Introduction of Reinforcement Learning into Automatic Stacking of Wave-dissipating Blocks

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His research interests include simulation of wave-dissipating block installation and applications of reinforcement learning in coastal engineering.

Background

Wave-dissipating block

- Crucial for dissipating wave energy and protecting coastal area, are commonly installed in harbors and seawalls
- Placement determines stability and performance

Mass (t)	Weight (kN)	Volume (m^3)	Surface Area (m^2)
3.991	39.138	1.735	9.796

Fig. 1 Shake Block 4-ton variant and specifications [1]

Breakwater structure

- Installation target for blocks

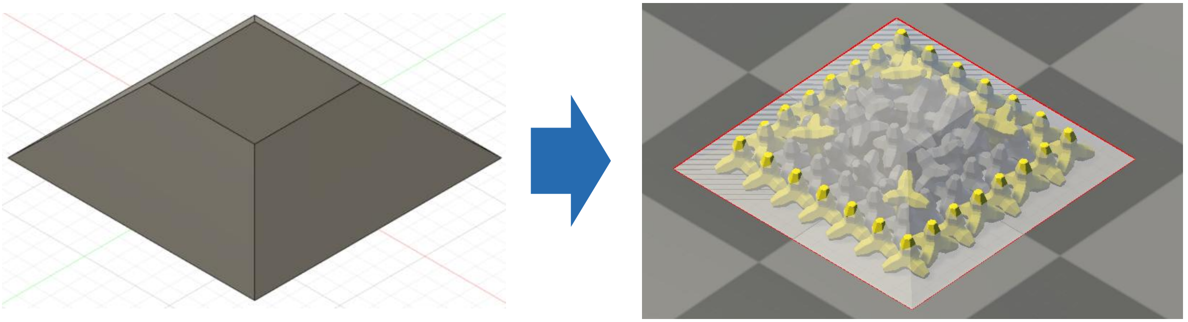


Fig. 2 Offshore breakwater model

[1] Honma Concrete Industry Co., Ltd, “Shake Block”, [Online] Available: https://www.honmacon.co.jp/02syouhin_list/01sye-kuburokku/01setumei.html, p. 3

Background

Current situation of installation work for wave-dissipating blocks

- Relies on the empirical knowledge and experience
- Trial and error on-site installation attempts
- Time-consuming and costly
- Hard to evaluate block placement

Placement of mat　　Placement of blocks　　Finished construction of breakwater

Fig. 3 Construction of breakwater [2]

[2] wakamatsukowan, "Manufacture and installation of wave-dissipating blocks.," [Online] Available: https://www.wakamatsu-kk.com/blank-3

Motivation

- Manual
- Inconsistent
- Labor-intensive
- Expensive

- Automation
- Reliable
- Scalable

- Objective solution
- Adaptive
- Long term

Artificial Intelligence (AI) has become relevant nowadays to tackle this problem

Related Works

Xu's Supervised CNN Approach [3]

