Applying Deep Reinforcement Learning in the Navigation of Mobile Robots in Static and Dynamic Environments

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Technical Aspects of Multimodal Systems

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Outline

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Motivation

Related Work

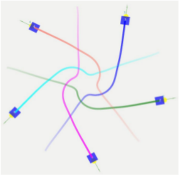

Figure 1: Multi robot scenario [1]

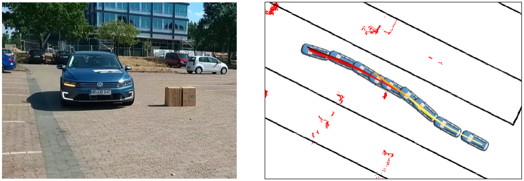

Figure 2: Self-driving car [2]

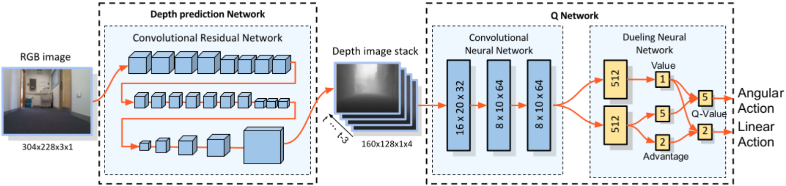

Figure 3: Dueling-Double DQN applied to very noisy depth images. [3]

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MiR100 robot

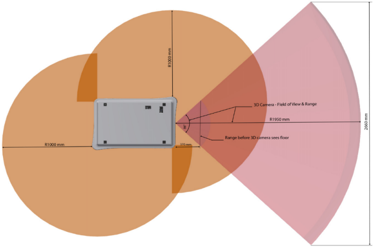

Figure 4: MiR100 robot of the company Mobile Industrial Robots ApS [1].

navigation: global planner + local planner

[1] accessed 2019-01-27: http://www.mobile-industrial-robots.com/de/products/mir100/

Reinforcement Learning (RL)

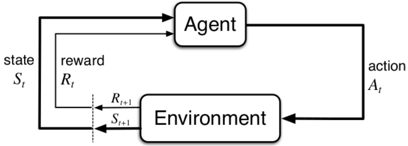

Figure 5: Reinforcement Learning Loop.[5]

$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+2} + \ldots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \qquad (1)$$

- Policy: Agent samples action from probability distribution $\pi(a|s)$.
- Value function $v_\pi(s)$: estimate of how good it is for the agent to be in state s.
- Action-value function $q_\pi(s, a)$: estimate of how good it is to take action a in state s.

RL – Q-Learning

Data: $\pi, \alpha \in (0,1]$
Initialize Q(s), for all $s \in \mathcal{S}$ arbitrarily;
for *each episode* **do**
    Initialize S_t **do**
        $A_t \leftarrow$ action given by π for S_t;
        Take action A_t, observe R_{t+1} and S_{t+1};
        $Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t)]$
        $S_t \leftarrow S_{t+1}$
    while *S is not terminal*;
end

$\rightarrow$ Deep RL (DRL): replace table Q(s,a) with function approximator

DRL – Proximal Policy Optimization (PPO) [7]

- Policy Gradient Method
  - optimization of the policy $\pi(a|s,\theta)$ directly
  - Actor-Critic Architecture
- builds on TRPO [6].
- learns relatively quickly/stable
- easy to tune

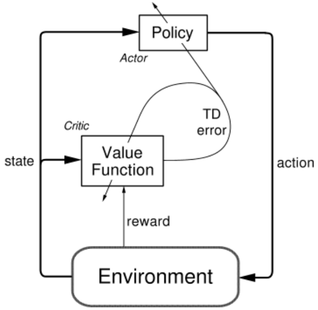

Figure 6: Actor-Critic Architecture.[5]

- **Clipped Surrogate Objective**
  - restricting the update size from one policy to another
  - stable updates
  - prevents optimization overshooting the maximum

