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Master‘s Thesis

END-TO-END REINFORCEMENT LEARNING OF A CNN TO ACHIEVE AN AUTONOMOUS DRIVING AGENT RESILIENT TO LIGHT CHANGES

Leipzig, 05.12.2023

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OUTLINE

- Previous Work at the ScaDS.AI
- Autonomous Driving Task
- Research Questions
- Related Work
- Implementation
- Experimentation
- Evaluation
- Conclusion

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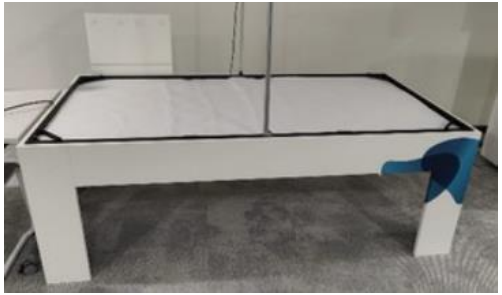
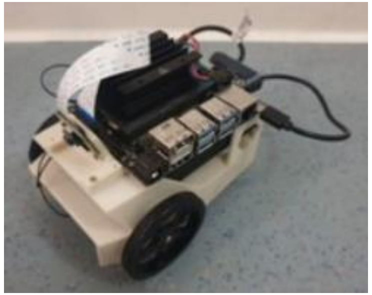
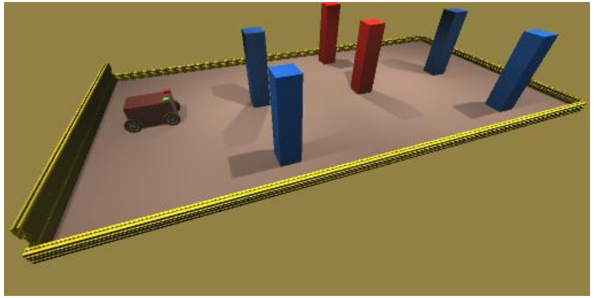
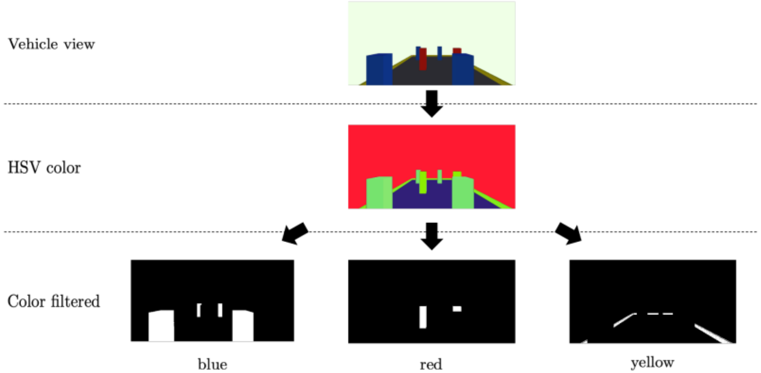
PREVIOUS WORK AT THE SCADS

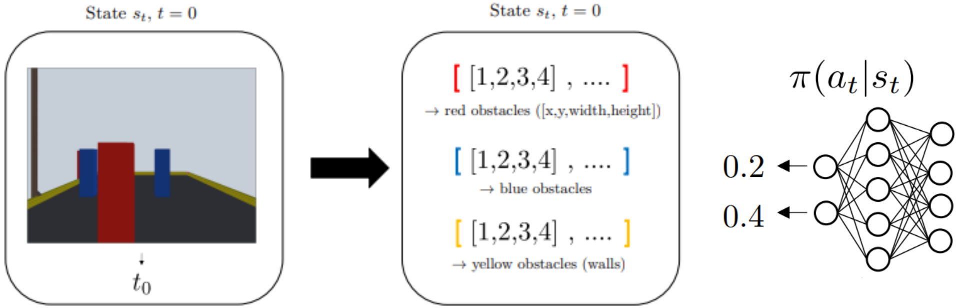
TRAIN AN AGENT TO DRIVE A VEHICLE IN A SIMULATED ENVIRONMENT USING REINFORCEMENT LEARNING











TRAIN AN AGENT TO DRIVE A VEHICLE IN A SIMULATED ENVIRONMENT USING REINFORCEMENT LEARNING

- A hand-crafted preprocessing pipeline extracts features from images.
- Extracted features of the last n frames are stacked together. (Memory)
- Extracted features are used by a neural network to produce two outputs.
  - Left and right wheel acceleration
- Agent struggled with difficult parcours.
- Agent was not resilient to light changes.