- CNN trained on simulation-labelled poses

Pros

- Accurate
- Fast inference

Cons

- Dataset dependence
- No adaptability
- Short-term greedy strategy

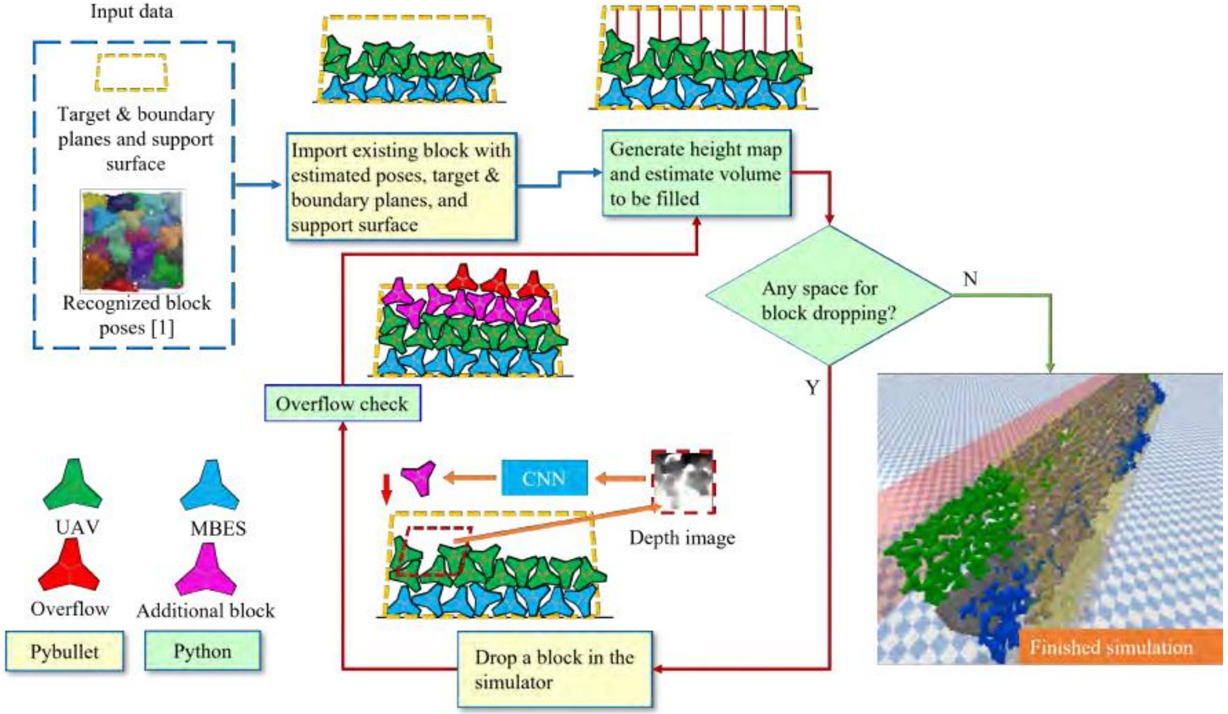


Fig. 4 Pipeline of block stacking operation

Physics-based Heuristic Approach

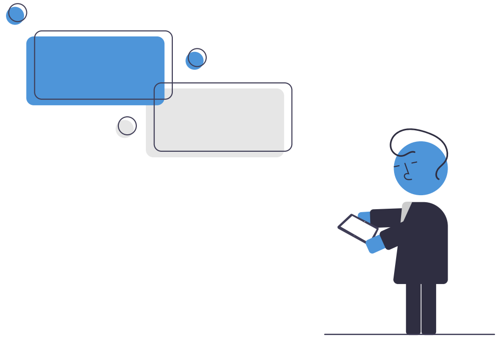
- Deterministic = No adaptability
- Break under uncertainty

[3] Y. Xu, A study on stacked object recognition and stacking operation planning combining 3D point cloud representation, deep-learning and physics engine, M.Eng. thesis, Graduate School of Information Science and Technology, Hokkaido University, Sapporo, Japan, 2020, doi:10.14943/doctoral.k15552.

Research Gap

CURRENT

- Supervised CNN: Accurate but inflexible
- Heuristic: Fast but brittle



MISSING

- Adapt to any conditions
- Planning strategically over multiple placements

SOLUTION

- Reinforcement Learning (RL): Flexible
- Commonly used in robotics [4]

[4] S. Gu, E. Holly, T. Lillicrap, and S. Levine, “Deep reinforcement learning for robotic manipulation,” in Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pp. 3389-3396, 2017.

Why Reinforcement Learning?

Adaptability

- Learn policies
- Generalize across different blocks and structure types

Strategic Optimization

- Multiple block placements
- Optimize long terms rewards

Reduced Data Dependency

- Learn from interaction
- Reduce reliance on dataset generation

3D-BW (3D Breakwater Simulator) [5]

- Developed based on Unity, a three-dimensional game development software since 2023
- Provides platform for off-site training
- Incorporates with ML-Agent, an open-source project that enables games and simulations to serve as environments for training intelligent agents

