Virtual Environment and Automated Physical Rolling Maze as Experimental Platform for Deep Reinforcement Learning

International Symposium on Ambient Intelligence and Embedded Systems

Hamburg, Germany, 2025

HAW HAMBURG

Prof. Dr.-Ing. Marc Hensel and Sandra Lassahn

http://www.haw-hamburg.de/marc-hensel

Agenda

1. Super engineers … and a little history
2. System overview
3. Solving the virtual environment
4. Ongoing and potential future work
5. References

Super engineers … and a little history

- Why we do what we do
- What we have done so far (selected activities)

Training engineers

No contradiction at all:

- Train competent engineers … AND have fun!

Let’s develop fancy learning platforms:

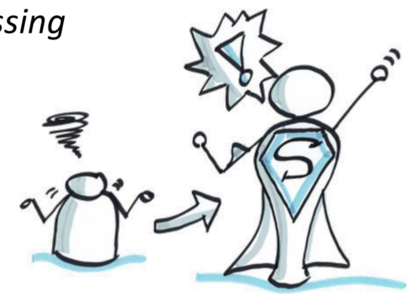
- Combine relevant technologies that offer challenging tasks
- Highly motivating for students

Deep learning

Image processing

Electronics

Software development



Mechanics / 3D printing

Microcontrollers

Actors & sensors

Okay, but what to us as “platform”? We felt free to try things out …

Selected theses

How about table soccer? a)

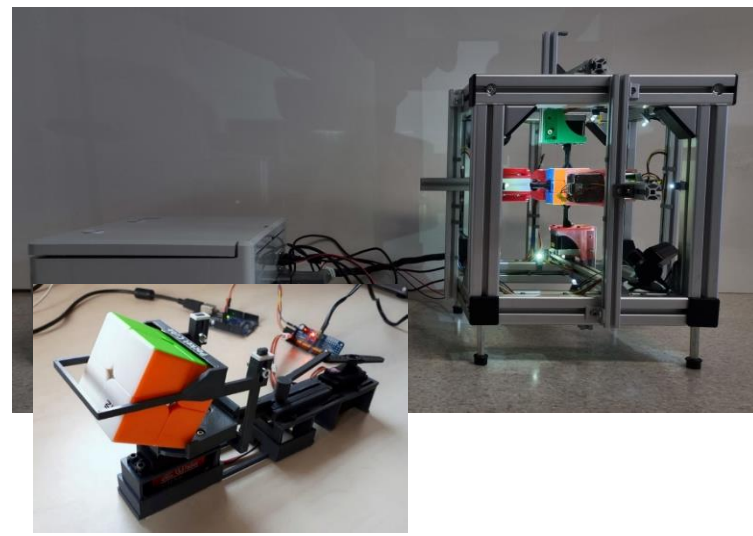
- ✓ Motorized and trained goal-keeper
- – Mechanically complex
- – High costs

⇒ No follow-up theses

And how about cubes? b)

- ✓ Developed AI and demonstrators
- – Not much imaging required
- – Low potential for follow-up theses

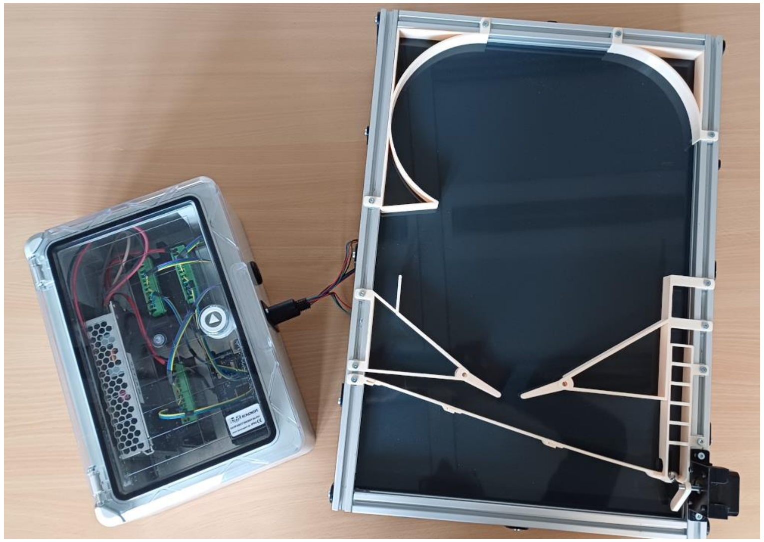
⇒ Continue as demonstrator



Selected theses

Pinball machine! c), d), e)