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AUTONOMOUS DRIVING TASK

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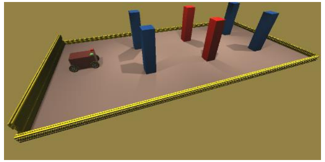
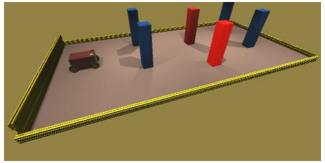
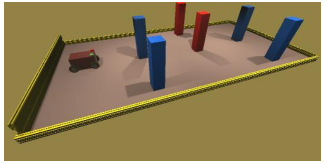
AUTONOMOUS DRIVING TASK



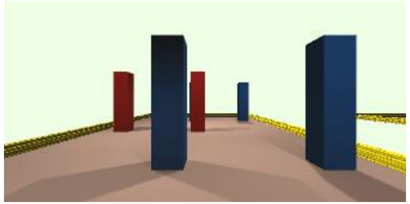
Easy



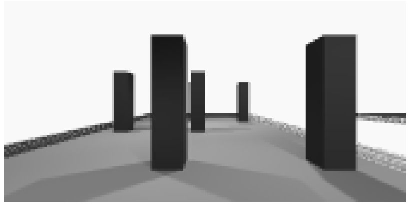
Medium



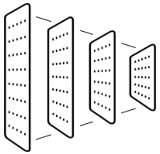
Hard



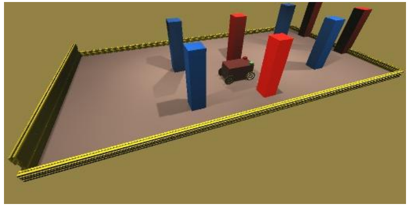
1. Agent Camera PoV



2. Preprocessing



3. CNN produces Wheel Acceleration values



4. Agent moves

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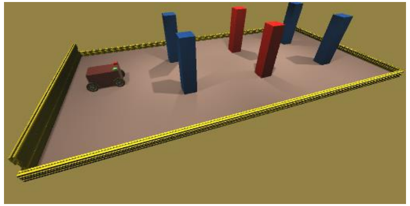
RESEARCH QUESTIONS

RESEARCH QUESTION 1

IS IT POSSIBLE TO TRAIN A CONVOLUTIONAL NEURAL NETWORK AGENT WITH END-TO-END REINFORCEMENT LEARNING TO RELIABLY TRAVERSE THE PARCOURS OF ALL DIFFICULTY LEVELS?

Evaluation:

- Pass through the 3 goals without collisions
- Fixed lighting



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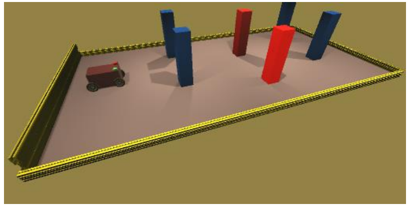

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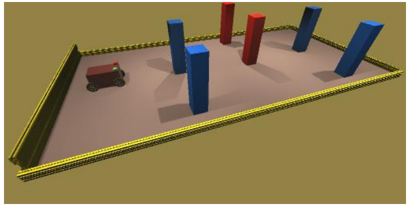


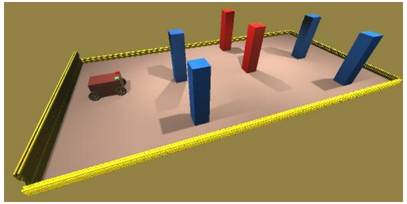
Difficult

RESEARCH QUESTION 2

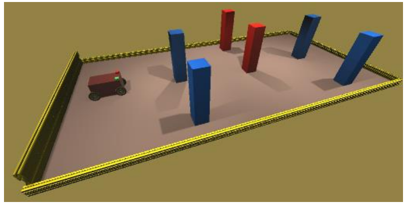
IS IT POSSIBLE TO USE AN END-TO-END TRAINED CNN TO MAKE THE AGENT ROBUST TO CHANGING LIGHT CONDITIONS?

