3D Mapping with Aerially Deployed Micro-UAVs

Moulindra Muchumari, Dylan Herman

{mm2177, dah242}@scarletmail.rutgers.edu

Advisor: Prof. Dana, Prof. Diez

RUTGERS THE STATE UNIVERSITY OF NEW JERSEY

Abstract

- Technology for Unmanned Aerial Vehicles (UAV) have made them smaller, lighter and last longer due to better battery technology. But, we need larger and expensive vehicles for longer travel.
- Swarming technology allows for multiple smaller UAVs called Micro-UAVs (MAVs) with cheap equipment to disperse themselves among an area.
- When aerially deployed by a carrier aircraft at an area of interest, they can cover more ground with cheaper equipment for a short amount of time.
- We show a novel approach to SLAM problem using micro-UAVs.

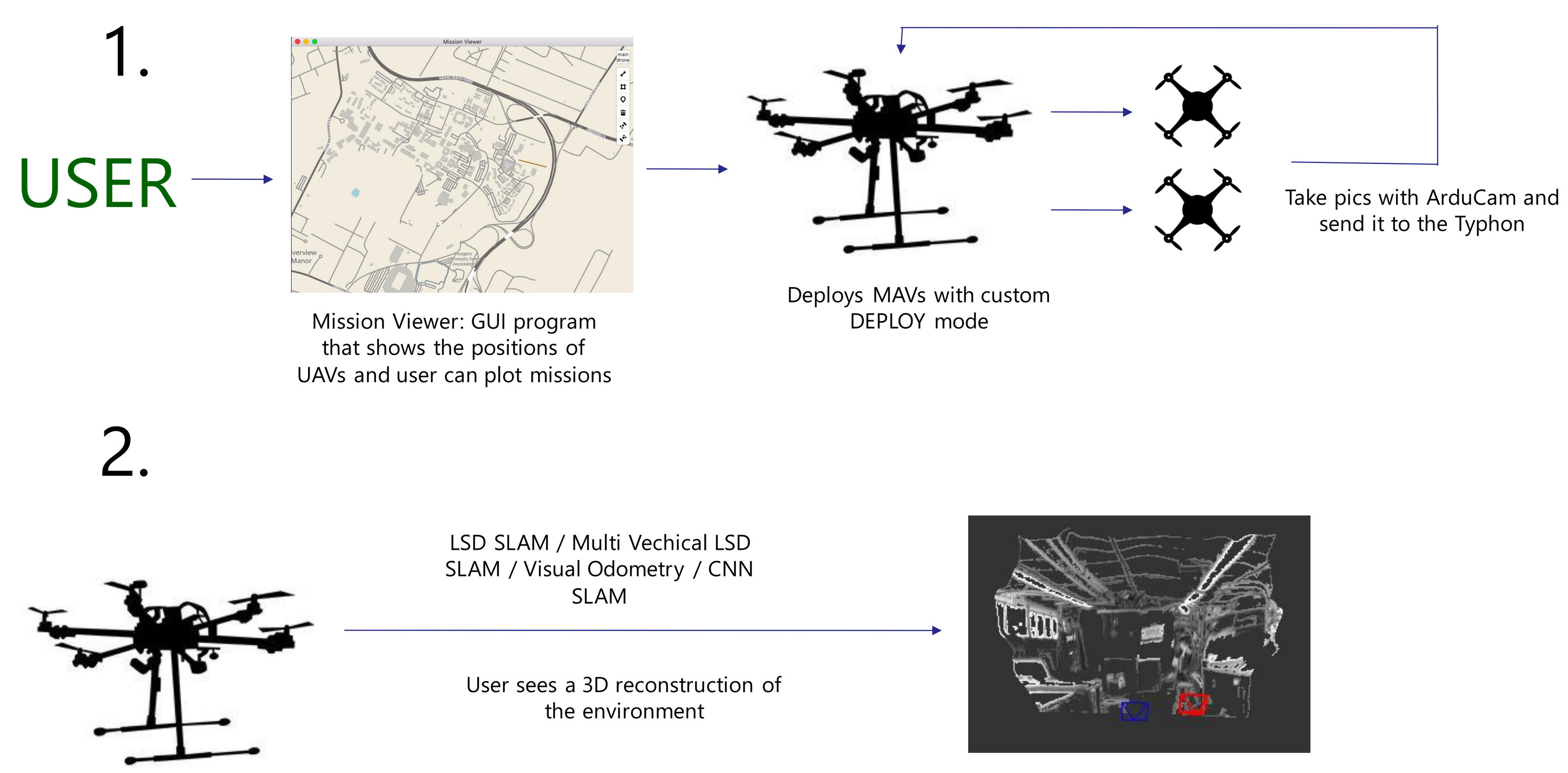
Background

- Our carrier drone, The Typhon, is a hexacopter, which deploys two MAVs. It also has Odriod for image processing
- The Typhon has a drop mechanism that deploys each MAV sequentially.
- MAVs have Raspberry Pi zero and an ArduCam. All drones use the Pixhawk flight controller using ArduPilot.