- ✓ Simple control task
- ✓ Can use different layouts
- ✓ Deal with high speed (e.g., imaging)
- ✓ Allows "infinite physical training"



Physical maze! f), g)

- ✓ Challenging control task
- ✓ Can use different layouts
- ✓ Low speed
- ✓ Challenging imaging at low speed

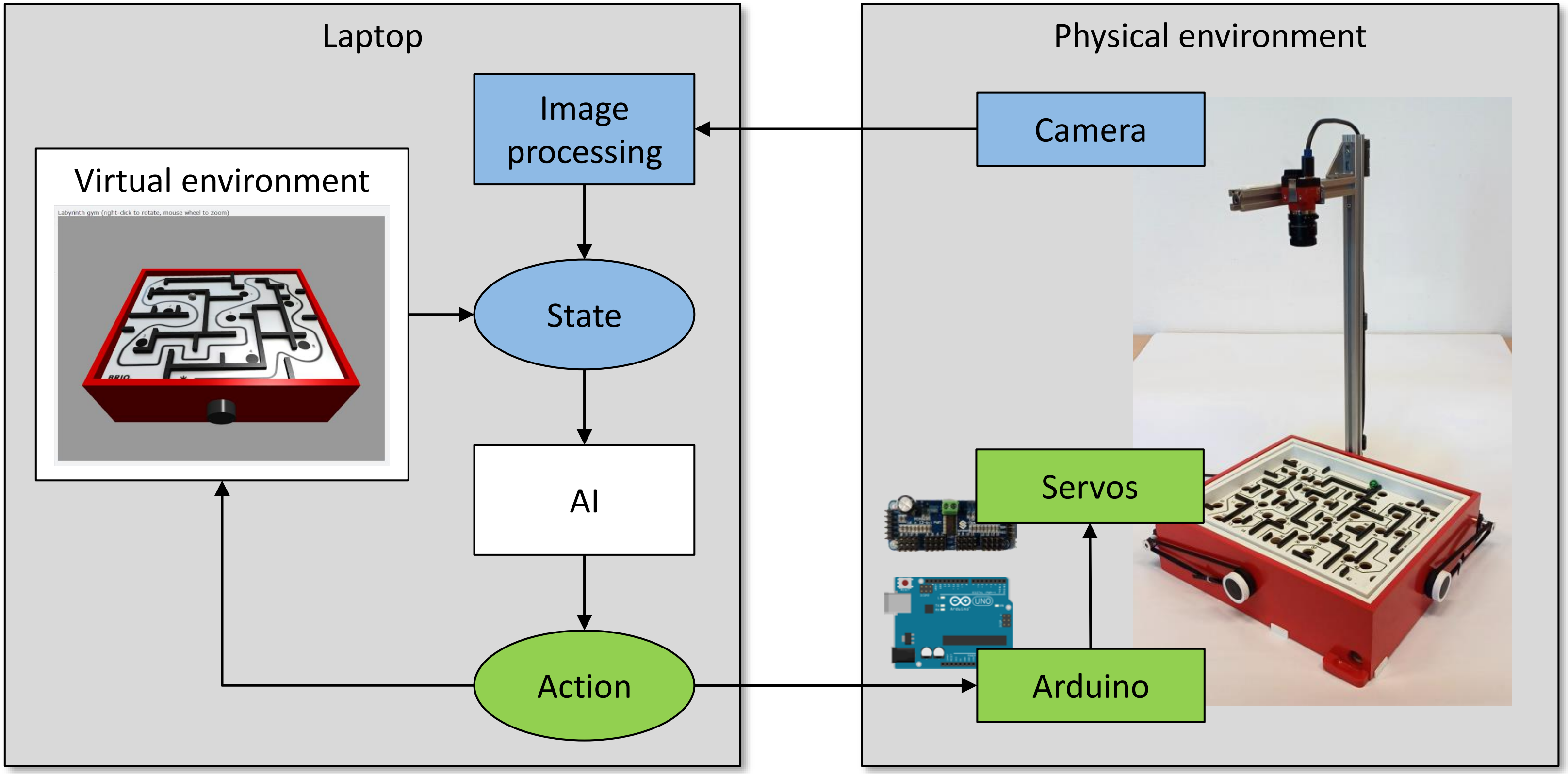
System overview

- Deep reinforcement learning