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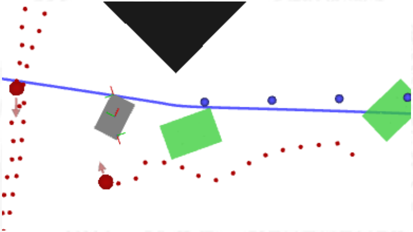
Simulation Environment

- Restricted to 2D-problem
- $\rightarrow$ 2D laser scanner as sensor source
  - + data approximates real world more realistically
  - + less computational expensive
  - – provides less features
- Flatland as base simulator [10]
- Pedsim for crowd simulation [9]
- three different obstacle types:
  - global static obstacle
  - local static obstacle
  - dynamic obstacle (pedestrian)



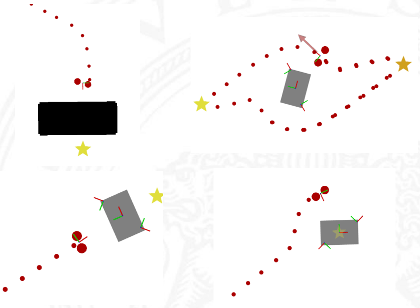
PedSim Crowd Simulator [9]

- Helbing's Social Force Model [8]
  - **Desired Force** f_{des}
  - **Pedestrian Force** f_{ij}
  - **Wall Force** f_{iW}
  - **Robot Force** f_r

$$\boxed{F_{sum} = f_{des} + \sum_j f_{ij} + \sum_W f_{iW} \; (+f_r)} \qquad (2)$$

- Semi-polite pedestrian

- Pedestrian-plugin:
  synchronises the pedestrian state of the PedSim simulator with the Flatland simulator



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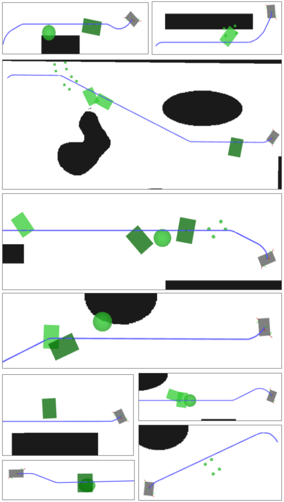
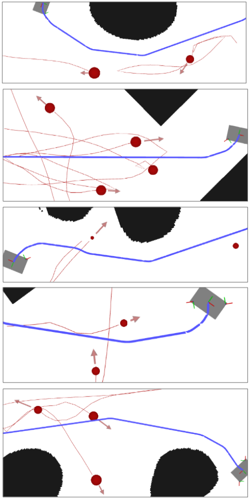
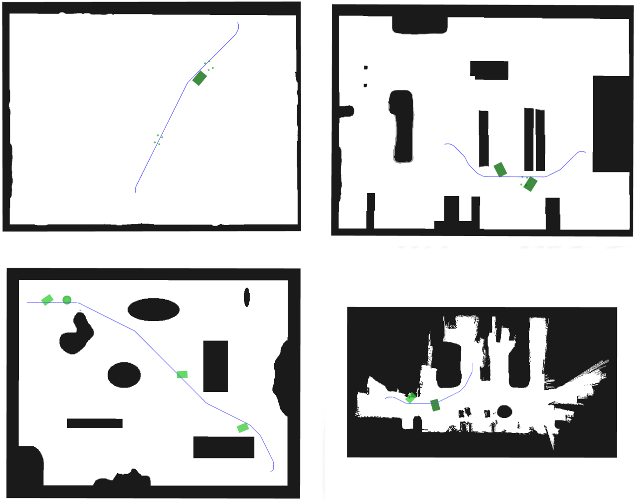
Task setup


(a) Static Setup


(b) Dynamic Setup

Global world setup



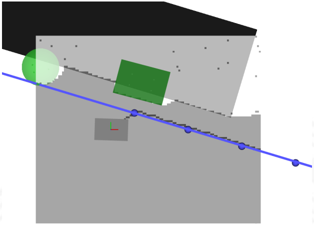
RL-agent setup

- RL-agent replaces traditional local planner
- Proximal Policy Optimization
  - PPO1/PPO2 implementation stable baselines library [11]
  - Tensorflow
- Wrapper class *Ros_env*
  - implements *gym.Env*-interface.
  - communicates with ROS side.