- Simultaneous Localization and Mapping (SLAM) is a problem where a robot must figure out where it is in an environment and know where all other objects are.
- There a range of solutions for SLAM. We focus on methods using visual odometry with pose-graph optimization for SLAM.

Acknowledgement

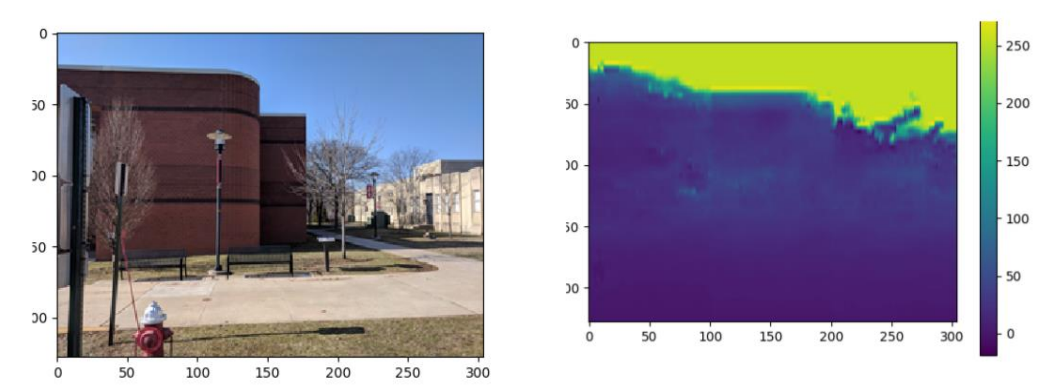
We would like to thank Professor Dana and Professor Diez in their guidance to make this project possible. We would like to thank Professor Godrich for consistent support throughout the project. Lastly, we would like to thank Alice Tchoudov, Adam Bennett, Brad Strzelewicz, Robert Panco, Ryan Mulroney, and Vaz Petrosyan.

Methodology



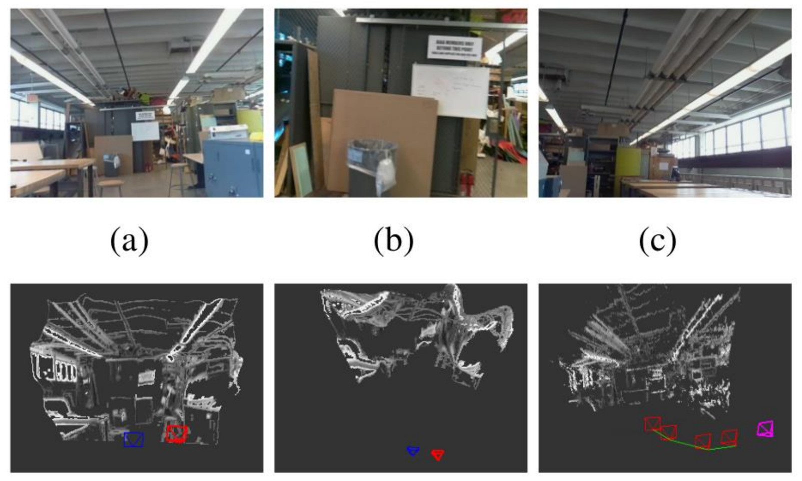
- **LSD SLAM**: Large-Scale Direct SLAM is a monocular SLAM algorithm that is split into two components, the tracker or front-end, and pose-graph optimization, the back-end. The tracker attempts to minimize the photometric residual between consecutive images.
- **Multi-vehicle LSD SLAM**: derivative of LSD SLAM that uses multiple pose graphs to display separate point clouds.
- **CNN SLAM**: A custom depth prediction network was trained on the Make3D data set and LSD SLAM is initialized with depth values.