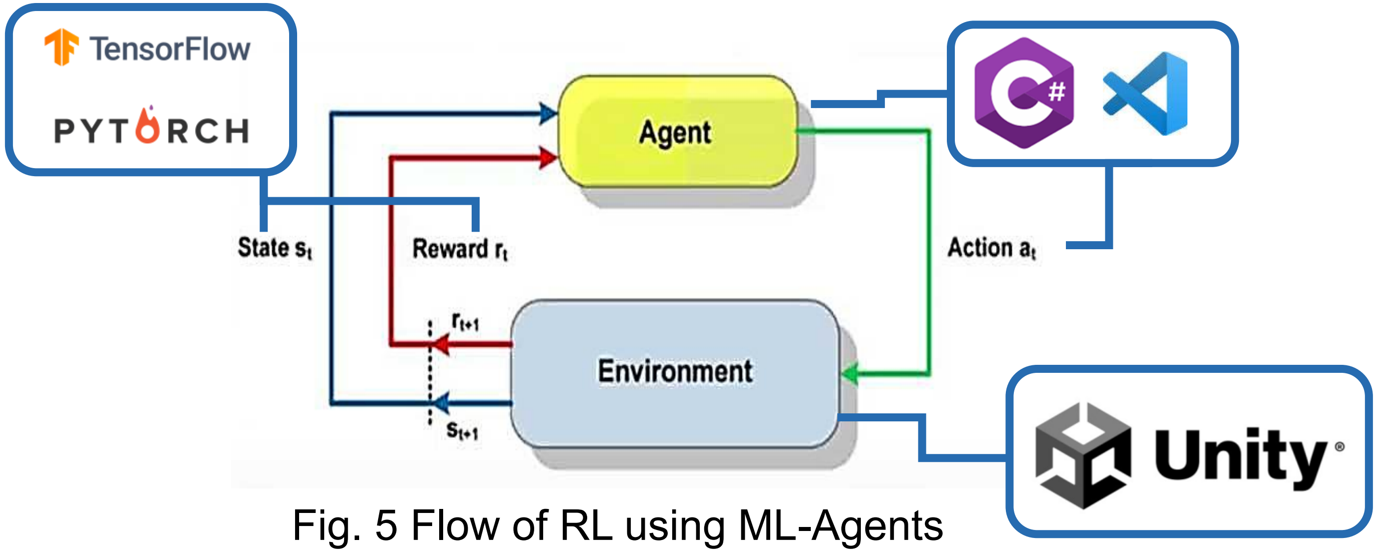


Fig. 5 Flow of RL using ML-Agents

Fig. 6 Interface of 3D-BW

[5] Chuah, H. M., Yamazaki, T., Iwasawa, R., Suto, T.: Development of Wave-Dissipating Block Installation for Inexperienced Worker Training. World Academy of Science, Engineering and Technology, International Journal of Computer and Systems Engineering vol. 18, no. 03 (2024)

Proximal Policy Optimization (PPO)

- Algorithm that updates the policy of the agent
- Policy: Strategy the agent uses to decide what action to take given its current observation or state

- The agent interacts with the environment
  - Observation: What it sees
  - Action: What it does
  - Reward: Feedback
- Advantages
  - Improves action (Learning from reward)
  - Avoids changing the policy too drastically (Stability)

