COMP4DRONES

Framework of Key Enabling Technologies for Safe and Autonomous Drones

WP4-44-AIK - Embedded AI Obstacle Detection and Avoidance

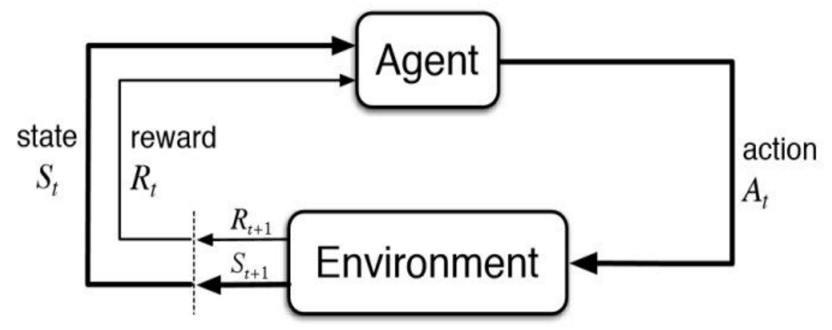
COMPONENT DESCRIPTION

This component provides an AI-based approach for **obstacle detection and avoidance** in unknown scenarios. It exploits an algorithm based on **Deep Neural Networks (DeepNNs)** that uses raw data from sensors (e.g., LIDAR, camera, GPS, IMU, etc…) to reach a goal position in a dynamic environment. Through sensor fusion the rover is able to react to the environment changes avoiding collisions. DeepNNs are trained in tailored synthetic scenarios, then tested in the same environment.

A particular learning approach called **Reinforcement learning** is used to train the network. This approach is tightly based on continuous interaction between the agent (the robot) and the environment.

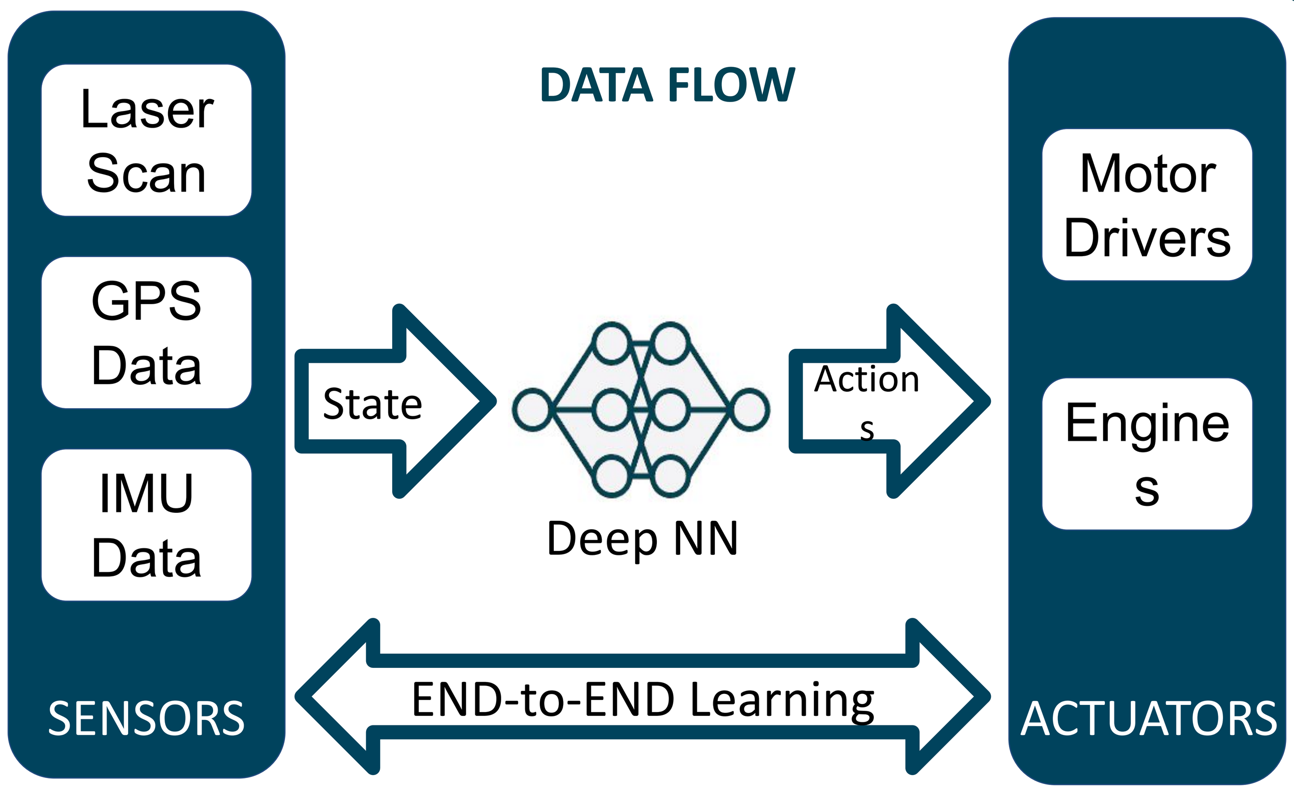
Within this work, the dynamics of the vehicle is ignored, while the kinematics is taken into account. This helps with the portability of the network between different scenarios. Furthermore, to evaluate the most suitable sensor set, a comparison between laser scan and depth image is carried out.