Observation and action space

Observation Space

- Raw Data Representation
- X-Image Representation
- X-Image Speed Representation



Action Space

- 6 discrete actions as combination of tranlational and rotational velocity.
  $[0, -\omega_{max}]$,
  $[v_{max}, 0]$,
  $[0, \omega_{max}]$,
  $[v_{max}, \omega_{max}/2]$,
  $[v_{max}, -\omega_{max}/2]$,
  $[0, 0]$,
  $([0.09, 0])$

Reward function 1

$$r_t = r_t(wp) + r_t(o) + r_t(g) \tag{3}$$

$$r_t(g) = \begin{cases} R_g & \text{if } d(p_{r,t}, p_g) < D_g \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

$$r_t(o) = \begin{cases} -R_o & \text{if collision with an obstacle } \in O \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

$$r_t(wp) = \begin{cases} 0 & \text{if } \min\limits_{o_i \in O}(d(p_{o_i,t}, p_{r,t})) < D_o \\ r'_t(wp) & \text{otherwise} \end{cases} \tag{6}$$

$$r'_t(wp) = r_{1t}(wp) + r_{2t}(wp) + r_{3t}(wp) \tag{7}$$

$$\text{diff}(p_{r,t}, p_{wp,t}) = d(p_{r,t-1}, p_{wp,t-1}) - d(p_{r,t}, p_{wp,t}) \tag{8}$$

$$r_{1t}(wp) = \begin{cases} w_1 \cdot \text{diff}(p_{r,t}, p_{wp,t}) & \text{if diff}(p_{r,t}, p_{wp,t}) > 0 \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

$$r_{2t}(wp) = \begin{cases} w_2 \cdot \text{diff}(p_{r,t}, p_{wp,t}) & \text{if diff}(p_{r,t}, p_{wp,t}) < 0 \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

$$r_{3t}(wp) = \begin{cases} R_{wp} & \text{if } d(p_{r,t}, p_{wp,t}) < D_{wp} \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

Reward function 2

$$r_{t,2} = r_t(wp) + r_{t,2}(o) + r_t(g) + r_t(vel) \tag{12}$$

$$r_{t,2}(o) = \min(r_t(so), r_t(ped)) \tag{13}$$

$$r_t(so) = \begin{cases} -R_{so} & \text{if collision with a static obstacle } \in SO \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

$$r_t(ped) = \begin{cases} 0 & \text{if } \min\limits_{ped_i \in PED}(d(p_{ped_i,t}, p_{r,t})) > D_{ped} \\ & \textbf{or } v \leq v_{reaction,max} \text{ for a duration of } t_{reaction} \\ -R_{ped} & \text{otherwise} \end{cases} \tag{15}$$

$$r_t(vel) = \begin{cases} -R_{vel1} & \text{if } v_t = 0 \text{ and } \omega_t = 0 \\ -R_{vel2} & \text{if } v_t = 0 \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