Evaluation:

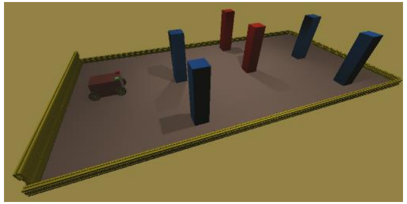
- Pass through the 3 goals without collisions
- Varying lighting



Bright



Standard



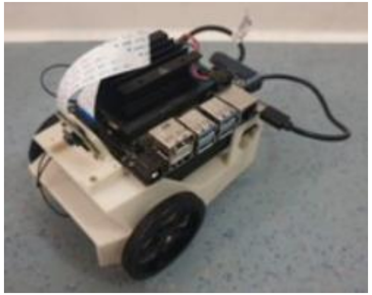
Dark

RESEARCH QUESTION 3

IS IT POSSIBLE TO USE A CNN WHICH IS SMALL ENOUGH TO BE USED IN THE JETBOT?

Evaluation:

- Create a replay of a successfully completed parcour
  - Replay consists of input-output pairs
- Give inputs to JetBot
- Is Output reproduced quick enough by the JetBot?



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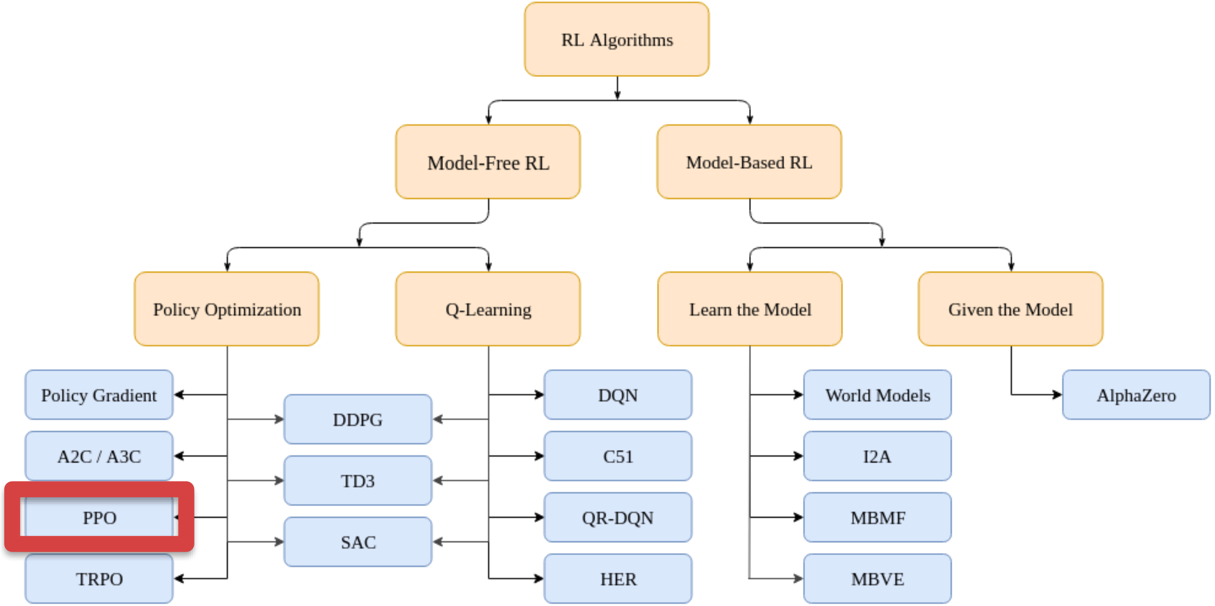
RELATED WORK

RELATED WORK

RL ALGORITHM CLASSIFICATION



RELATED WORK

PLAYING ATARI WITH DEEP REINFORCEMENT LEARNING

- Introduces DQN, an extension of Q-learning
- Plays Atari games using convolutional neural networks
- Utilized greyscaled and stacked images

Figure 1: Screen shots from five Atari 2600 Games: (*Left-to-right*) Pong, Breakout, Space Invaders, Seaquest, Beam Rider

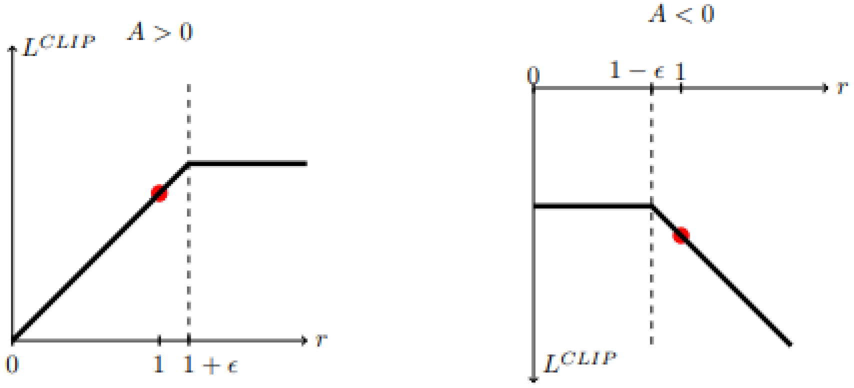
RELATED WORK

PROXIMAL POLICY OPTIMIZATION ALGORITHMS

- Introduces PPO, a stable and sample efficient policy based approach
- Great performance on continuous control tasks
- PPO restricts the size of policy updates