- Software simulation (“virtual environment”)
- Physical device

System overview

Main components:

- Laptop with AI agent and software simulation of maze
- Motorized physical maze with camera

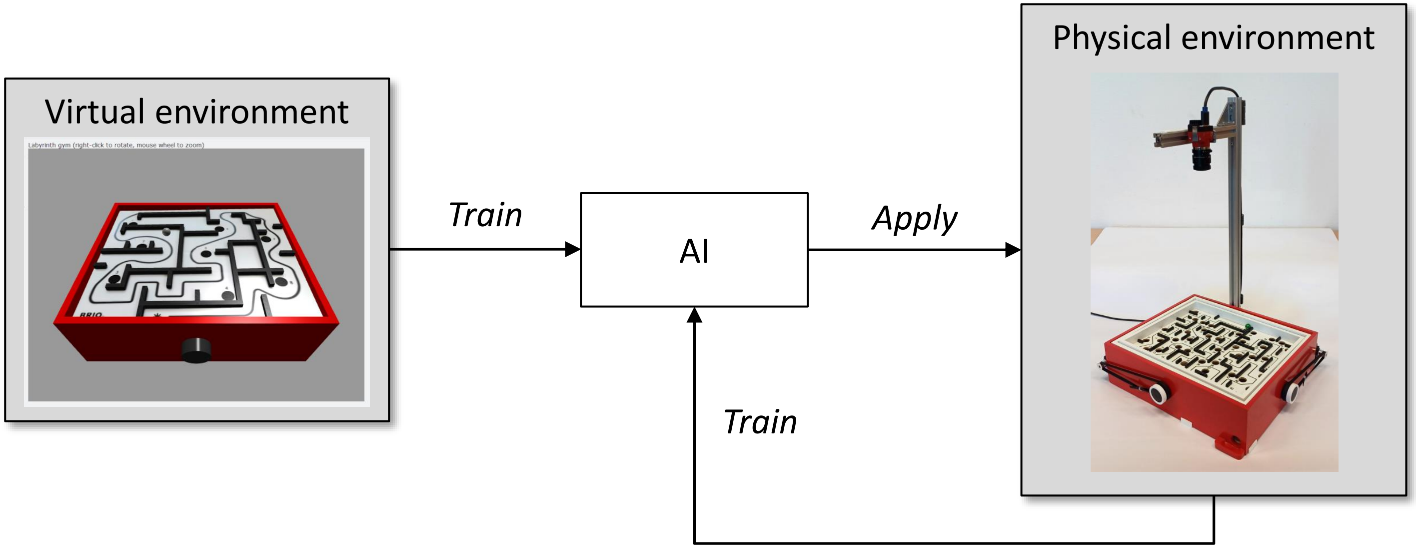


Supported by:
Allied Vision Technologies GmbH (industrial camera), **Kowa Optimed Deutschland GmbH** (lens)

Environments

Virtual and physical environments:

