MMAE 539

Unscented FastSLAM

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1 Introduction

EKF FastSLAM allows autonomous vehicles to simultaneously localize and map an unknown environment in real-time. While EKF FastSLAM is applicable to nonlinear systems, its use of the Taylor Series for linearization can produce inaccurate maps and filter divergence. In addition, computationally-intensive derivations of Jacobian matrices are required for the EKF implementation. Kim et al. has addressed this issue by developing an Unscented FastSLAM framework (UFastSLAM) [1]. UFastSLAM improves upon the EKF-based FastSLAM 2.0 by computing the proposal distribution with measurement updates of the unscented filter in the sampling step of the particle filter and updating each feature state by the unscented filter without accumulating linear approximation error or calculating the Jacobian for an observation model. The goal of my project is to implement UFastSLAM in Python and analyze the results for the Sydney Victoria Park dataset [2].

2 Methods and Results

The Python implementation of UFastSLAM is shown in Figure 1, where boxes are a classes, arrows are inputs, and methods are written outside of the boxes. After initializing the objects, the methods are called in three parts: vehicle state estimation, feature state estimation, and importance weight calculation. For vehicle state estimation, a proposal distribution is constructed (prediction step) and the prior is sampled from (measurement update step). Feature state estimation is done by defining the sigma points of the features (feature update) and calculating the mean and covariance of new features (feature initialization). Importance weights for UFastSLAM are computed using the most recent

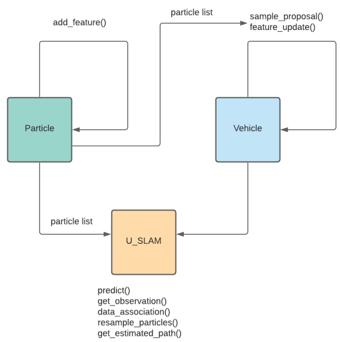

Figure 1: Implementation of UFastSLAM.

Figure 2: GPS readings from the Victoria Park dataset.

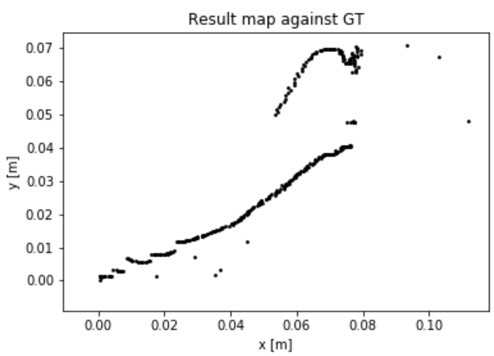

Figure 3: Vehicle position estimates with 1 particle.

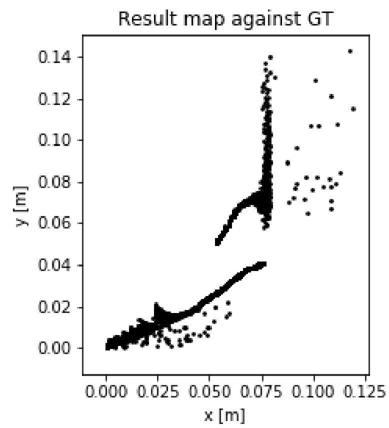

Figure 4: Vehicle position estimates with 10 particles.

observations and the particles are resampled.

Figures 3 and 4 show the vehicle position estimates produced by my implementation of UFastSLAM for part of the Victoria Park dataset. When comparing the outputs to the GPS data, in Figure 2, the position accuracy of using only one particle is comparable to the 10 particles case. This analysis supports the claim in Kim et al., that the UKF-based SLAM is robust to divergence due to a reduced linear approximation error [1]. My current implementation of UFastSLAM plots vehicle positions but has errors when plotting covariance ellipses or lines to landmarks. Future work would include finalizing the graphing functions and testing the implementation with other datasets and motion models.

[1] C. Kim, R. Sakthivel and W. K. Chung, "Unscented FastSLAM: A Robust and Efficient Solution to the SLAM Problem," Aug. 2008.
[2]http://www-personal.acfr.usyd.edu.au/nebot/victoria_park.htm