$$L^{CPI}(\theta) = \hat{\mathbb{E}}_t\left[\frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{\text{old}}}(a_t \mid s_t)}\hat{A}_t\right] = \hat{\mathbb{E}}_t\left[r_t(\theta)\hat{A}_t\right]$$

$$L^{CLIP}(\theta) = \hat{\mathbb{E}}_t\left[\min(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t)\right]$$



RELATED WORK

DEEP REINFORCEMENT LEARNING FOR AUTONOMOUS DRIVING: A SURVEY

- Gives a good overview of RL for autonomous driving
- Describe modern autonomous driving system pipelines
- Describe extensions to RL such as Reward shaping

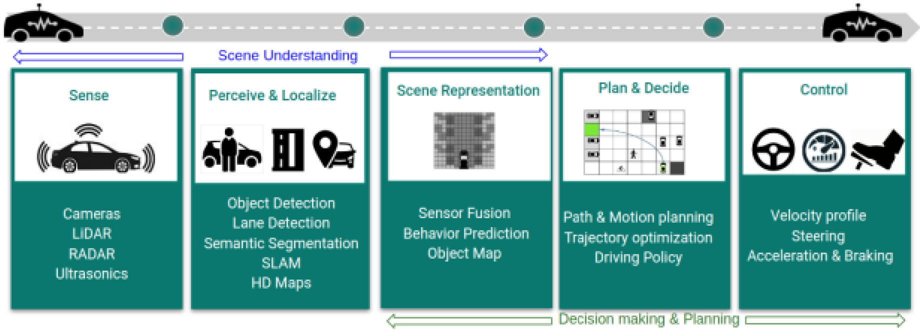


Fig. 1. Standard components in a modern autonomous driving systems pipeline listing the various tasks. The key problems addressed by these modules are Scene Understanding, Decision and Planning.

RELATED WORK

END-TO-END DRIVING VIA CONDITIONAL IMITATION LEARNING

- Imitation learning with a convolutional neural network
- Extensive use of Data Augmentation
  - Transformations like changes in contrast, brightness and tone
  - Gaussian blur, Gaussian noise, salt-and-pepper noise

(a) Aerial view of test environment (b) Vision-based driving, view from onboard camera (c) Side view of vehicle

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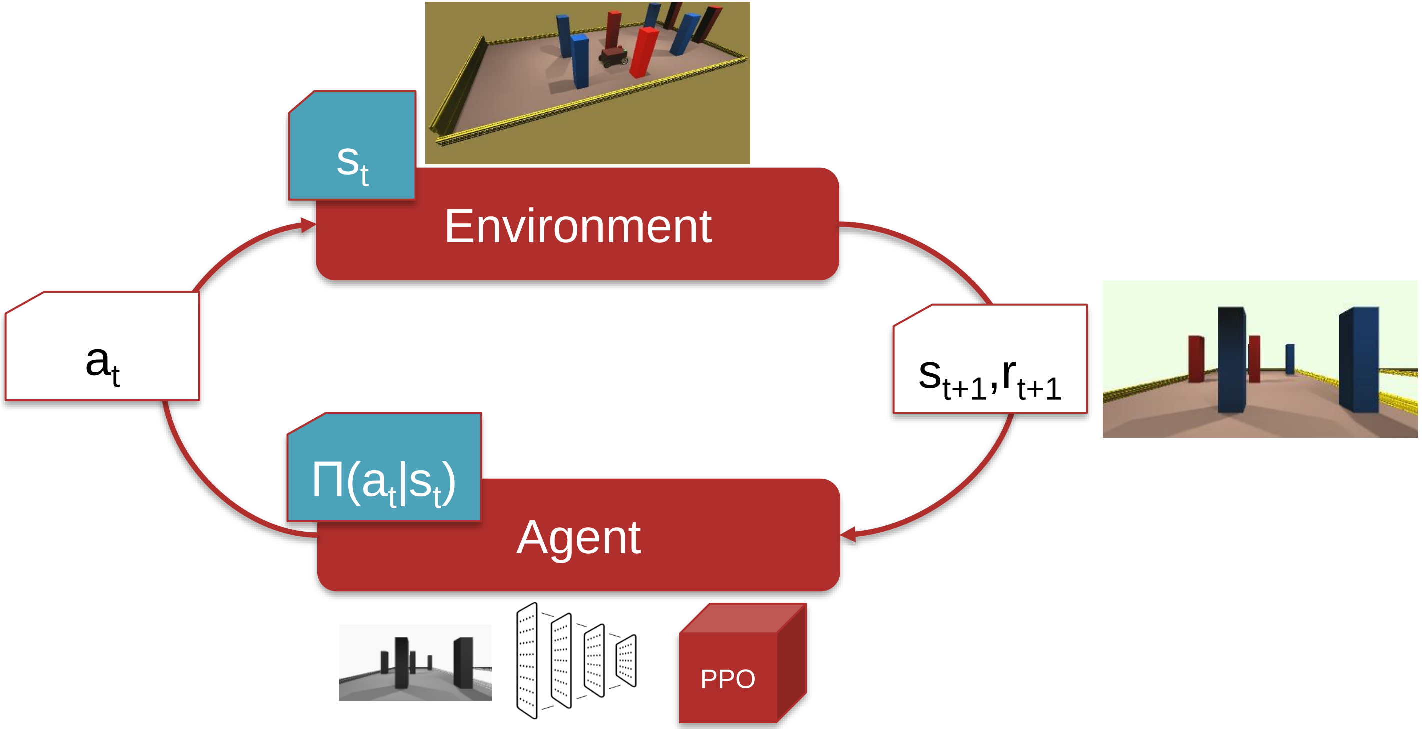
IMPLEMENTATION / METHODS