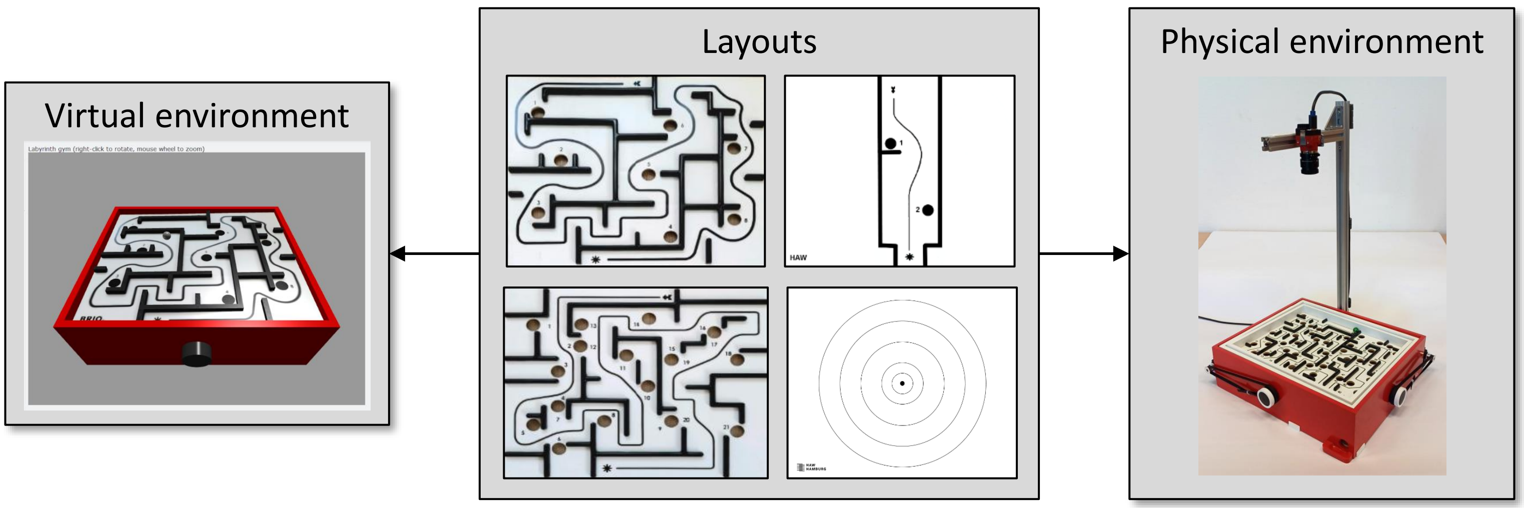
1. Deep reinforcement learning agent trained in virtual environment
2. Transfer trained model to physical device (and see what happens …)
3. Refine pre-trained model on physical device



Layouts

Use same layouts in software and hardware:

- Labyrinths provided with original game
- Custom labyrinth with simple task
- Layout without holes (“infinite training” on physical device)



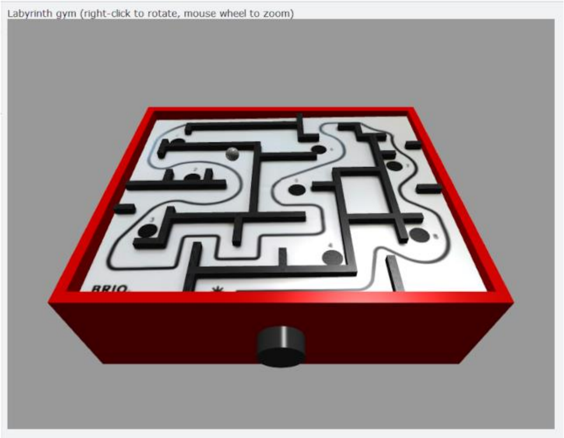
Solving the virtual environment

- Selected results for Master's thesis Sandra Lassahn [f)]
- Virtual environment
- Deep reinforcement learning

Virtual environment

Software simulation of maze:

- Compatible with OpenAI gymnasium
- Same physical dimensions and layouts as physical maze
- Modelled physical properties (e. g., ball physics, servo speed)
- 3D visualization for demonstration purposes



