

Instruction for WASP Poster Template

All WASP PhD students and researchers are welcome to use the WASP poster template when making posters about their research being conducted within WASP. It is not mandatory but an offered support. You are free to modify the elements, such as text boxes etc., according to your specific needs.

Fonts

In WASP's graphical profile, Myriad Pro and Minion Pro are recommended free fonts available in most operative systems. If not available please use another standard font. Comic sans is forbidden.

Example

On the next page you'll find an example of how the template has been used.

Robust Learning for Autonomous Robots

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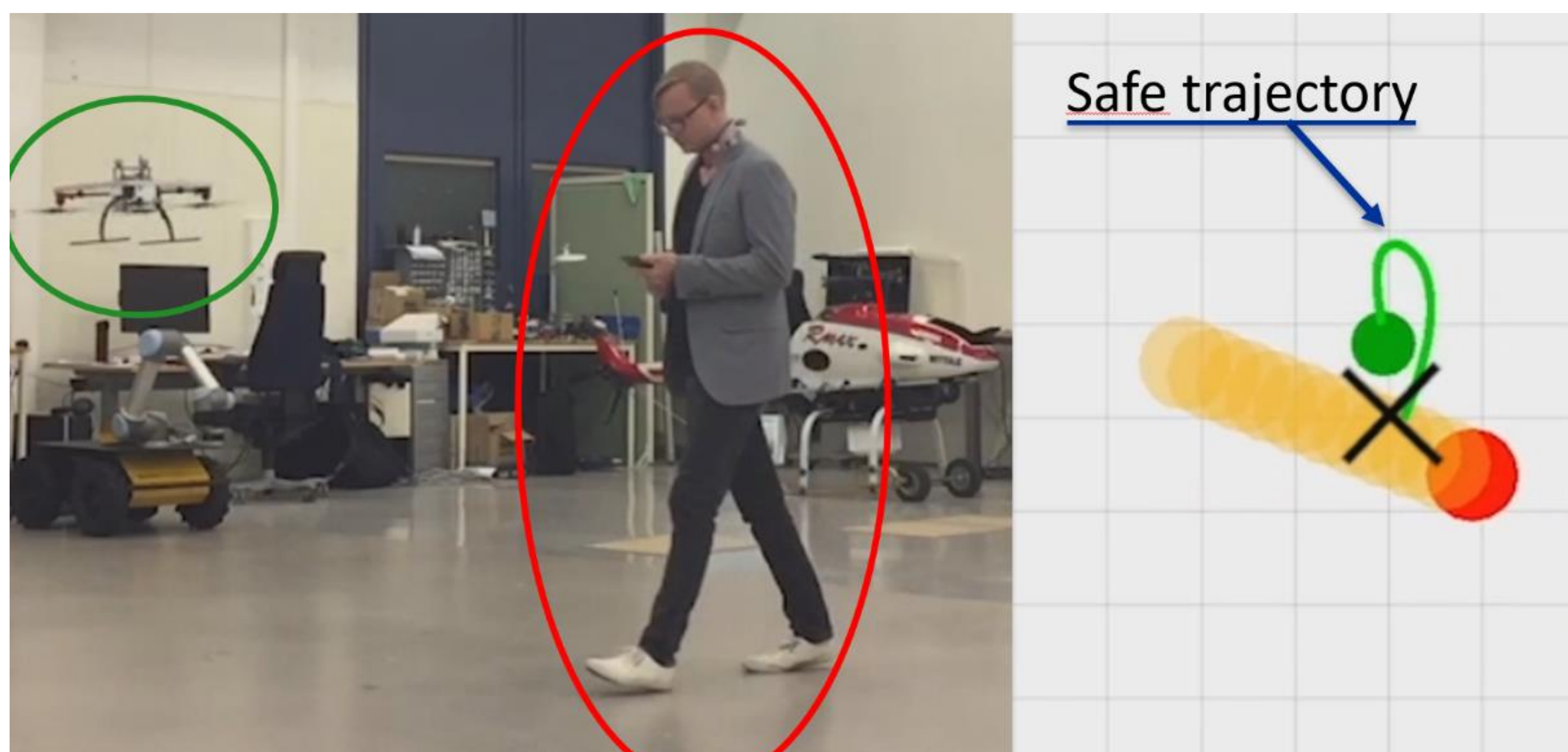
Artificial Intelligence and Integrated Computer Systems

Main advisor: Patrick Doherty



Motivation & Research Goals

Robots are increasingly expected to go beyond controlled environments in laboratories and factories, to enter real-world public spaces and homes. However, robot behavior is still usually engineered for narrowly defined scenarios. To manually encode robot behavior that works within complex real world environments, such as busy streets or work places, can be a daunting task. The aim of this research is to examine efficient methods for automatically **learning robot behavior under uncertainty**, lowering the costs of deploying robots to the real world. A key focus is satisfying the **safety requirements** and the **resource constraints** imposed by autonomous robots.