RL TRAINING ALGORITHM - PPO



RL TRAINING REWARD FUNCTION

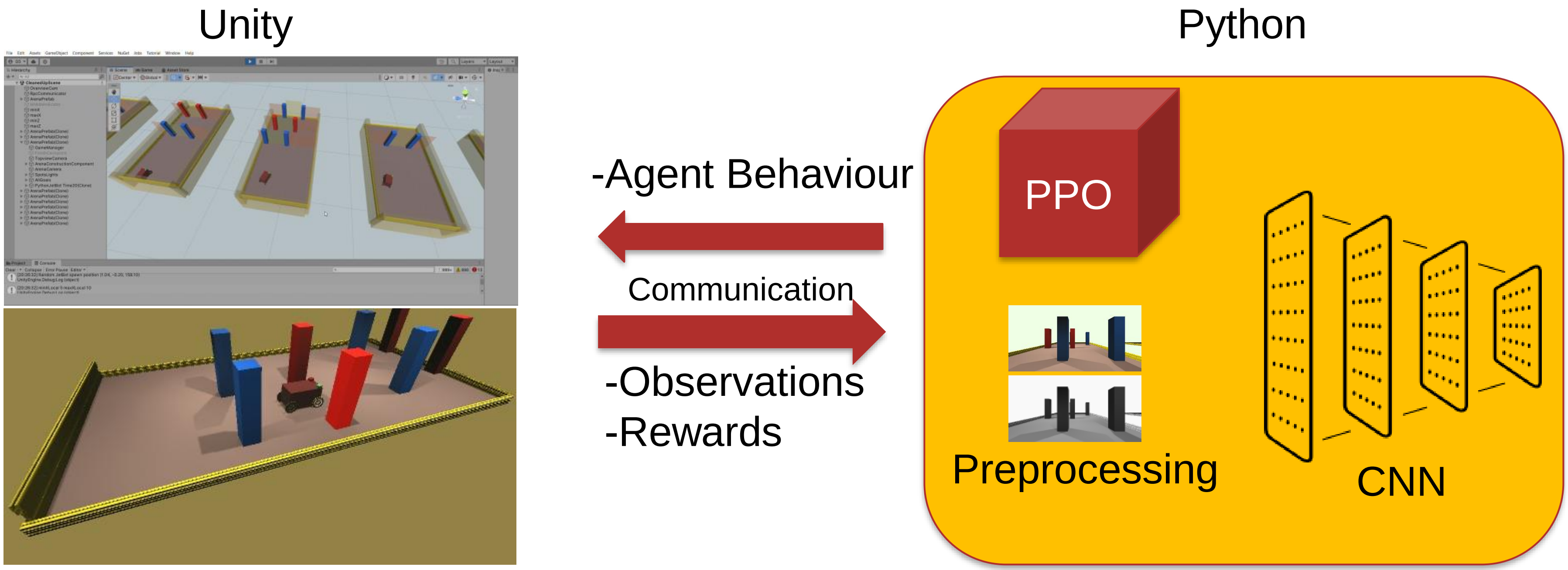
$$
\begin{aligned}
R(s_t, a_t) &= c_1 \cdot DistanceReward(s_t, a_t) + c_2 \cdot OrientationReward(s_t, a_t) \\
&\quad + c_3 \cdot VelocityReward(s_t, a_t) + c_4 \cdot EventReward(s_t, a_t) \\
DistanceReward(s_t, a_t) &= \Delta distance(Agent, NextGoalPosition) \cdot \Delta T \\
OrientationReward(s_t, a_t) &= S_C(NextGoalPosition - AgentPosition, agentDirection) \cdot \Delta T \\
VelocityReward(s_t, a_t) &= v \cdot \Delta T \\
EventReward(s_t, a_t) &= \begin{cases} 100, \text{completed the parcour} \\ 1, \text{passed a goal} \\ -1, \text{missed a goal} \\ -1, \text{collision with wall or obstacle} \\ -1, \text{timeout} \\ 0, \text{otherwise} \end{cases}
\end{aligned}
$$