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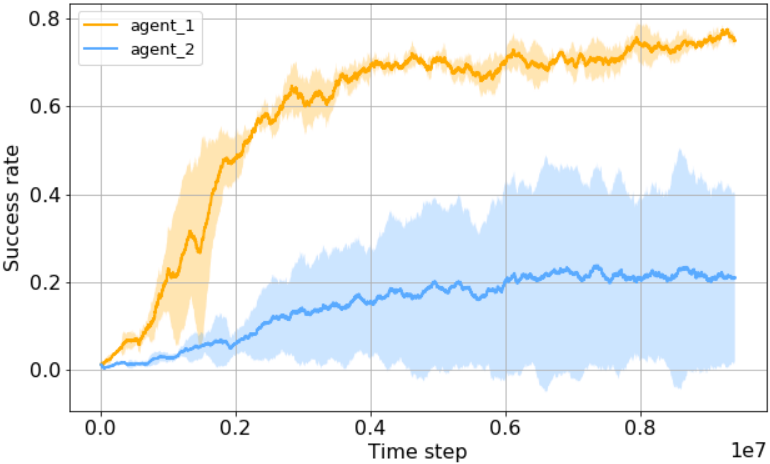
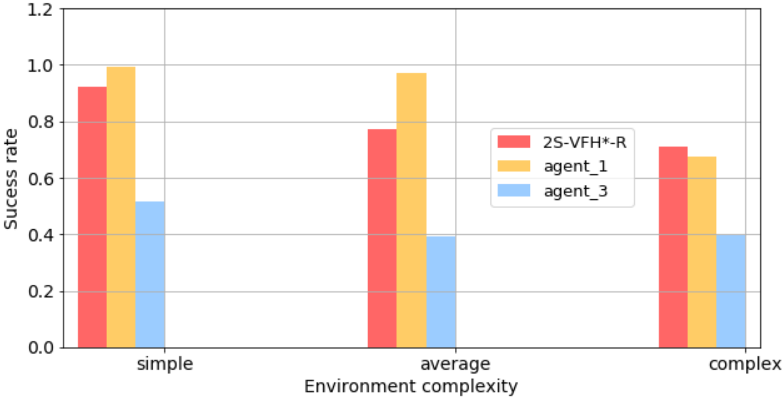
Static agents

	agent_1	**agent_3**
Action Space	discrete $v_{max} = 0.5$ $\omega_{max} = 0.5$	
State Input	1-Image Representation	Raw Data Representation
Network architecture	4-layered 2D-CNN	1D-CNN
Reward function	reward function 1	
Reward function parameters	table 1	

Static Agents – training results



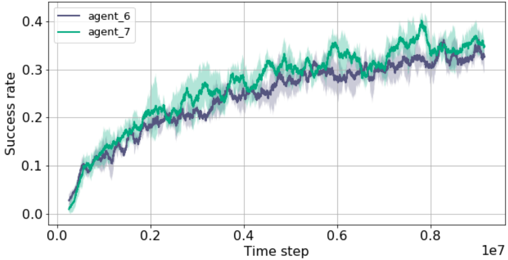
Static agents – test results

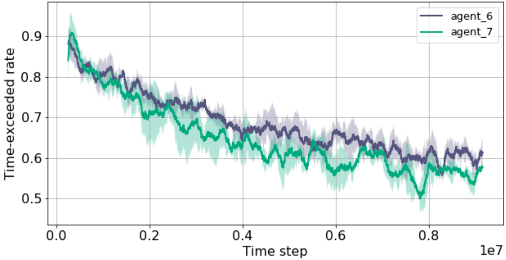


Dynamic agents

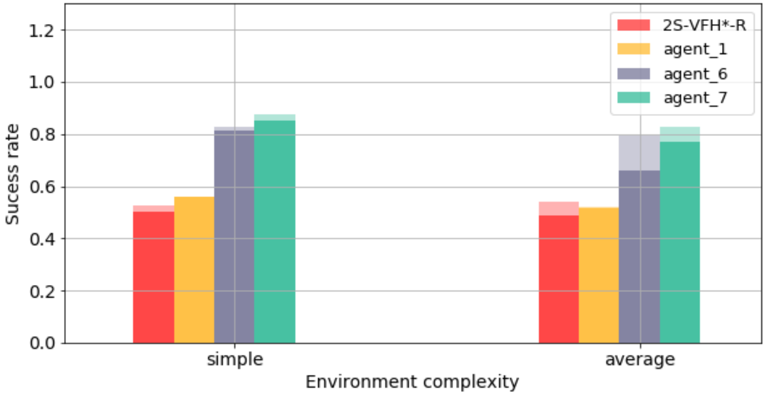
	agent_6	agent_7
Reward function	reward function 2	
Reward function parameters	table 2	table 3
Action Space	discrete $v_{max} = 0.5$ $\omega_{max} = 0.7$	discrete $v_{max} = 0.5$ $\omega_{max} = 0.7$ $+ [0.09, 0]$
State Input	4-Image Speed Representation	
Network architecture	6-layered 2D-CNN	

Dynamic agents – training results





Dynamic agents – test results



Video

https://www.youtube.com/watch?v=laGrLaMaeT4

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Conclusion

Implementation

- successful integration of the DRL-library stable-baselines [11] in the ROS navigation stack.
- fusion of the Flatland simulator with the PedSim crowd simulator.

