Celebi's Choice: Causality-Guided Skill Optimisation for Granular Manipulation via Differentiable Simulation

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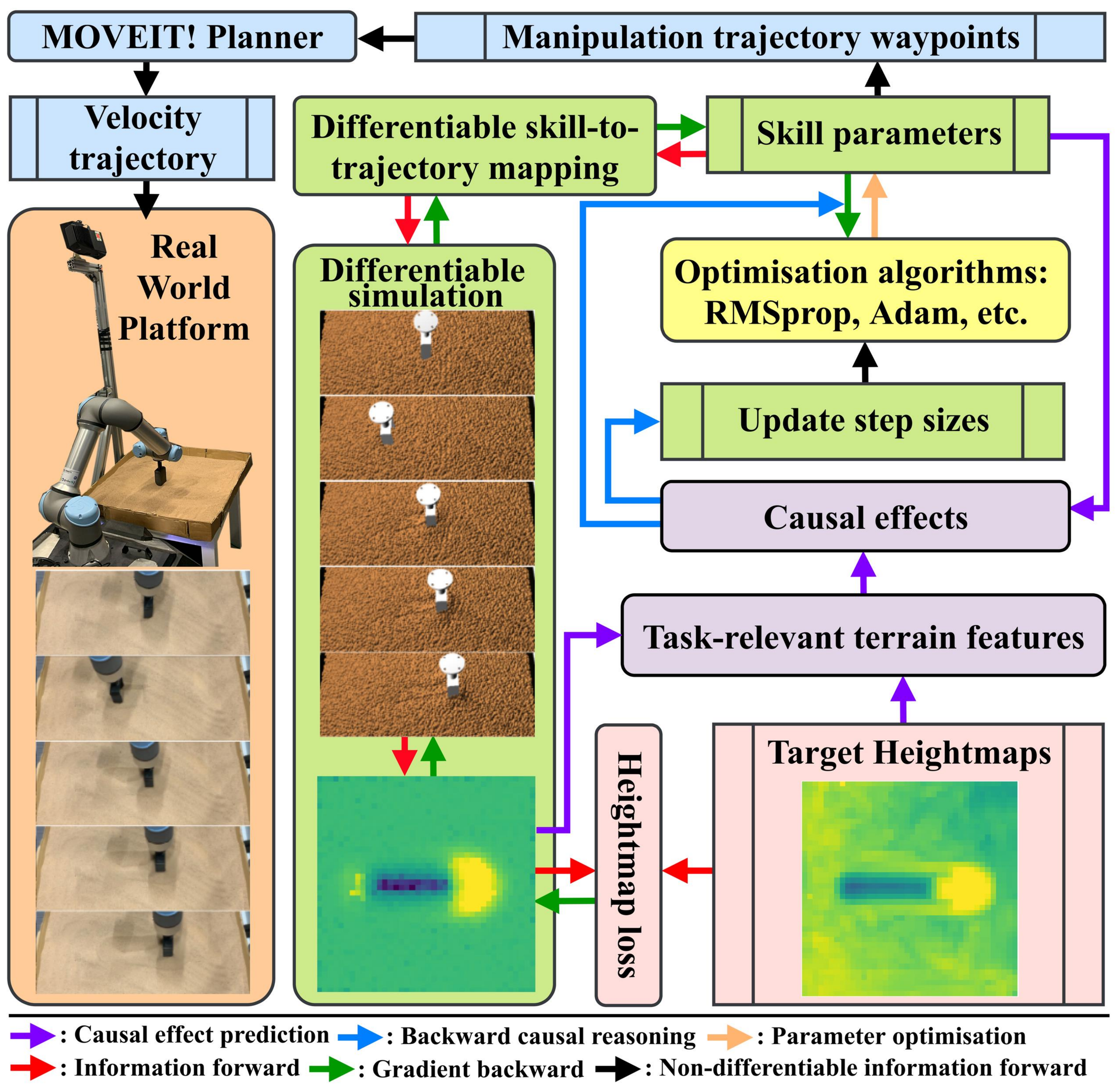
Abstract

