requiring further on-site visits.

Academic Perspective

In robotics learning, data is the fundamental bottleneck. Methods such as behavioral cloning depend on real-world demonstrations, which are expensive and limited in quantity. Scaling model performance beyond what small datasets allow demands disproportionate effort. The ability to generate large-scale, physically plausible synthetic data within accurate reconstructions of real environments would remove this bottleneck - enabling not only more efficient imitation learning but also continuous reinforcement learning in simulation, opening the path toward systems that can learn from virtually infinite data.

Expected Outcomes and Deliverables

- Primary: A reusable simulation framework - a pipeline that takes imagery of any real-world environment and produces a simulation-ready digital twin, including visual reconstruction, collision geometry, and interactive assets.
- Secondary (PoC): Demonstrate improved behavioral cloning performance using synthetic data generated by the framework, achieving better results with less real-world data.
- Research Direction: Evaluate the feasibility of continuous reinforcement learning within the simulated environments, in collaboration with team members developing RL algorithms.

2. Stakeholders

Stakeholder	Role	Involvement
VBTI	Robotics company providing automation solutions to industrial clients	Hosts the project, defines practical requirements, provides hardware and domain expertise
Fontys University	Academic institution	Assesses the project as part of the ICT Bachelor thesis programme
Anton Novokhatskiy	Fontys ICT Bachelor thesis at VBTI	Responsible for the simulation framework - 3D reconstruction, digital twin pipeline, simulation-ready asset creation
TU/e Researcher Intern	Master thesis student at VBTI	Develops RL algorithms and training strategies that consume the simulation environments

3. Goals

Primary Goal

Verify that moving robotics development into a simulation-based workflow improves model quality and makes it easier to implement solutions, compared to a purely real-world data collection approach.

Secondary Goals

- Develop a reusable pipeline for creating digital twins and simulation-ready assets from real-world imagery.
- Build an MVP of a data engine capable of generating scene variations, enabling training and testing on edge cases that are difficult or impossible to recreate in the physical world.

Success Metrics

- Data efficiency: Reduced time spent collecting real-world data at client setups, while maintaining or improving model performance.
- Iteration speed: Faster development cycles - from idea to tested model - by iterating inside simulation rather than on physical hardware.
- Task success rate: Compare the BC-only baseline against the simulation-enhanced model on the tomato sorting task. The difference represents the pure method gains from the simulation framework.

Proof of Concept

The tomato sorting task will serve as the PoC. The team will establish a BC baseline on this task, then apply the simulation framework to generate additional training data and RL training opportunities. The final evaluation compares real-world performance before and after simulation-based development.

4. Research Questions

Main Research Question

How can simulation environments based on reconstructed digital twins improve the development workflow and model quality for robotic manipulation tasks?

Sub-Questions

1. How can real-world environments be reconstructed into simulation-ready scenes using Gaussian splatting?

Investigates the pipeline from image capture to a functional 3D reconstruction - including pose estimation, GS training, cleanup, and mesh extraction for collision geometry.

2. How can physically accurate interactive assets be created and integrated into the simulation?

Explores methods for generating sim-ready objects with correct physics properties (mass, friction, softness) and collision geometry, using CAD tools or generative approaches.

3. Does synthetic data generated from the digital twin improve model performance compared to a purely real-world data collection approach?

The core validation question. Compares the BC baseline trained on real data against models trained with simulation-generated data on the tomato sorting PoC.

4. What is the sim-to-real transfer gap and how can it be minimized?

Analyzes the performance difference when deploying simulation-trained models to the physical robot, and evaluates strategies such as domain randomization and parameter tuning to close the gap.

5. Methodology

This project follows the Fontys ICT DOT (Development Oriented Triangulation) framework, combining methods from five research strategies to ensure methodologically sound and reproducible results. The project follows an iterative regulatory cycle: Analysis -> Design -> Realisation -> Evaluation, with multiple iterations per phase.