Methods

Formally, we seek general-purpose approximations to **planning and control** under **uncertainty**

$$\begin{aligned} & \arg \min_{\pi(x)} \mathbb{E} [c(\tau_{t:t+H})] \\ & \text{subject to} \\ & \Pr(g(\tau_{t:t+H}) \geq 0) > p \end{aligned}$$

...with the **computational limitations** and **safety constraints** of real robot platforms

These are typically intractable. We instead leverage both **machine learning** techniques, and engineering techniques from **robotics** and **control**, to compute **approximations that satisfy safety constraints**. These have certain **robustness advantages** over deep reinforcement learning approaches [5].

In particular we draw upon:

- Bayesian Learning & Bayesian Optimization
- Deep Learning & Deep Reinforcement Learning
- Trajectory optimization & Model-Predictive Control (MPC)

References

1. Andersson et al, *Model-Predictive Control with Stochastic Collision Avoidance using Bayesian Policy Optimization*, Int. Conf. on Robotics and Automation (**ICRA**), 2016.
2. Andersson et al, *Deep Learning Quadcopter Control via Risk-aware Active Learning*, **AAAI**, 2017.
3. Andersson, O. *Methods for Scalable and Safe Robot Learning*, Licentiate Thesis, Linköping University, 2017.
4. Andersson et al, *Receding-horizon lattice-based motion planning with dynamic obstacle avoidance*, **CDC**, 2018
5. Andersson et al, *DeepRL for Autonomous Robots – Limitations and Safety Challenges*, ICML'18 RML Workshop

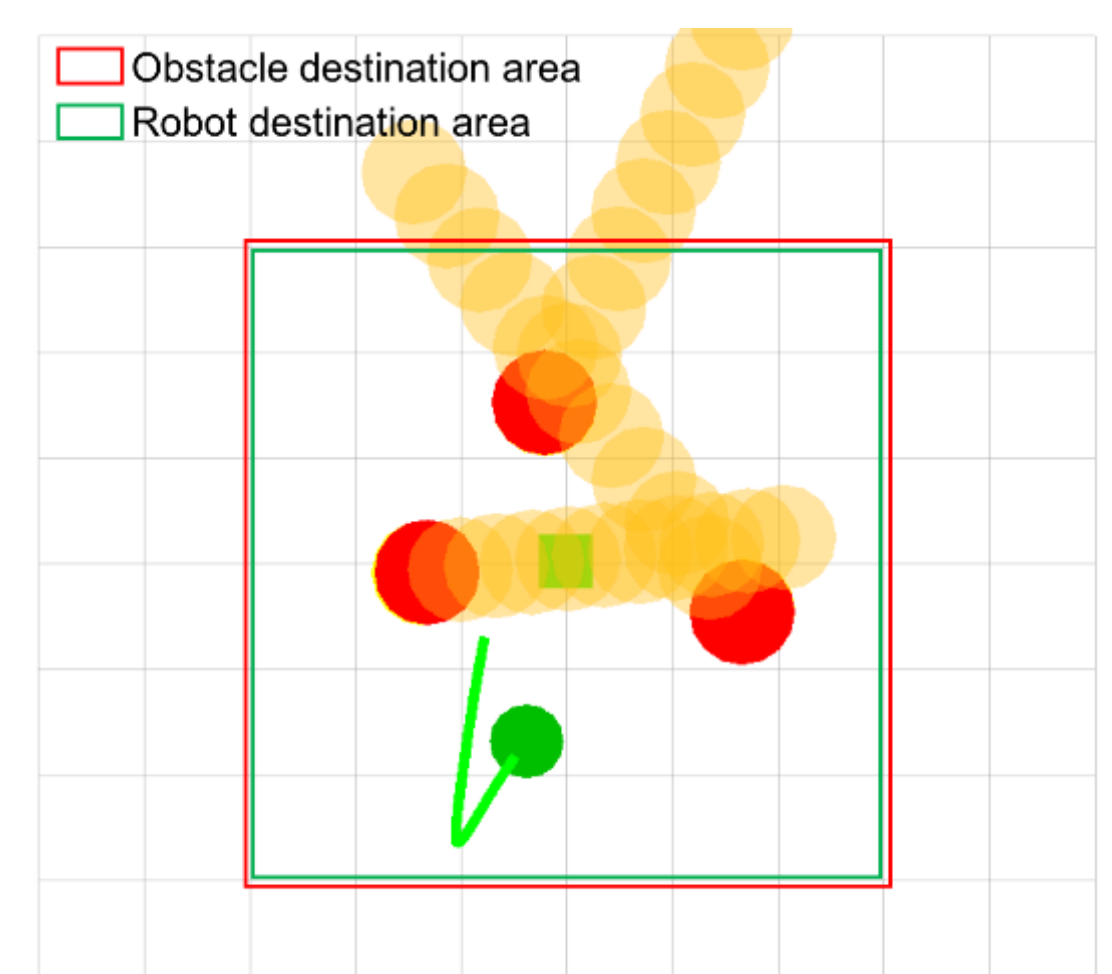
Selected Results

Collision avoidance in **mixed human-robot** environments is one example of a behavior that is difficult to manually engineer