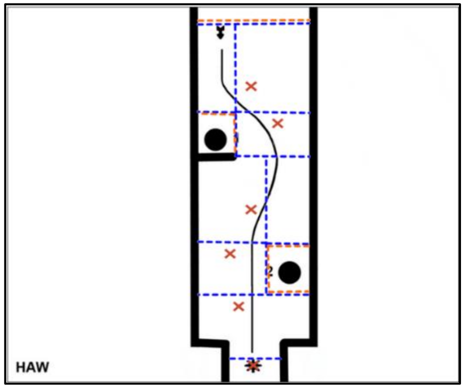
Deep reinforcement learning

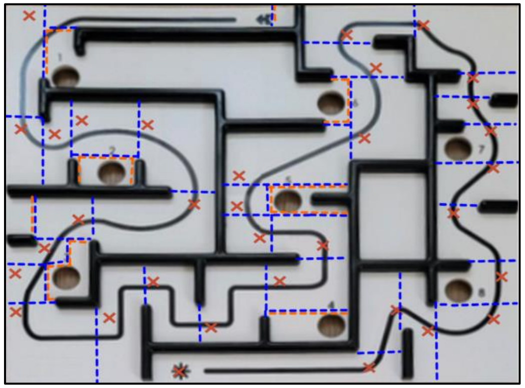
General approach:

- Deep Q-learning Network (DQN)
- Dedicated model for each labyrinth layout
- Observation space: tilt angles in *x* and *y*, current and previous ball location
- Action space: tilt angles ∈ $\{\pm 1°, \pm 0.5°, 0°\}$ in *x* and *y*

Rewards:

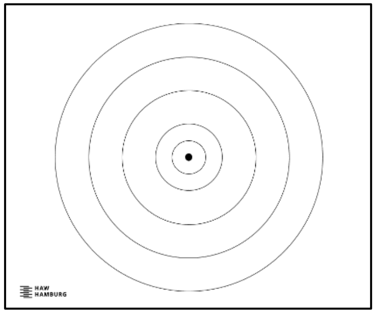
- Divided each labyrinth into zones
- Each zone has a target coordinate (X) where to leave the zone.
- Positive reward for movements into direction of current target

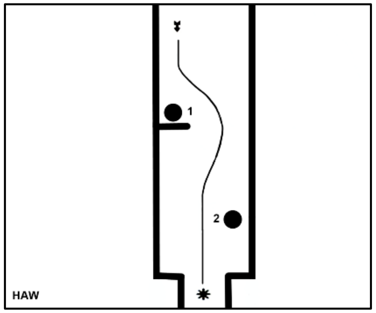


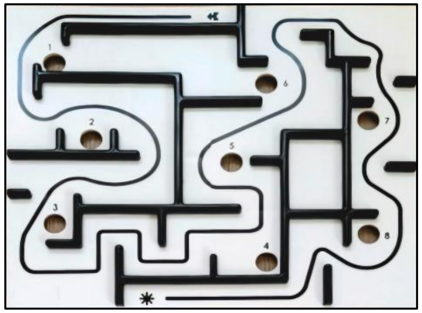


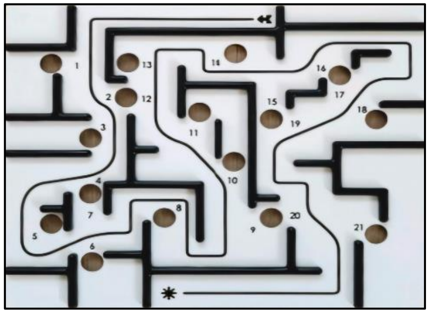
Deep reinforcement learning

Neural networks (fully connected):