Results



(a) Scene photo (b) Scene depth

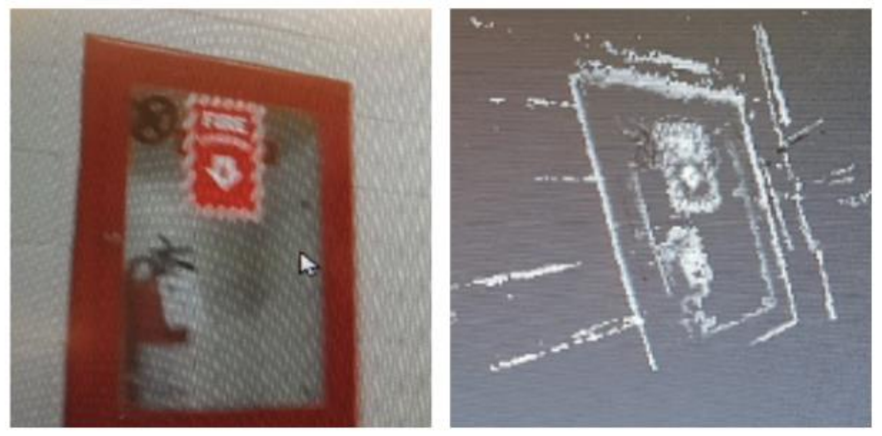
(b) shows the output of the depth prediction network for (a). The units of (b) are in meters and represent the distance from the camera each pixel is. Pixels that are lighter are further away. Distances greater than 70m are removed



(a) (b) (c)

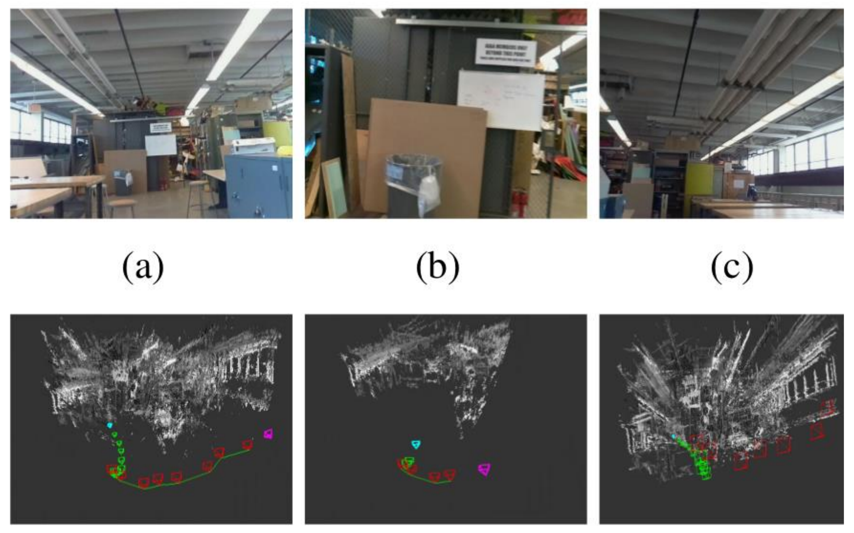
(d) (e) (f)

(d), and (e) show two different views of the 3D reconstruction of scene shown in (a), (b), and (c). The depth map for LSD-SLAM was initialized with a depth map from the Neural Network. (f) shows the reconstruction initialized with a random depth map.



(a) (b)

(b) shows the 3D reconstruction of (a) utilizing LSD-SLAM.



(a) (b) (c)

(d) (e) (f)

(d), (e), and (f) show three different views of the 3D reconstruction of scene shown in (a), (b), and (c). The blue camera frame represents one drone and the pink camera frame represent another. The green frames represent the pose graph for the blue drone, and the red frames represent the pose graph for the pink drone.

References

[1] Jakob Engel, Thomas Schöps, and Daniel Cremers. 2014. LSD-SLAM: Large-Scale Direct Monocular SLAM. Computer Vision – ECCV 2014 Lecture Notes in Computer Science (2014), 834–849. DOI:http://dx.doi.org/10.1007/978-3-319-10605-2_5

[2] Christian Kerl. 2012. Odometry from RGB-D Cameras for Autonomous Quadrocopters. thesis