- There is considerable **uncertainty** due to inexact models, sensors, and especially difficult-to-predict human motion
- Cluttered environments such as busy workplaces or streets require the **dynamics** of the robot and its environment to be taken into account

Example: Warehouse scenario

- Humans and UAV in small workspace
- UAV wants to pick up green packages
- 3 **non-cooperative** moving obstacles given destinations randomly

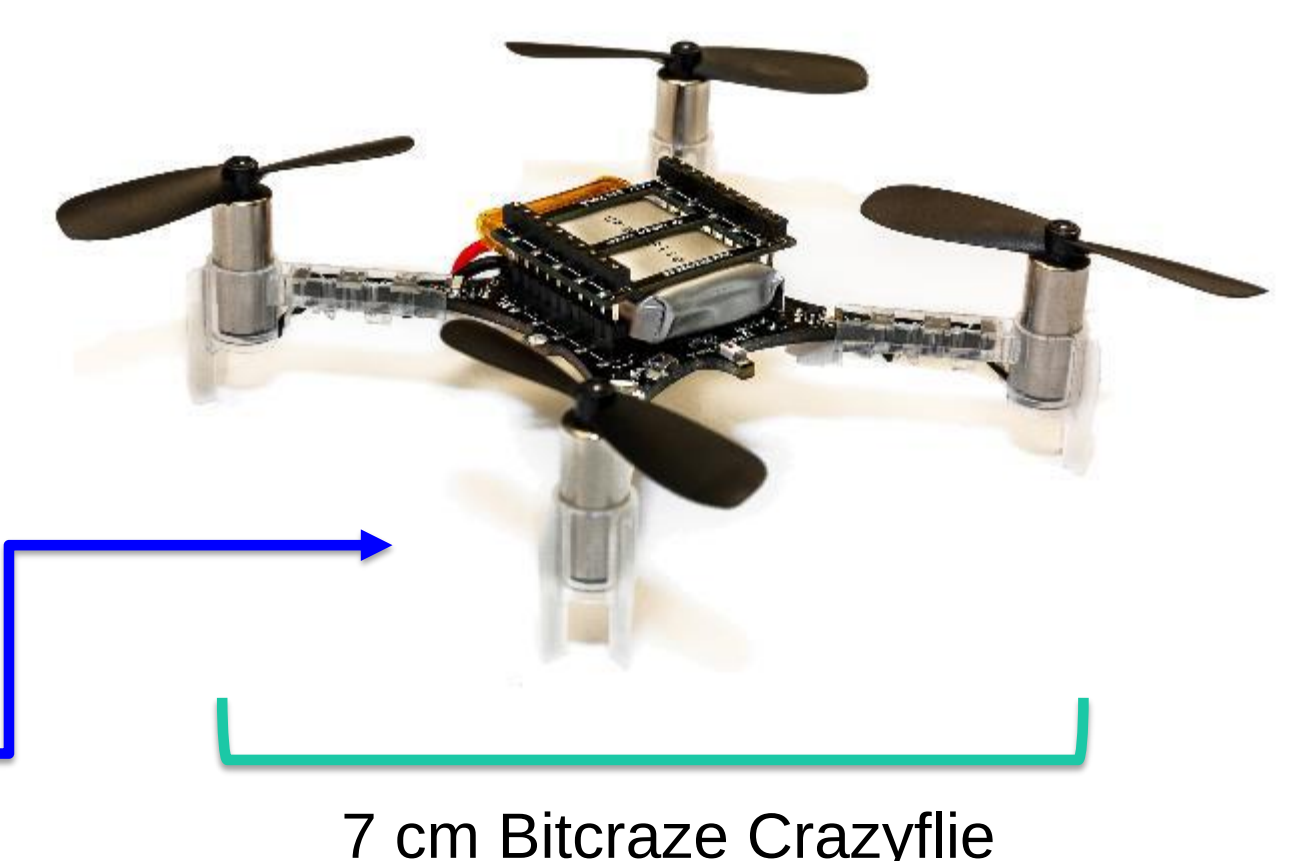


Contributions (see [1]):

- Novel **constrained Bayesian policy optimization** to find deterministic **MPC approximations** that satisfy the **safety constraints under uncertainty**
- Demonstrated **real-time MPC solution to non-cooperative collision avoidance** under **uncertainty** and **dynamics** for flights with a **real quadcopter**

MPC with safe collision avoidance possible in real-time, but still requires capable on-board CPU.

- Want to synthesize behavior for **smaller robots and embedded systems**.



Contributions (see [2]):

- Learn fast **deep neural network** approximations for problems with **safety constraints**
- Demonstrated by embedding neural network for collision avoidance scenario **on-board nano-quadcopter** microcontroller

In a recent collaboration with other WASP students we also considered lattice approximations for motion planning with moving obstacles. This is compatible with the techniques from [1].

Contributions (see [4]):

- Real-time 3D motion-planning in time for moving obstacles
- Unified optimization-based planning & control architecture

