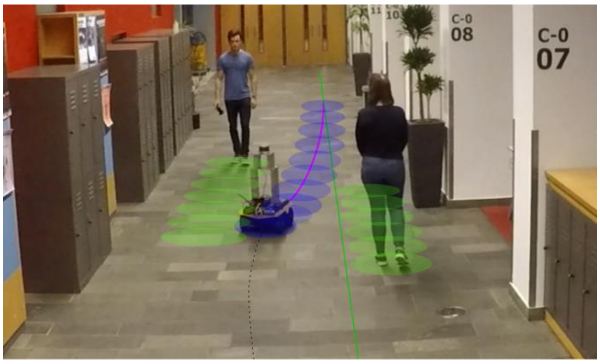
Predictive Safety Filter for Online Safe Learning

MSc. Project Proposal at the Autonomous Multi-Robots Lab, Cognitive Robotics, TU Delft

Brief description: Reinforcement Learning (RL) is a powerful paradigm for learning optimal policies from data in a wide variety of problems, ranging from autonomous driving to mobile manipulation tasks. However, to find optimal policies, most RL algorithms require to explore all possible actions which can be harmful in human environments. Recent works on safe RL propose to employ safety filters to overwrite the learning policy's action if necessary to ensure safety. Nevertheless, such approaches damage the performance of the learned policy. Hence, this proposal aims to enable the safe application of RL algorithms to learn a navigation policy among humans. To this end, the goals are twofold: Firstly, to research how safety is approached in RL, and how in particular predictive safety filter techniques [1,2] can be employed to ensure safe (i.e., collision-free motions) learning; Secondly, how can the safety constraints be incorporated into the RL framework without damaging the learned navigation policy [3].



You will test your approach in experiments with a mobile robot (Jackal) and on-board sensing and computing (RealSense D435i, NVIDIA Xavier) at the CoR Lab and the Cyberzoo at TUD.

Desired qualities:
- Motivated and independent
- Good knowledge of Maths or Control Theory
- Experience/interest in optimization algorithms, reinforcement learning and/or autonomous navigation
- Excellent programming Python skills and good knowledge about Tensorflow/Pytorch

For further questions or to apply, please contact L. Knödler <L.Knodler@tudelft.nl>, B. Brito <bruno.debrito@tudelft.nl> or Associate Prof. Dr. J. Alonso-Mora <j.alonsomora@tudelft.nl>. When applying, please provide a short motivation, up to date CV, a transcript of your current degree program and intended start date.

Group information: http://www.alonsomora.com/

References:

[1] Wabersich, Kim P., and Melanie N. Zeilinger. "Safe exploration of nonlinear dynamical systems: A predictive safety filter for reinforcement learning." arXiv preprint arXiv:1812.05506 (2018).

[2] Wabersich, Kim Peter, et al. "Probabilistic model predictive safety certification for learning-based control." IEEE Transactions on Automatic Control (2021).

[3] Berkenkamp, Felix, et al. "Safe model-based reinforcement learning with stability guarantees." Advances in Neural Information Processing Systems 30 2 (2018): 909-919.