Abbildung 4.3.: Complete reward function R with all its components

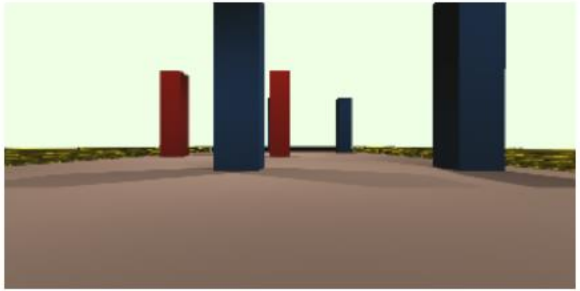
S_C: cosine similarity $\quad c_i$: weights

s_t: state t $\quad a_t$: action in state t

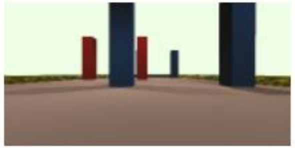
REINFORCEMENT LEARNING TRAINING SETUP



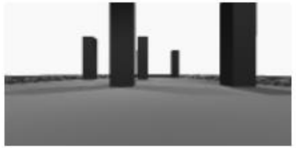
AGENT DESIGN: PREPROCESSING STEPS



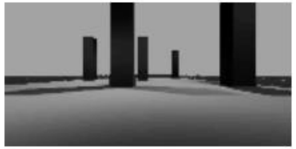
(a) Original Image



(b) Downsampled image



(c) greyscale



(d) histogram equalized image

Abbildung 4.4.: 4 Stages of preprocessing images for the CNN

AGENT DESIGN: CONVOLUTIONAL NEURAL NETWORK

- Agent recieves an image at each iteration
- Apply image preprocessing steps
- concatenate with last n images (memory)
- Image stack is fed to a Convolutional Neural Network

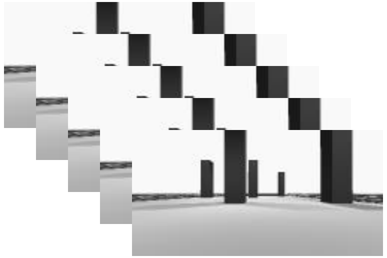
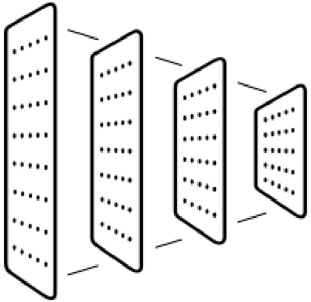