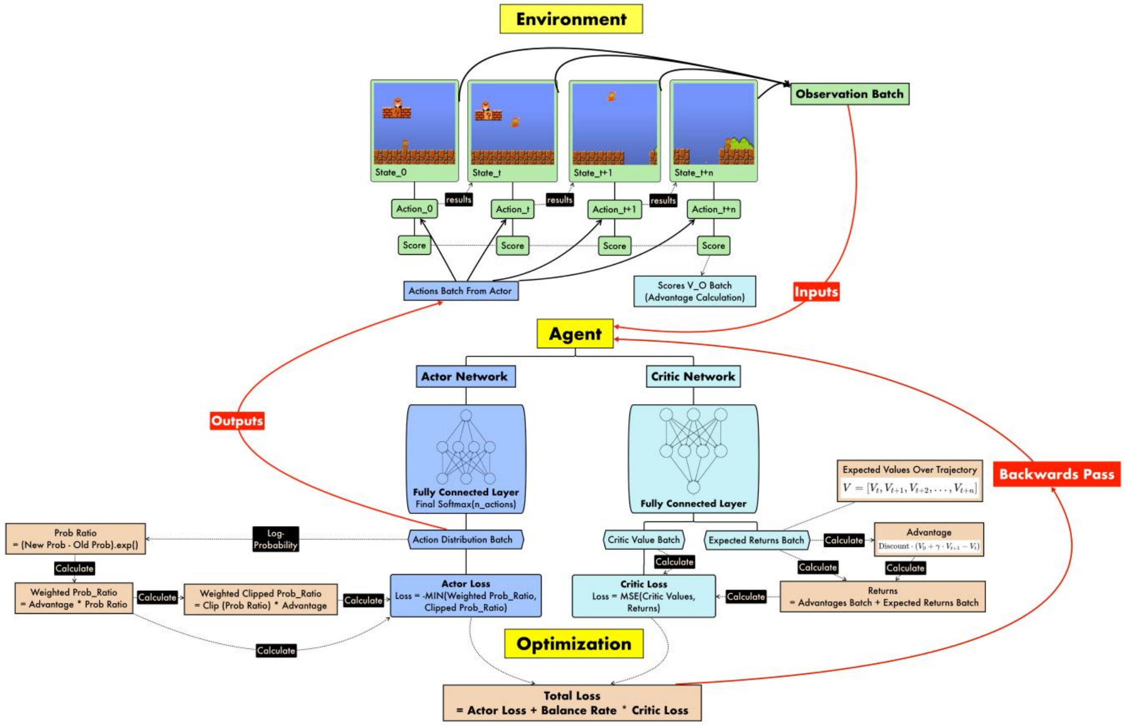


Fig. 7 PPO Flowchart [6]

Observation

$$obs_{x,z} = \frac{roofHeight_{x,z} - blockHeight_{x,z}}{\max_{i,j} roofHeight_{i,j} - blockHeight_{i,j}}$$

- Convert the breakwater into a 2D grid map
- Normalize the differences between block vertices and structure vertices in each grid cell
- Transform it into a gap map

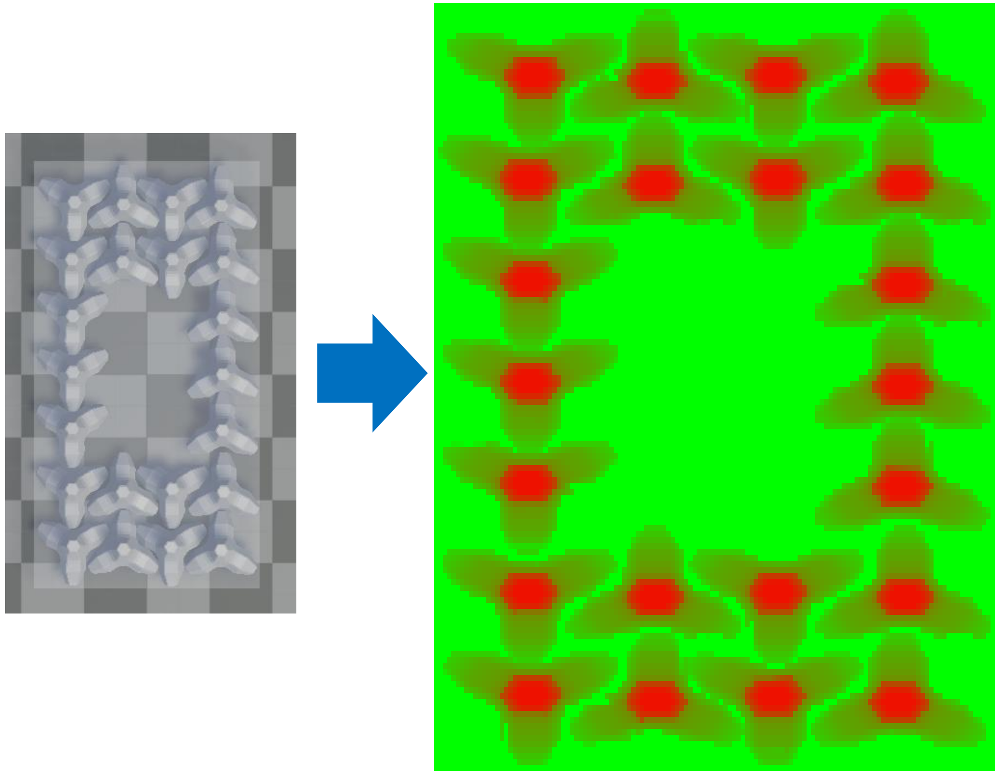
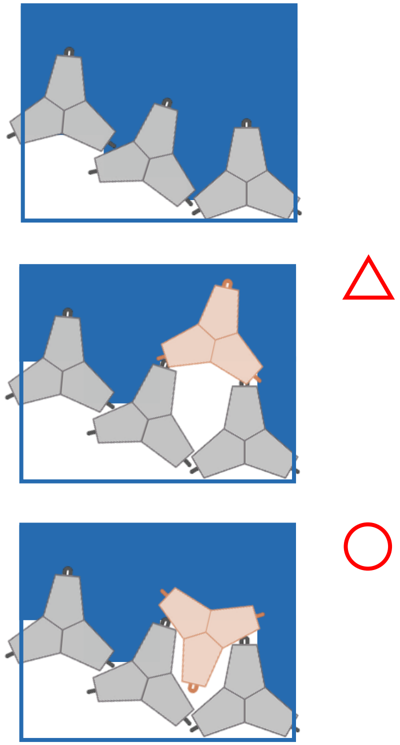