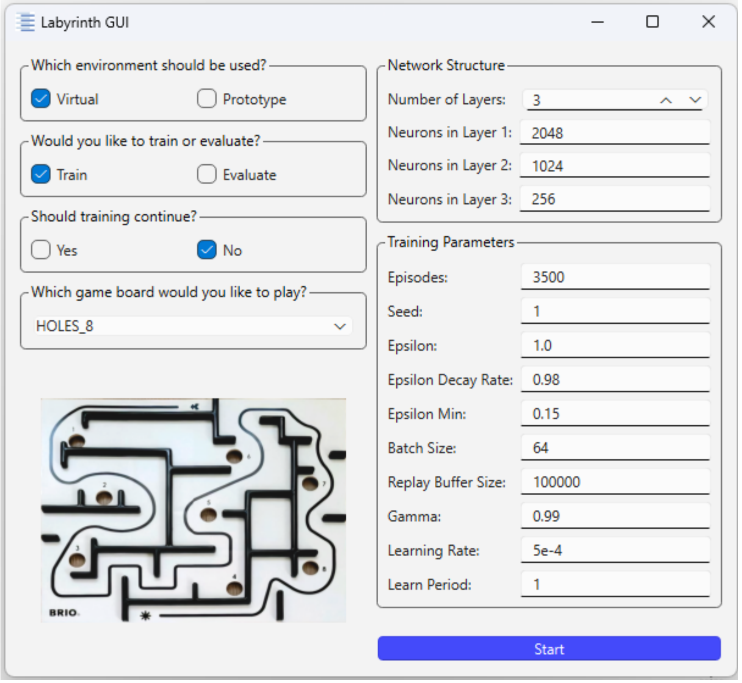
6 inputs (state: 2 angles and two ball coordinates)			
512	128	2048	2048
128	128	1024	1024
		256	256
10 outputs (approx. Q values of actions: 5 discrete angles in *x* and *y*)			

- ReLU activation, Adam optimizer, batch normalization
- Exploration and exploitation by epsilon greedy
- 1,000 to 3,500 episodes

Results

Proof of concept in virtual environment:

- Dedicated models solving the different layouts
- Application for training and demonstration



Ongoing and (potential) future work

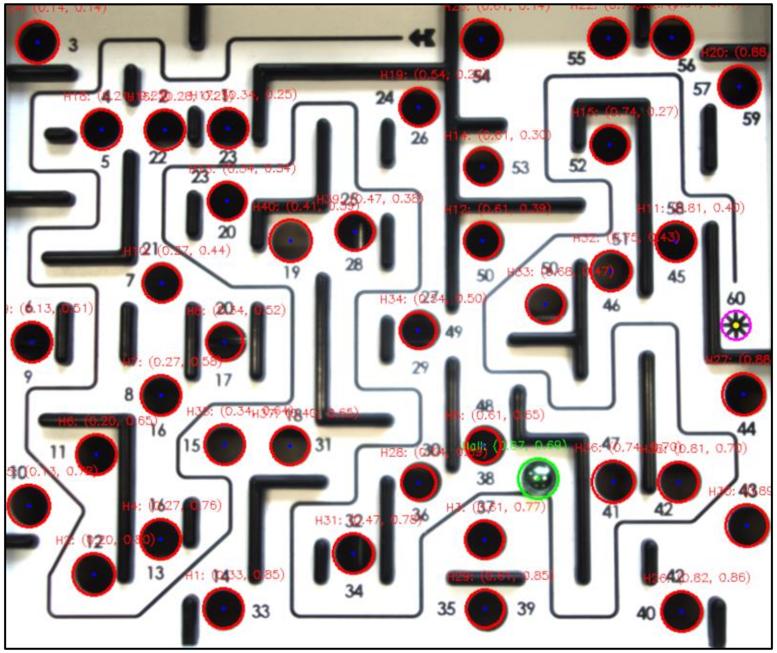
- What we currently do
- Ideas for future work

HAW HAMBURG

Ongoing work

Master's thesis Shabir Rastagar: g)