Image stack



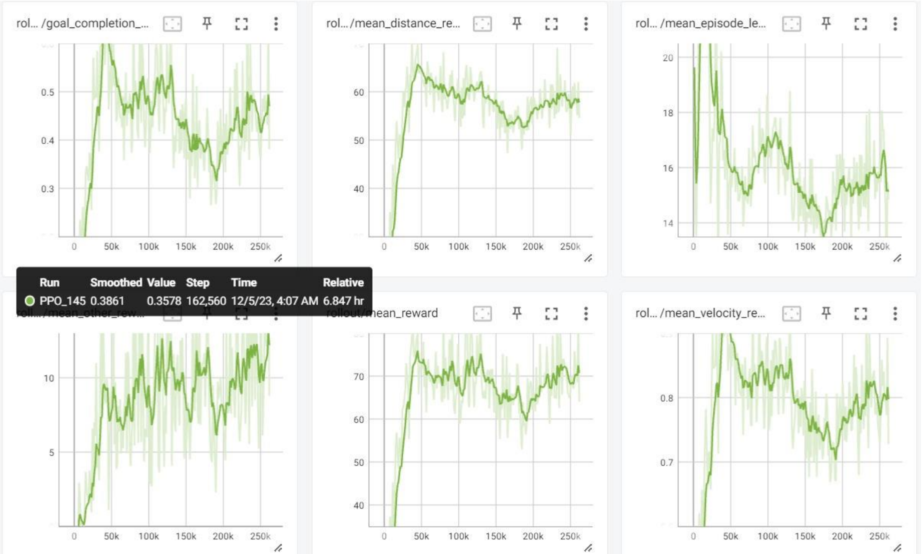
Left and right wheel acceleration

RL TRAINING MONITORING

LOGGING TO TENSORBOARD

Standard and custom measurements

- Mean reward per episode
- Percentage of passed goals
- Percentage of successfully completed parcours
- Loss
- …



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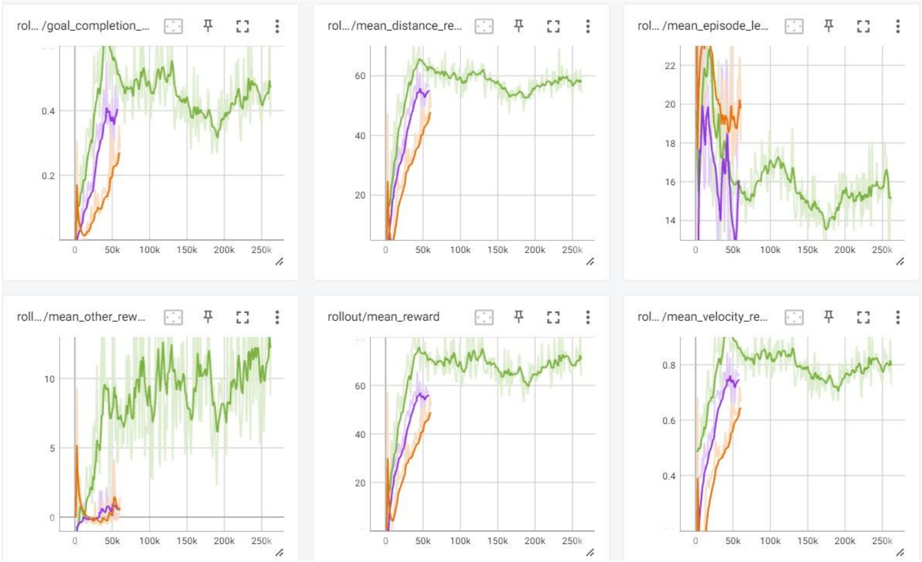
EXPERIMENTATION

EXPERIMENTATION

CHOICE OF PARAMETERS AND PREPROCESSING STEPS

- Network size
- Preprocessing steps
  - Brightness change
  - Contrast change
  - Histogram equalization
- Reward function weights
- Amount of frame stacking (memory)



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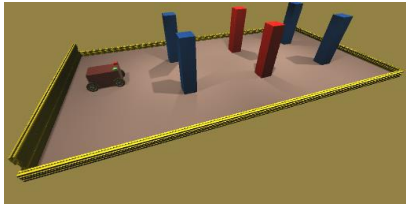
EVALUATION

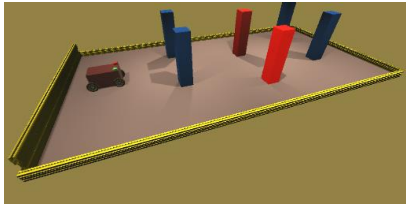
AGENT EVALUATION - Q1

AGENT IS EVALUATED ON THE THREE EVALUATION TRACKS WITH STANDARD LIGHTING

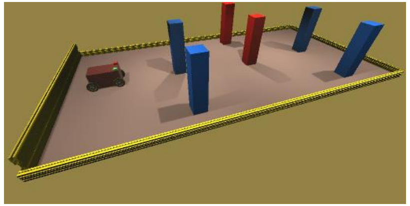
– Rate of successfully completed attempts