Robotic soil manipulation is essential for automated farming, particularly in excavation and levelling tasks. However, the nonlinear dynamics of granular materials challenge traditional control methods, limiting stability and efficiency. We propose Celebi: causality-enhanced soil levelling and excavation skill optimisation via backpropagation with physical information. To enable gradient-based optimisation, we construct a differentiable simulation environment for granular material interactions. We further define skill parameters with a differentiable mapping to end-effector motions, facilitating efficient trajectory optimisation. By modelling causal effects between task-relevant features extracted from point cloud observations and skill parameters, Celebi selectively adjusts update step sizes and directions to enhance optimisation stability and convergence efficiency. Experiments in both simulated and real-world environments validate Celebi's effectiveness, demonstrating robust and reliable performance in robotic excavation and levelling tasks.

Similar to Celebi's time-travelling ability in mythology, we enable robots to "predict the future".

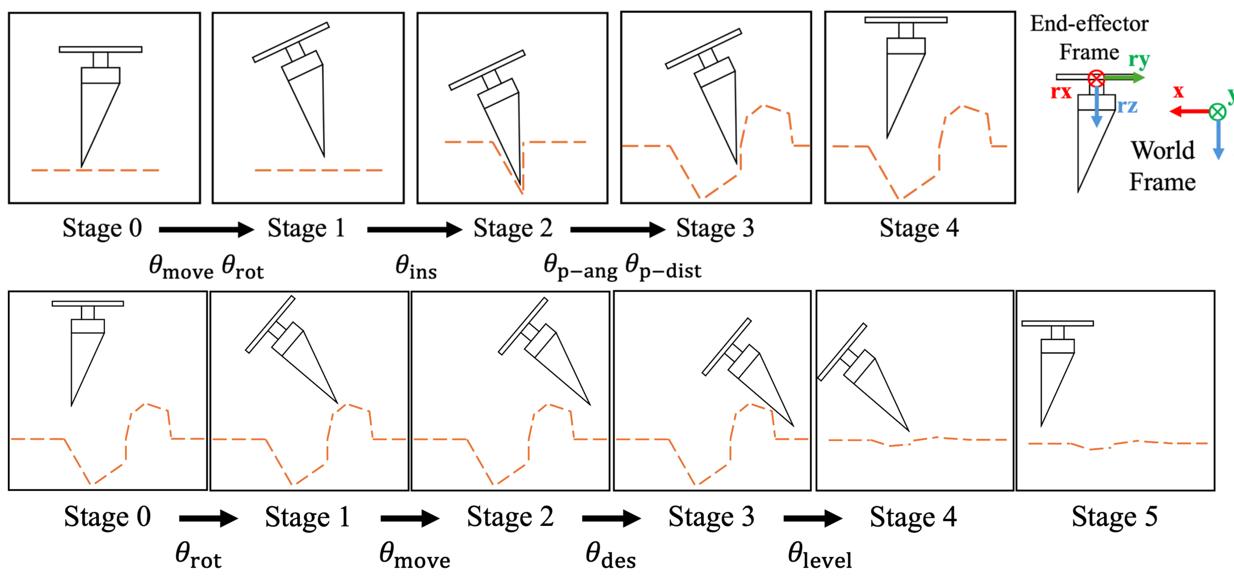
In other words, the robot predicts how its various skill parameters causally influence the manipulation results. The causal effects are used to selectively adjust the optimisation step sizes and correct the gradient directions of under-optimised skill parameters.

Method



- A robotic platform (orange) with a UR5e arm for real-world manipulation and a Zivid One+ camera for high-resolution surface point cloud collection.
- A differentiable physics simulator (green) that simulates the manipulation and provides system dynamic derivatives.
- A differentiable loss function (pink) that computes the differences between the target and simulated manipulation results.
- A causal reasoning module (purple) that extracts features, establishes causal effects between features and skill parameters, and guides skill optimisation.
- A gradient-based optimisation algorithm (yellow) that updates the skill parameters.
- A ROS-based module (blue) that plans velocity trajectories using optimised skill parameters to control the robot via MOVEIT! Planner [1].