Static Training

- Image Representation and discrete action space generates the best results.
- stable avoidance of static objects.

Dynamic Setup

- different reasonable policies were trained.
- high potential for improvements, but "proof-of-concept" is fulfilled.

Future Work

- Increase success rate and improve learned policy of agent_6 and agent_7.
- Train in a more complex and realistic dynamic (and static) setup.
  - Apply normal walking speed of the pedestrians.
  - Train in more complex maps with more clutter and narrow corridors.
  - Train with more complex pedestrian behaviors $\rightarrow$ learning social behavior.
- Fusion of the traditional local planner with the rl-local planner. The rl-local planner is triggered, when moving objects are detected.

Questions?

Appendix: reward parameter sets

Parameter	Value
R_g	10
R_o	15
D_o	0.96
w_1	2.5
w_2	3.5
R_{wp}	1.0
D_{wp}	0.2

Table 1: Parameter set for Reward Function 1.

Parameter	Value
D_{ped}	0.85
D_o	0.66
D_{wp}	0.2
R_g	10
R_{ped}	7
R_{so}	15
R_{vel1}	0.001
R_{vel2}	0.01
R_{wp}	0.3
$t_{reaction}$	0.8
$v_{reaction,max}$	0.0
w_1	4.5
w_2	5.5

Table 2: Parameter set 1 for Reward Function 2.

Parameter	Value
D_{ped}	0.85
D_o	0.66
D_{wp}	0.2
R_g	10
R_{ped}	7
R_{so}	15
R_{vel1}	0
R_{vel2}	0
R_{wp}	0.3
$t_{reaction}$	0.8
$v_{reaction,max}$	0.1
w_1	4.5
w_2	5.5

Table 3: Parameter set 2 for Reward Function 2.

Appendix: Neural Network architectures (1)

Layer	Type	Activation	Size	Filter Size	Filter Stride
1	Convolution	ReLu	32 Filter	$[5 \times 1]$	$[2 \times 0]$
2	Convolution	ReLu	32 Filter	$[3 \times 1]$	$[2 \times 0]$
3	Fully-Connected	ReLu	256 Neurons	-	-
4	Fully-Connected	ReLu	128 Neurons	-	-
5	Fully-Connected	Linear	Output Size	-	-

Table 4: 1D-Convolutional Neural Network

Layer	Type	Activation	Size	Filter Size	Filter Stride
1	Convolution	ReLu	32 Filter	$[8 \times 8]$	$[4 \times 4]$
2	Convolution	ReLu	64 Filter	$[4 \times 4]$	$[2 \times 2]$
3	Convolution	ReLu	64 Filter	$[3 \times 3]$	$[1 \times 1]$
4	Fully-Connected	ReLu	512 Neurons	-	-
5	Fully-Connected	Linear	Output Size	-	-

Table 5: 4-layered 2D-Convolutional Neural Network

Appendix: Neural Network architectures (2)

Layer	Type	Activation	Size	Filter Size	Filter Stride
1	Convolution	ReLu	64 Filter	$[8 \times 8]$	$[4 \times 4]$
2	Convolution	ReLu	64 Filter	$[4 \times 4]$	$[2 \times 2]$
3	Convolution	ReLu	32 Filter	$[3 \times 3]$	$[1 \times 1]$
4	Convolution	ReLu	32 Filter	$[2 \times 2]$	$[1 \times 1]$
5	Fully-Connected	ReLu	512 Neurons	-	-
6	Fully-Connected	ReLu	216 Neurons	-	-
7	Fully-Connected	Linear	Output Size	-	-

Table 6: 6-layered 2D-Convolutional Neural Network

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