Research Methods per Sub-Question

Sub-Question	DOT Strategy	Methods	Output
SQ1: 3D reconstruction pipeline	Library + Lab	Literature study on GS tools; prototyping and benchmarking reconstruction quality (PSNR, SSIM, LPIPS)	Validated reconstruction pipeline with quality metrics
SQ2: Sim-ready asset creation	Library + Workshop + Lab	Literature study on physics estimation; co-creation sessions with VBTI experts; iterative prototyping	Asset creation workflow with physics validation
SQ3: Synthetic data impact	Lab + Showroom	Controlled experiment comparing BC baseline vs. simulation-augmented training; peer review	Quantitative comparison (task success rate, data efficiency)
SQ4: Sim-to-real transfer gap	Lab + Field	Experimental testing on physical robot; domain randomization experiments; gap analysis	Transfer performance metrics and mitigation strategies

DOT Strategies Used

- Library: Literature research on Gaussian splatting, sim-to-real transfer, and simulation-based robotics training to inform design decisions and position the work within existing research.
- Field: Real-world observation and testing with the physical robot at VBTI to gather ground truth data and validate transfer performance.
- Lab: Controlled experiments in both simulation and real-world settings to measure pipeline quality and model performance with quantitative metrics.
- Workshop: Collaborative sessions with the second researcher intern and our supervisors from VBTI to align simulation requirements with training pipeline needs.
- Showroom: Demonstration of results to stakeholders for validation and feedback on practical applicability.

Validation Approach

A/B Comparison Design

Two workflows are compared end-to-end on the tomato sorting task:

Method A (Manual): Collect demonstrations on-site with physical robot → train BC → evaluate on real robot. Each iteration requires a site visit.

Method B (Simulation): Brief site visit for camera capture only → reconstruct digital twin → generate synthetic data in simulation → train BC + RL → evaluate on real robot. Iterations happen in simulation without revisiting the site.

Both methods are evaluated on the same physical robot and task setup to isolate the effect of the simulation framework.

Metrics

Metric	Definition	Target
Task success rate	Tomato picked and placed in correct bin	Method B ≥ Method A
Customer downtime	On-site hours required for data collection	Method B < Method A
Data scaling	Success rate vs. number of training samples	Find minimum real data needed when supplemented with synthetic
Sim-to-real gap	Success rate in sim − success rate on real robot	Δ < 15%

- All reconstruction quality is measured using established metrics: PSNR (>30 dB target), SSIM (>0.9), and LPIPS (<0.1).
- Model performance is evaluated via task success rate on the physical robot, comparing BC-only baseline against simulation-enhanced models.
- The experimental setup (task, robot, environment) remains constant across comparisons to isolate the effect of the simulation framework.
- Results and methods are documented to ensure reproducibility.

6. Technical Approach

The project follows the full development cycle of a simulation-driven robotics pipeline: from real-world data collection and behavioral cloning, through digital twin construction, to reinforcement learning in simulation and sim-to-real transfer. NVIDIA's native stack (IsaacSim, IsaacLab) is used throughout to ensure consistency across phases and avoid integration issues when transitioning between stages.

Phase 1: Behavioral Cloning & Baseline

Collect real-world data for the target task using a leader arm. Train an initial model using VLA architectures via the lerobot framework. Evaluate the model on the physical robot to establish a baseline task success rate. This phase is carried out in collaboration with the TU/e researcher and serves as the reference point against which all simulation-based improvements are measured.

Phase 2: Digital Twin Creation

This is the core of the project. The goal is to construct a high-fidelity digital twin of the real-world task environment.

- Scene decomposition: Classify the scene into environment (static background), assets (interactive objects), lighting, and physics properties.
- Environment reconstruction: Capture the scene using Gaussian splatting from real images or video. Post-process and clean the reconstruction. Generate collision meshes to enable physical interaction within the simulation.
- Asset creation: Create or generate simulation-ready assets using CAD tools or generative methods (MarbleLabs, SAM3D). Assign physics properties - mass, friction, softness - to match real-world behavior.
- Simulation assembly: Load the robot model into NVIDIA IsaacSim. Configure joint parameters, virtual cameras, and sensor inputs to match the real-world setup.
- Validation milestone: Verify that the digital twin behaves reasonably similar to the real environment.

