Final Project: Localization in a Chilean Mine

Josephine King, Peter Johnson

I. Introduction

As the mining industry shifts towards automation, robotic mine navigation is increasingly important. The automation of the mining industry has the potential to improve safety and working conditions and increase efficiency and productivity. Mines, which are GPS-inaccessible, dimly-lit environments, present a challenge in mapping and localizing autonomous vehicles. This paper proposes an Unscented Kalman Filter (UKF), to localize an autonomous vehicle in a mine. The UKF is a common state estimation technique [2].

The formulated UKF will be simulated using the public Chilean Underground Mine robotic dataset, which was collected using a robot that travelled 2 km in the Chuquicamata copper mine (Figure 1) [1]. The vehicle collected data using a stereo camera, 3D lidar, 2D radar, and encoders for the left and right wheels, all of which are included in the public dataset [1].

Fig. 1. Image of data-collection robot in the Chuquicamata copper mine [1].

II. Method

To localize the robot, the UKF will estimate the pose $\mathbf{x_t}$ of the robot in a global coordinate frame such that $\mathbf{x_t} = [x_t\ y_t\ \theta_t]^T$, where θ_t is the yaw angle. The UKF will use the encoder data to predict and the lidar data to correct. The correction will also utilize a map of the section of mine that was navigated. Instead of utilizing the full 3D lidar data, the filter will only use a 2D scan which can be compared to the expected scan given the predicted state and the map. See Figure 2 for a block diagram of the system.

III. Data

In the Chilean Underground Mine robotic dataset, a Clearpath Husky A200 sensor platform was used to navigate a section of the mine. The internal encoder readings from both the left and right wheels of the robot were recorded at 10 Hz [1]. A Riegl VZ-400 survey-grade 3D lidar was mounted near the center of the robot. This sensor has a quoted range limit of 350 m, with a range accuracy of 5 mm [1]. While traversing,

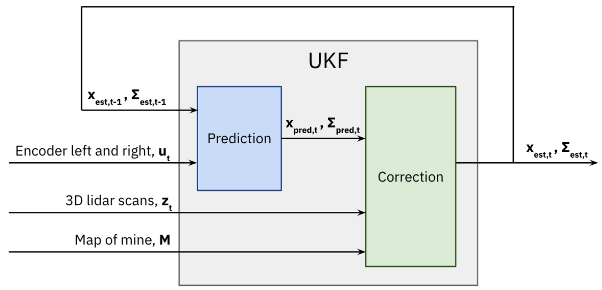

Fig. 2. UKF Block Diagram.

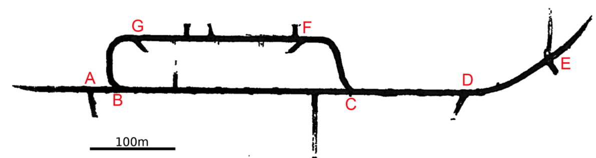

Fig. 3. Map of the robot's path in the mine. Consecutive letters indicate the endpoints of segments where continuous measurements were taken [1].

the sensor continuously rotated to produce scans at a frequency of one scan per six seconds, and at vertical and horizontal resolutions of 1 degree. Prior to dataset collection, the relative pose between each sensor reference frame was determined. The relative poses are available on the dataset website for use in developing motion and measurement models [1].

IV. Experiment

To evaluate the filter, the collected data will be replayed in simulation and the state estimates will be compared to ground truth. The dataset includes ground truth measurements for 44 different poses of the robot inside the mine. The ground truth poses were measured by placing reflective markers at tunnel junctions and performing high-resolution laser scans. These high-resolution scans were also used to construct a map, as shown in Figure 3. These ground truth data can be used to evaluate the Root Mean Squared Error (RMSE) of the UKF's pose estimate at each of the 44 time stamps where known poses are available.

$$RMSE_t = \sqrt{\frac{1}{t+1}\sum_{i=0}^{t} error_i^2} \tag{1}$$

References

[1] Keith Leung et al. *Chilean Underground Mine Dataset*. http://dataset.amtc.cl/.

[2] Sebastian Thrun, Wolfram Burgard, and Dieter Fox. *Probabalistic Robotics*. The MIT Press, 2006.