Easy



Medium

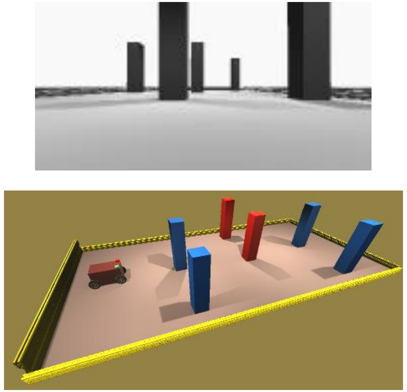


Difficult

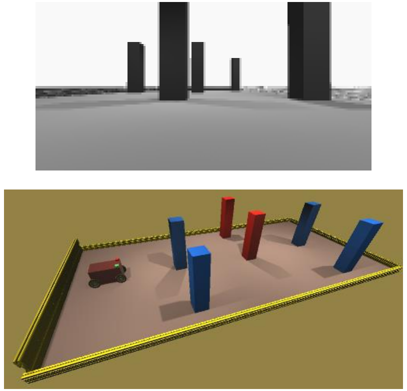
AGENT EVALUATION – Q2

AGENT IS EVALUATED ON THE THREE EVALUATION TRACKS WITH VARYING LIGHTING

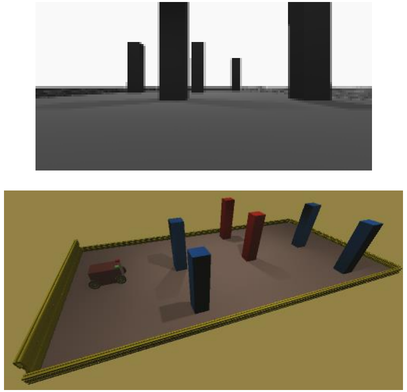
- Rate of successfully completed attempts



Bright



Standard



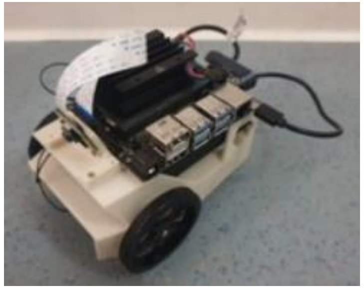
Dark

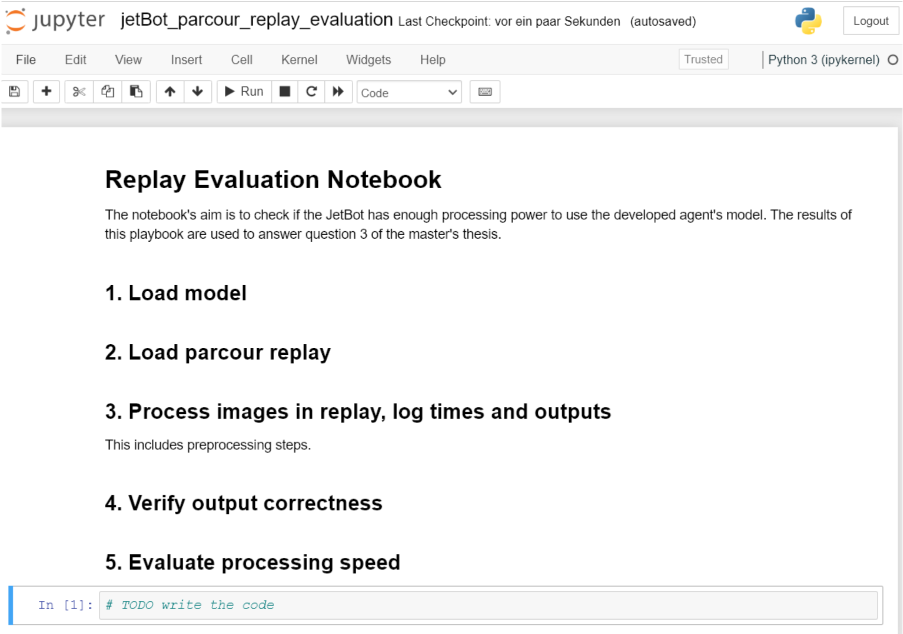
JETBOT PROCESSING POWER EVALUATION – Q3

GENERATE REPLAY OF PARCOUR IN PYTHON AND EVALUATE REPLAY ON JETBOT

Replay consists of

- Input-output pairs
- Processing times
- Neural Network model





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CONCLUSION

CONCLUSION

The thesis investigates training an agent that is resilient to light changes.

- Train an autonomous driving agent with Reinforcement Learning
- The agent uses a convolutional neural network as its policy
    - Input is a preprocessed image
- Agent is evaluated on tracks of 3 difficulty levels with different light settings

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THANK YOU!

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