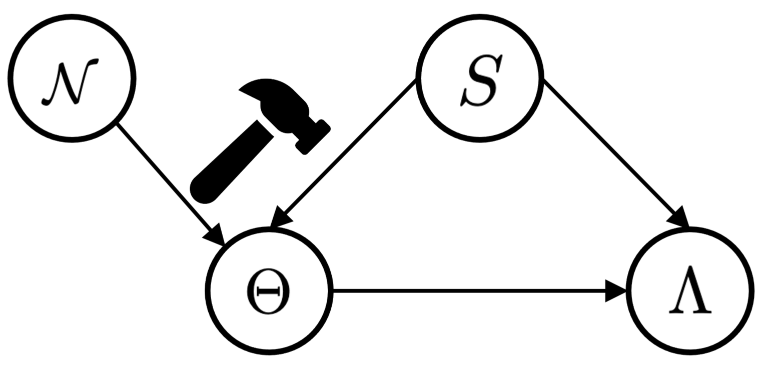
Visualisation of the Excavation (top) and Levelling (bottom) tasks.



Feature extraction: Task-relevant terrain features are obtained from height maps via morphological transformations and binary masking, yielding Λ_e for excavation and Λ_l for levelling.

$\Lambda_e = \{\lambda_d, \lambda_s, \lambda_l\}$: the depth, initial point, and length of the largest hole.

$\Lambda_l = \{\lambda_{ha}, \lambda_{hs}, \lambda_{ps}, \lambda_{pe}\}$: the area of the largest hole, the initial point of the first hole, and the start and end points of the first peak.



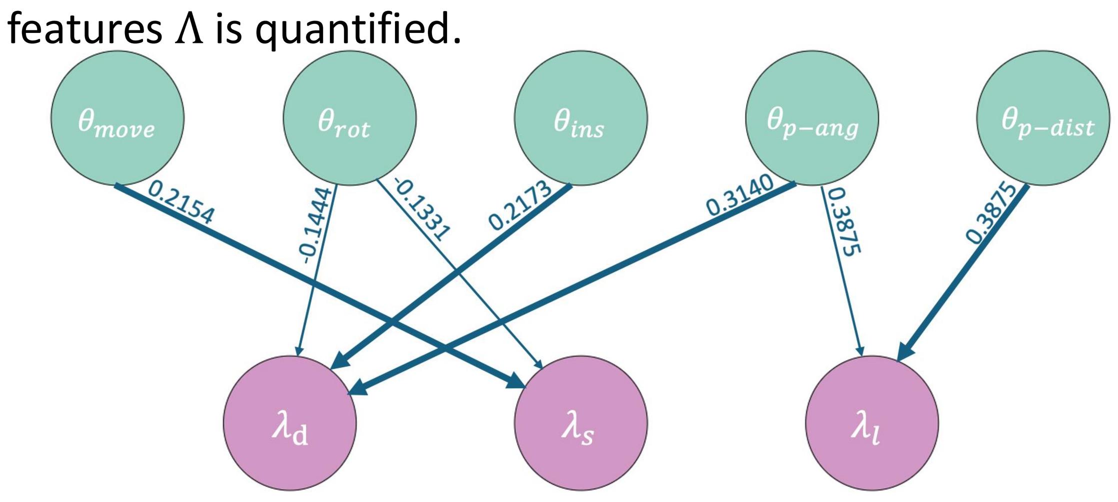
Causal reasoning: Based on the Structural Causal Model (SCM) [2], removing the influence of the environment bias variable S on the selection of skill parameters Θ and the calculation of features Λ, to establish the causal effect of Θ on Λ.

