# Project Proposals for Waterloo-KIT Collaborative Research

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July 29, 2020

1. **Cooperative State Estimation for Autonomous Mobile Robots**

   **Overview of Project**: Autonomous mobile robots implement simultaneous localization and mapping (SLAM) algorithms and Visual-Inertial Navigation (VIN) solutions to improve navigation and perform various tasks including service, delivery, or manipulation at a target place. Navigation and state estimation approaches are however prone to errors due to complexities in dynamic environment, reliability of visual navigation in presence of dynamic objects, loss of GPS signal, noises in inertial measurement units, and model uncertainties. In this direction, cooperative state estimation is a promising solution to improve reliability by leveraging connectivity between autonomous mobile robots and a base station or infrastructure. Such cooperative approaches have their own challenges due to delay and packet drop in the networked robotic systems, as well as the volume of data transfer. This project aims to develop cooperative (and computationally efficient) state estimation and navigation systems for autonomous mobile robots, in presence of model uncertainties, (such as slips in the dead reckoning approach and dynamic objects) and investigating how machine learning can improve reliability of the cooperative scheme.

   **Project Specifics and Objectives**: This research project aims to develop a reliable cooperative state estimation and navigation system for autonomous mobile robots through connectivity, in a distributed scheme, considering computational constraints as well as wheel slip components in local visual-inertial solutions. The algorithms will be evaluated by existing University of Waterloo RoboHub's *JACKAL* unmanned ground vehicle (UGV) robots equipped with GPS/IMU integrated with ROS (Robot Operating System). The robots will be connected through the long range *LoRa* wireless RF technology.

   You will first develop an observer model for visual-inertial navigation and state estimation by using existing visual odometry solutions, robot kinematic/dynamic model, and considering the actuators' bandwidth. (see [1, 2, 3, 4, 5, 6]). Then, you will design a model-based distributed estimator for navigation and augmented perception in a network of two-three *Jackal* mobile robots by using consensus Kalman filter [7, 8, 9]. In order to model uncertainty using a data-driven approach [10] and with the aim of not increasing the local observers' dimensions for large systems, you will study and test how distributed estimation algorithms will be enhanced with machine learning methods. Further challenges are:

   - Computational complexities and distributed linear programming might be a challenge for larger networked robotic systems
   - Due to communication constraints, you need to investigate what data and with which rate, while maintaining reasonable accuracy, should be transmitted between the robots

   More specifically, tasks to achieve the main objectives include: *i)* develop a state observer for visual-inertial navigation (and state estimation) in local agents/robots by using constrained optimization programs and augmenting the observer with the robot dynamic model; *ii)* design a distributed observer, such as distributed Kalman filter, in order to enhance navigation by shared perception, and investigate sufficient conditions for robust filter design using the dissipativity theory [11]; *iii)* devise a learning-aided distributed scheme to improve reliability in cooperative navigation; and *iv)* testing the developed algorithm/system on unmanned *Jackal* mobile robots at the University of Waterloo RoboHub.

**Pre-requisites**: Linear systems, constrained optimization, machine/deep learning, graph theory, and MATLAB/SIMULINK®
**Desirable**: System identification, observer design, distributed estimation

**Learning Outcomes**:

- Developing visual-inertial navigation solutions by data fusion and constrained optimization
- Understanding design for continuous-time and discrete-time dynamics
- Designing distributed observer to enhance navigation in a cooperative scheme through connectivity
- Implementing machine learning tools for system identification and withing the structure of distributed observers for shared perception
- Working with ROS and Vision/GPS/LiDar sensor on *Clearpath* mobile robotic platforms in real-time implementation

# References


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