Phase 3: Simulation Training (RL)

Using the digital twin as the training environment, apply reinforcement learning to improve the pre-trained model beyond the BC baseline.

- Reward engineering: Design a reward function that encourages task completion and efficiency.
- Parallel training: Run distributed training in NVIDIA IsaacLab across duplicated environments.
- Metric tracking: Record task success rate within simulation and compare against the Phase 1 baseline.

Phase 4: Sim-to-Real Transfer & Validation

Deploy the simulation-trained model to the physical robot and evaluate real-world performance.

- Deployment: Run the optimized model on the real robot.
- Visual validation: Verify that camera inputs in the real world are sufficiently similar to simulation inputs.

- Performance evaluation: Record the final task success rate. Calculate the difference between the BC baseline (Phase 1) and the simulation-enhanced result - this is the pure method gain.
- Gap analysis: If performance degrades in transfer, analyze the source - physics mismatch, lighting differences, motion dynamics - and iterate on the simulation (return to Phase 2/3 with domain randomization or parameter tuning).

7. Scope

In Scope

Task	Responsibility
Data collection for behavioral cloning	Collaboration
Training and evaluating BC models	Collaboration
3D scene reconstruction using Gaussian splatting	Author
Creating simulation-ready assets (CAD/generative)	Author
Building the digital twin pipeline	Author
RL training in simulation	Collaboration
Sim-to-real transfer and validation	Collaboration

Out of Scope

Task	Status
Development of new RL algorithms (handled by TU/e collaborator)	Out of Scope
Production-grade deployment to client sites	Out of Scope
Hardware design or robot construction	Out of Scope

8. Risks

Risk	Impact	Mitigation
3D reconstruction does not achieve sufficient visual fidelity	Models trained in simulation may not transfer to real world	Iterate on reconstruction quality; supplement with domain randomization
Physics simulation does not match real-world object behavior	Grasping and manipulation fail in transfer	Research physics estimation for GS representations; tune mass, friction, softness parameters manually if needed
Sim-to-real gap is too large for direct transfer	Model performs significantly worse on real robot	Apply domain randomization across world parameters (gravity, joints, cameras); fine-tune with minimal real data
Action space too large for RL to train effectively	Training does not converge	Constrain the action space; collaborate with TU/e researcher on reward shaping
Results are indifferent or worse than BC-only baseline	Project hypothesis not validated	Document findings as negative result; analyze which simulation components contributed to the gap
Computational constraints limit training scale	Cannot run enough parallel environments	Optimize simulation scene complexity; prioritize critical training scenarios

9. Timeline & Milestones

Project duration: February 1 - June 30, 2026

Phase	Name	Duration	Key Activities
Phase 1	Behavioral Cloning & Baseline	Feb 3 - Feb 10	Configure SO-101 robot, collect real-world data, train using lerobot, establish baseline success rate
Phase 2	Digital Twin Creation	Feb 11 - Mar 30	Scene analysis, Gaussian splatting reconstruction, mesh generation, asset creation, simulation assembly
Phase 3	Simulation Training / RL	Mar 1 - Mar 30	Reward engineering, parallel training in IsaacLab, metric recording
Phase 4	Sim-to-Real Transfer	Apr 1 - Apr 15	Deploy model to physical robot, record final metrics, calculate method gains, analyze transfer gaps
Phase 5	Infrastructure Scaling	Apr 16 - Jun 30	Solidify pipeline into reusable infrastructure, deliver working proof of concept and documented pipeline

10. Technical Stack & Resources

- Simulation Engine: NVIDIA IsaacSim & IsaacLab
- 3D Reconstruction: Gaussian splatting tools, with potential use of MarbleLabs and SAM3D for generative assets
- Training Framework: LeRobot for behavioral cloning; IsaacLab for RL training
- Hardware: SO-101 robot arm, camera setups, later the tomato sorting robot
- Compute: NVIDIA GPU infrastructure for both training and simulation

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VBTI - Vision Based Technology Innovations

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