Causal effects: Quantified using the Average Causal Effect (ACE), where the normalised ACE of a skill θ_n with value β on a feature λ_m is given by:

$$ACE_{do(\theta_n=\beta)} = \frac{\mathbb{E}[\lambda_m | do(\theta_n = \beta)]}{\mathbb{E}[\lambda_m | do(\theta_n = 0)]} - 1$$

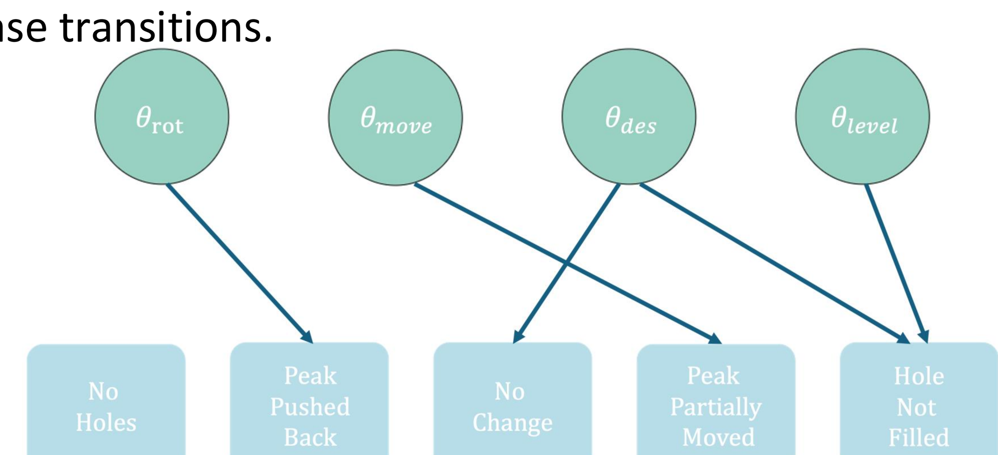
The causal effects are obtained via uniform grid search over $[\theta^{min}, 0]$ and $[0, \theta^{max}]$.

Excavation: The impact of skill parameters Θ on terrain features Λ is quantified.



Causal effects of skill parameters and features in the excavation task, where the numbers are ACE values, and the bold arrows denote strong causal effects.

Levelling: The target is a flat surface. Material phases are defined from features, and the impact of Θ is evaluated on phase transitions.



Causal effects of skill parameters and different phases in the levelling task.

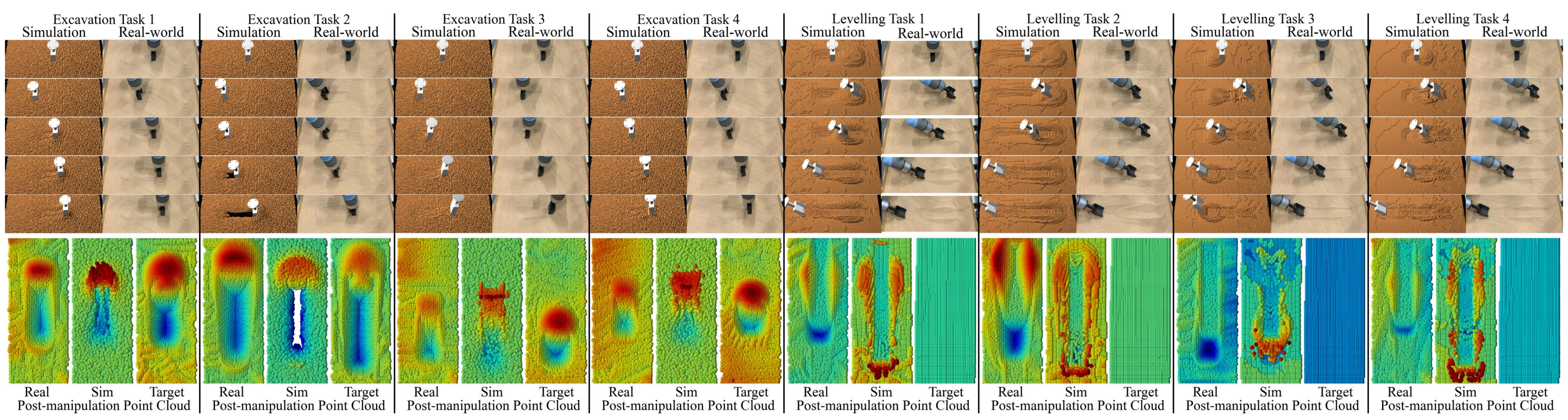
Conditions	Phases
$\lambda_{h_a} < \tau_a$	No Holes
$\lambda_{psi} > \lambda_{ps}$	Peak Pushed Back
$\lambda_{psi} \approx \lambda_{ps}$ and $\lambda_{pei} \approx \lambda_{pe}$	No Change
$\lambda_{psi} \approx \lambda_{ps}$ and $\lambda_{pei} > \lambda_{pe}$	Peak Partially Moved
$\lambda_{hsi} > \lambda_{hs}$	Hole Not Filled