At each iteration of this loop the agent stores one sample of experience in memory. A bunch of experience samples will be used for the training. Each sample is made up by the following elements:



- S(t), S(t+1) are the current and next vehicle state,
- A(t) is the action at time t;
- R(t+1) is the reward (score) given to the state S(t+1) as a consequence of the action A(t)

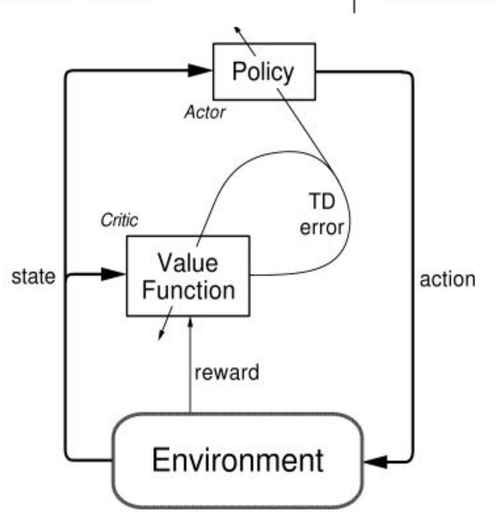
The DeepNN covers all the aspects involved in autonomous driving, from perception to actuator control, going through sensor fusion. This kind of approach is called **End-to-End Learning**. Data from sensor are fed to the network as input (first end point) and then the network itself generates actions as output that are directly remapped in motor command (second end point). Same data flow holds for the depth image case study.



TRAINING AND TESTING IN SIMULATED SCENARIO

HOW TRAINING WORKS

Hyper-parameter	Value
learning rate actor	$5 \cdot 10^{-5}$
learning rate critic	10^{-3}
τ actor	10^{-3}
τ critic	10^{-2}
γ	0.99
Batch size	32
Buffer size	100000



TOOLS

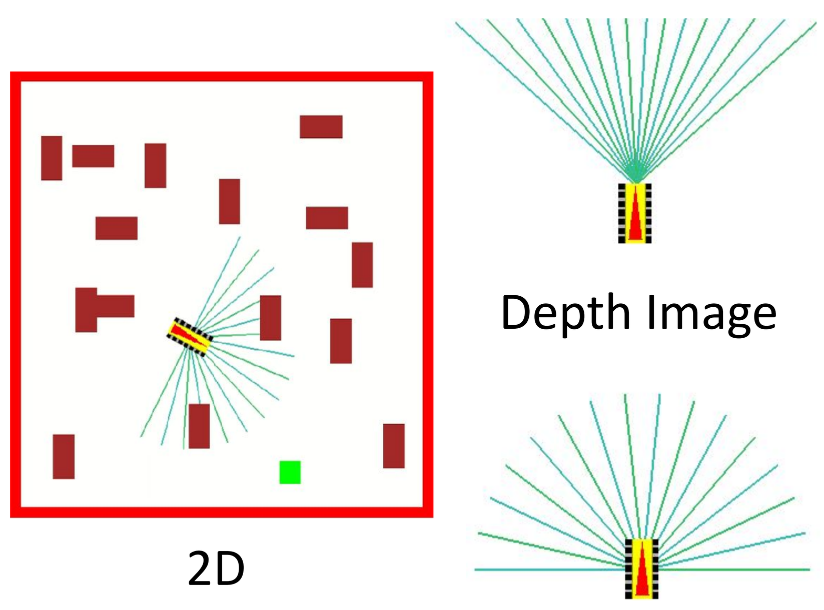
TensorFlow

ROS

GAZEBO

2D ENVIRONMENT

Vehicle start position and obstacles (red boxes) are randomly generated to avoid overfitting.