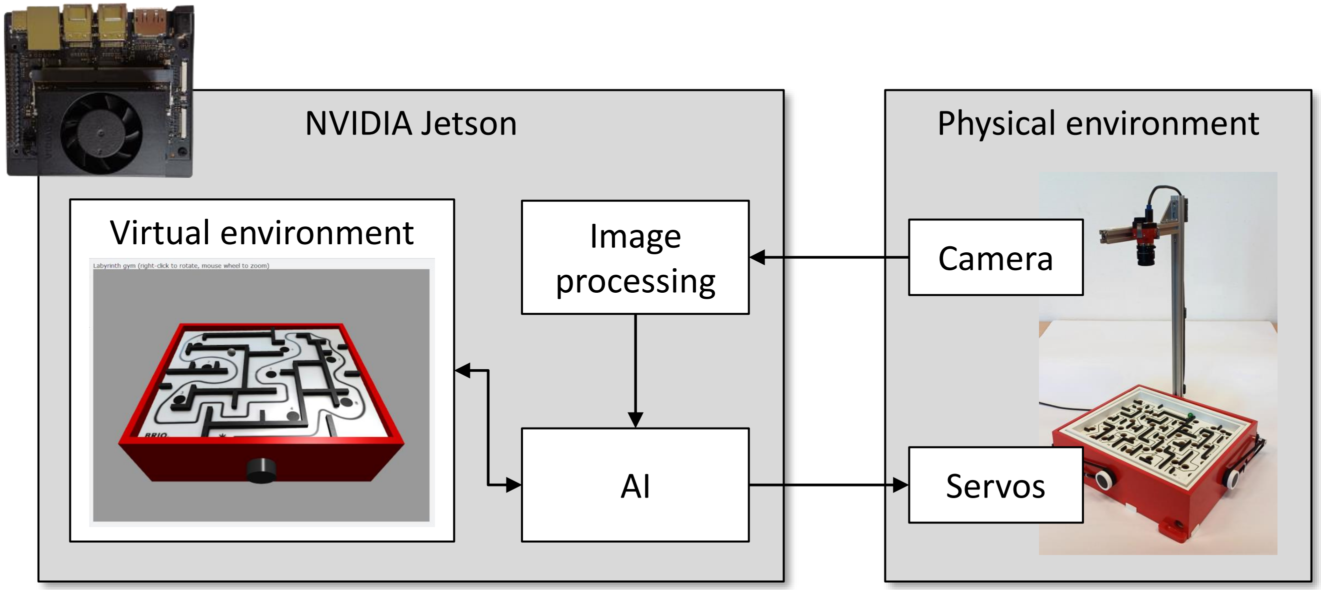
- Initial image processing
- Operational physical demonstrator



Future work …?

Selected ideas:

- Transfer pre-trained models to the physical device
- Different reward systems and learning approaches
- Custom layouts (e.g., path without walls)
- Generic agent (i.e., solve labyrinths not seen in training)
- Replace laptop and Arduino by NVIDIA Jetson



References

Referenced theses

Table soccer:

a) Jonas Kempke, “Entwicklung eines KI gesteuerten Tischkickers unter Verwendung von Reinforcement Learning,“ Master‘s thesis, HAW Hamburg, 2023.

Cubes:

b) Finn Lanz, “Deep Reinforcement Learning zum maschinellen Erlernen von Strategien zur Lösung von Zauberwürfeln,“ Master‘s thesis, HAW Hamburg, 2023.

Pinball machine:

c) Alexander Wessels, “Entwicklung und prototypischer Aufbau eines durch Reinforcement Learning gesteuerten Flipper-Automaten,“ Bachelor‘s thesis, HAW Hamburg, 2024.

d) Pascal Gutthardt, “Deep Reinforcement Learning zur autonomen Steuerung eines Flipperautomaten mit kamerabasierter Umgebungserfassung,“ Master‘s thesis, HAW Hamburg, 2025.

e) Arbin Medi, “Deep Reinforcement Learning und Bildverarbeitung zur autonomen Steuerung eines Flipperautomaten,“ Master‘s thesis, HAW Hamburg, 2025.

Physical maze:

f) Sandra Lassahn, “3D-Simulation und prototypischer Aufbau eines durch Reinforcement Learning gesteuerten Labyrinths,“ Master‘s thesis, HAW Hamburg, 2024.

g) Shabir Rastagar, “Deep Reinforcement Learning und Bildverarbeitung zur generalisierbaren Steuerung physischer Labyrinthe,“ Master‘s thesis, HAW Hamburg, 2025.

Thank you for your attention!

Vielen Dank für Ihre Aufmerksamkeit!

Prof. Dr.-Ing. Marc Hensel

HAW Hamburg
Berliner Tor 7
20099 Hamburg

marc.hensel@haw-hamburg.de
http://www.haw-hamburg.de/marc-hensel