Phase Determination in Levelling Tasks (*i* = initial state).

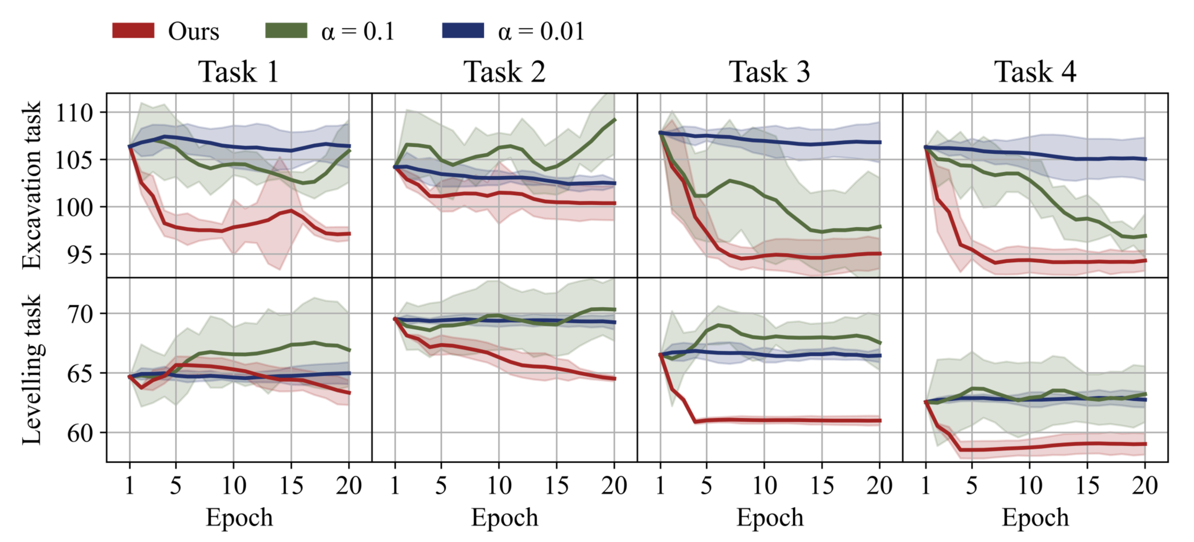
Optimisation: For excavation, causal effects scale step sizes based on feature differences and adjust gradient directions via ACE signs. For levelling, they identify the active phase for parameter update selection, with gradient correction driving updates toward the target phase.

Results

Tasks: four excavation tasks by manually digging four holes as targets with corresponding levelling tasks.
Setup: physical parameters calibrated with DPSI framework [3] for sim-to-real consistency.
Baselines with fixed step sizes (α = 0.1 and α = 0.01) without gradient direction correction.
Ours: small loss values, low variances, and fast convergence.



Visualisation of the trajectories and the resultant point clouds in simulation and the real world for the most performant skill parameters optimised by our method.



Optimisation loss curves of excavation (top) and levelling (bottom).

More Info

Paper
Video
Personal Website

References

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