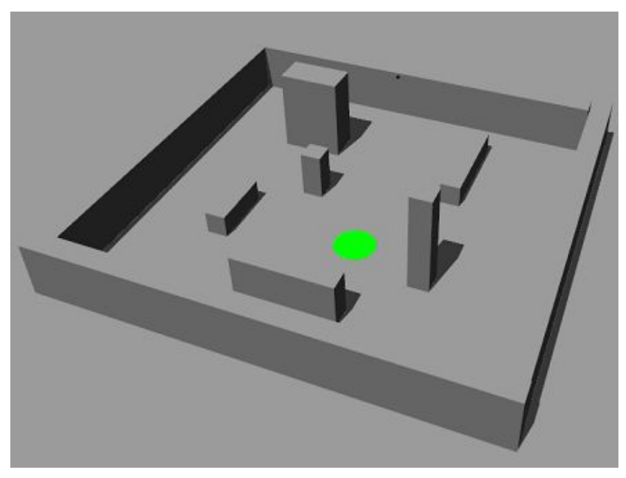
2D Environment

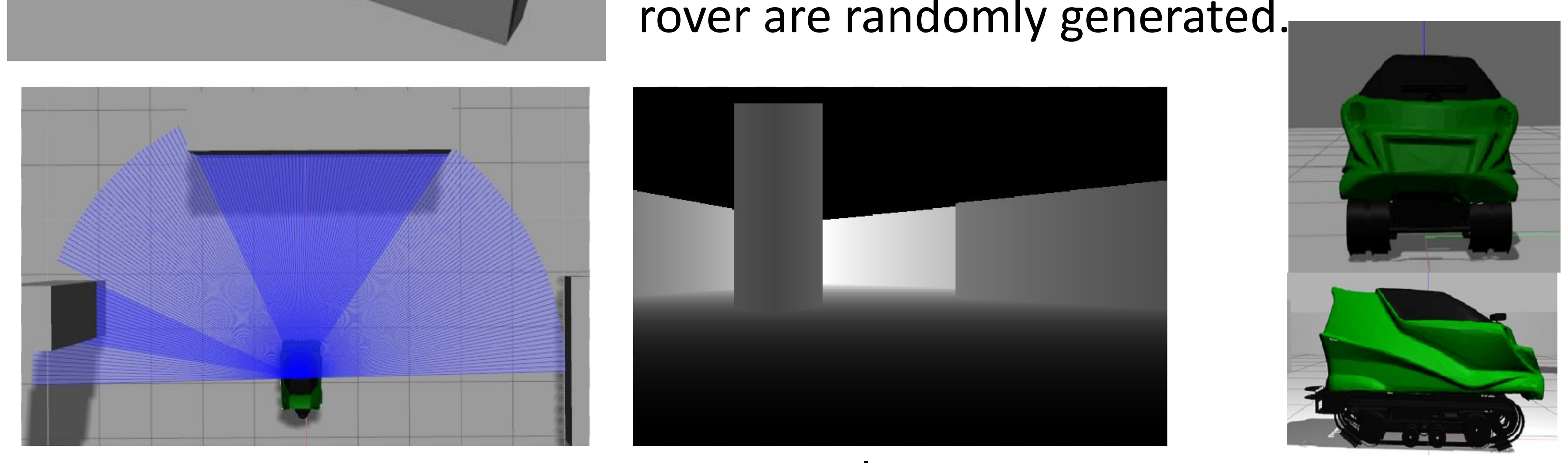
Depth Image

Laser scan

3D ENVIRONMENT

Once the Network has been trained in 2D environment, the training results are validated in a more complex scenario with kinematic constraints. In this scenario, as seen in the 2D case, the target position (green circle) and the starting position of the rover are randomly generated.