Fig. 7 Example of a grid map of 128x128

Action

- Drop from a fixed height
- Selects a discrete placement coordinate (x, z) from the grid map
- Randomized rotation angle

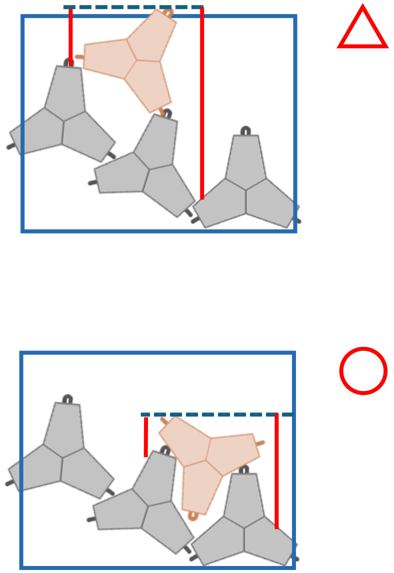
Proposed Reward Design



: Empty Spaces

Compactness

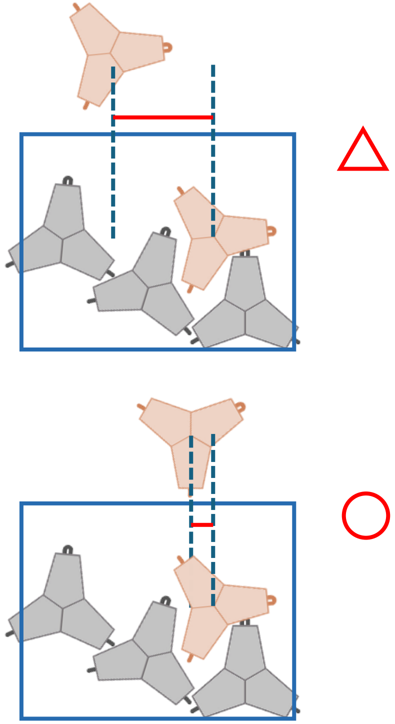
Difference between volume before and after within breakwater



: Height

Slope

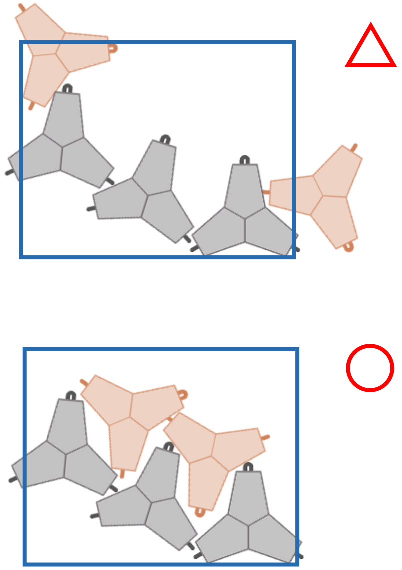
Height difference between neighbouring cells



: Distance moved

Stability

Distance moved after dropping block



Overflow

Overflowing from the top/side of breakwater

Challenges

Computational Cost

- Training takes time and resources

Reward Sensitivity

- Too strong/weak signals lead to poor polices

Slow Exploration

- May waste many episodes on random moves

<u>Possible solutions</u>

1. **Curriculum learning:** Gradually increase difficulty
2. **Behavioural Cloning:** Imitating expert demonstrations

Conclusion

- Propose an RL approach for automating and optimizing the placement of wave-dissipating blocks
- RL = Adaptability + Strategic optimization
- Careful reward design is compulsory

Future Work

- Simple experiment to test reward design
- Refine reward design
- Multiple test cases to test adaptability