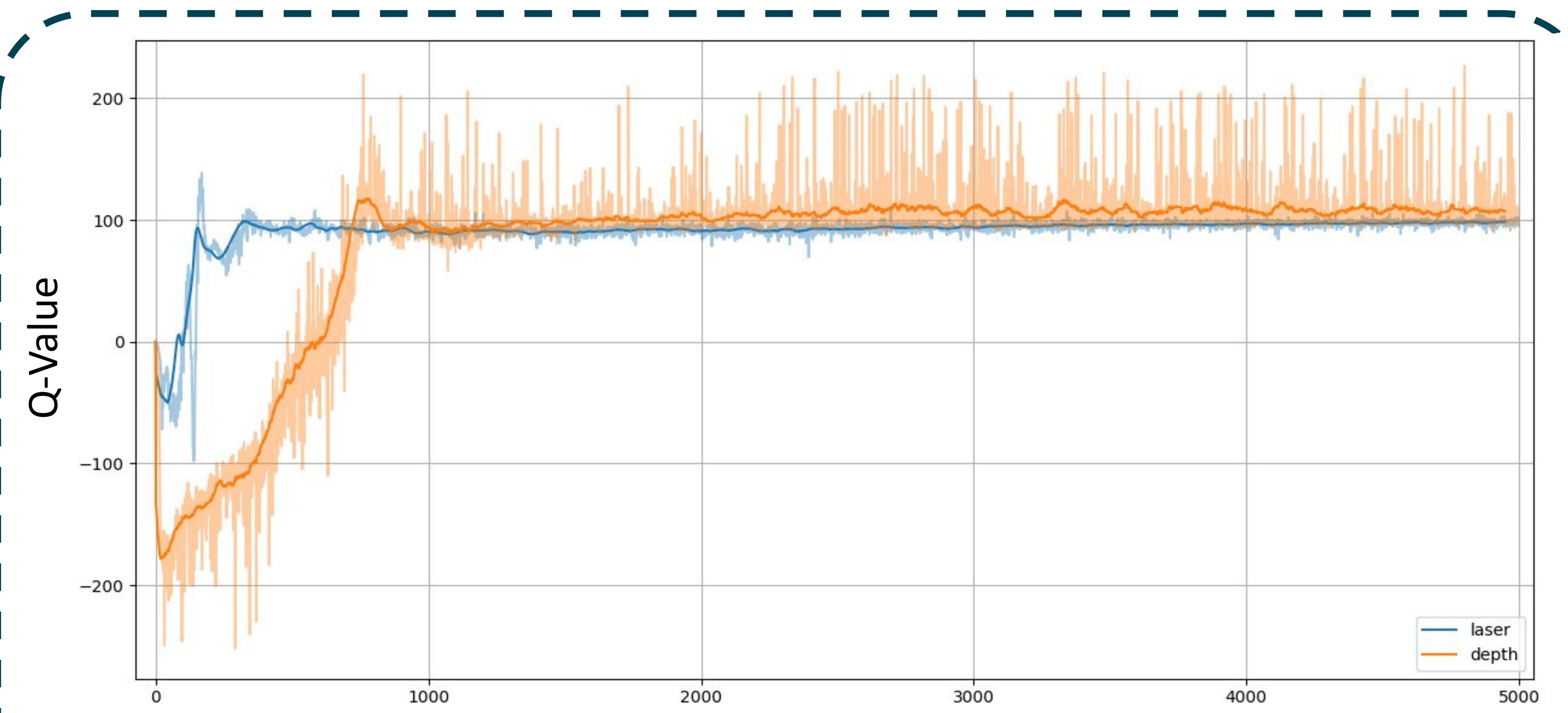


Laser scan

Depth Image

Rover

RESULTS AND FUTURE PLAN



The network trained in 2D environment achieved satisfactory results also in 3D environment. One of the main difference between the information provided by the two analyzed sensors is the Field of View (FoV). Laser has a wider FoV than the camera. Figure on the left reports the value of the collected reward (Q-value) during the training with both laser (blue line) and depth image (orange line). The FoV difference influences the training, indeed the Q value with depth image increases slower. Despite of these differences, in both cases the agent achieves good performance with comparable number of training steps.

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The proposed approach could be used in a agricultural use case to improve the ability of a rover to avoid unexpected obstacles while it is following the mission path.

This component has been developed within the UC5 to address precision farming issues. Furthermore, the ease of integration of Neural Network in embedded component has been pursued and it will be object of further development.

OUR PLAN

This component is going to be tested in real environment, using the same Network trained in synthetic scenario, exploiting accelerated HW board (Nvidia Jetson) and related framework (TensorRT) for lightweight network inference.

What we plan to implement to improve the overall performance is listed below.

- Include vehicle dynamics, this will enhance the behaviour of the vehicle, but could lead to a more specific training.
- Add a control layer that takes the output actions of the network as a reference to follow (reduce the End-to-End pipeline). This will make the output action more generic and suitable for different vehicles (with same kinematics).
- Fuse both depth image and laser scan to have a more detailed description of the surrounding environment.

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ECSEL Joint Undertaking

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