Information-driven Trajectory Planning for Target Tracking under Uncertainty

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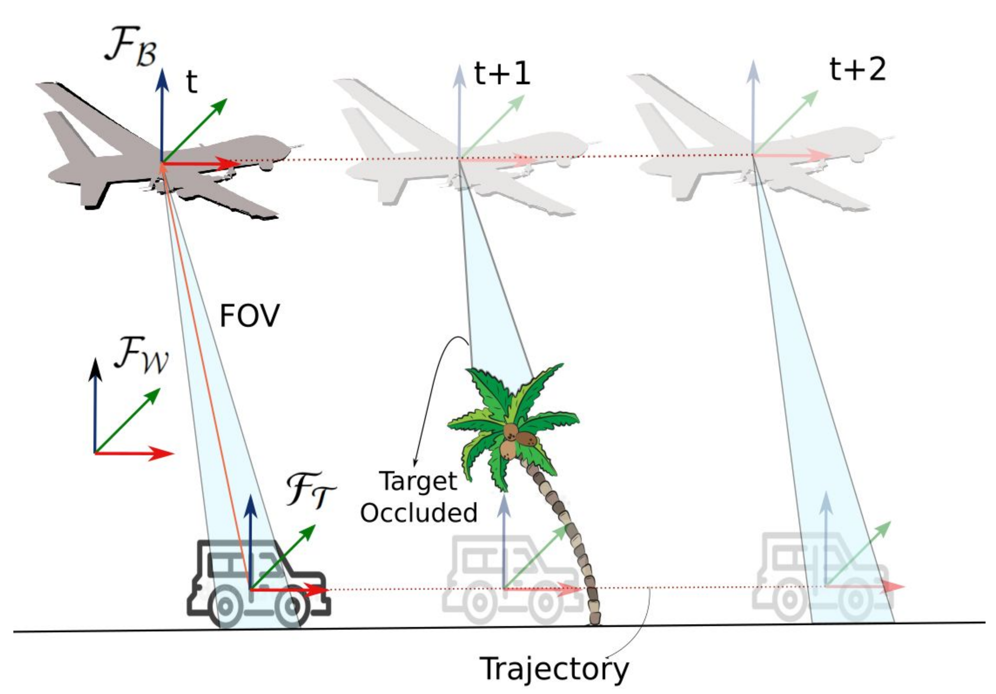
Introduction



Target Tracking example

- Sensor measurements can be intermittent due to occlusions.
- In these scenarios, target tracking becomes challenging due to growing uncertainty.
- Thus, an intelligent guidance law is required such that the target tracking uncertainty can be minimized

Proposed Approach

We propose a novel guidance approach for a mobile agent equipped with a camera sensor and tasked with target tracking under occlusions. The proposed framework first creates the motion model with a Deep Neural Network (DNN) that estimates target velocity as a function of target position.

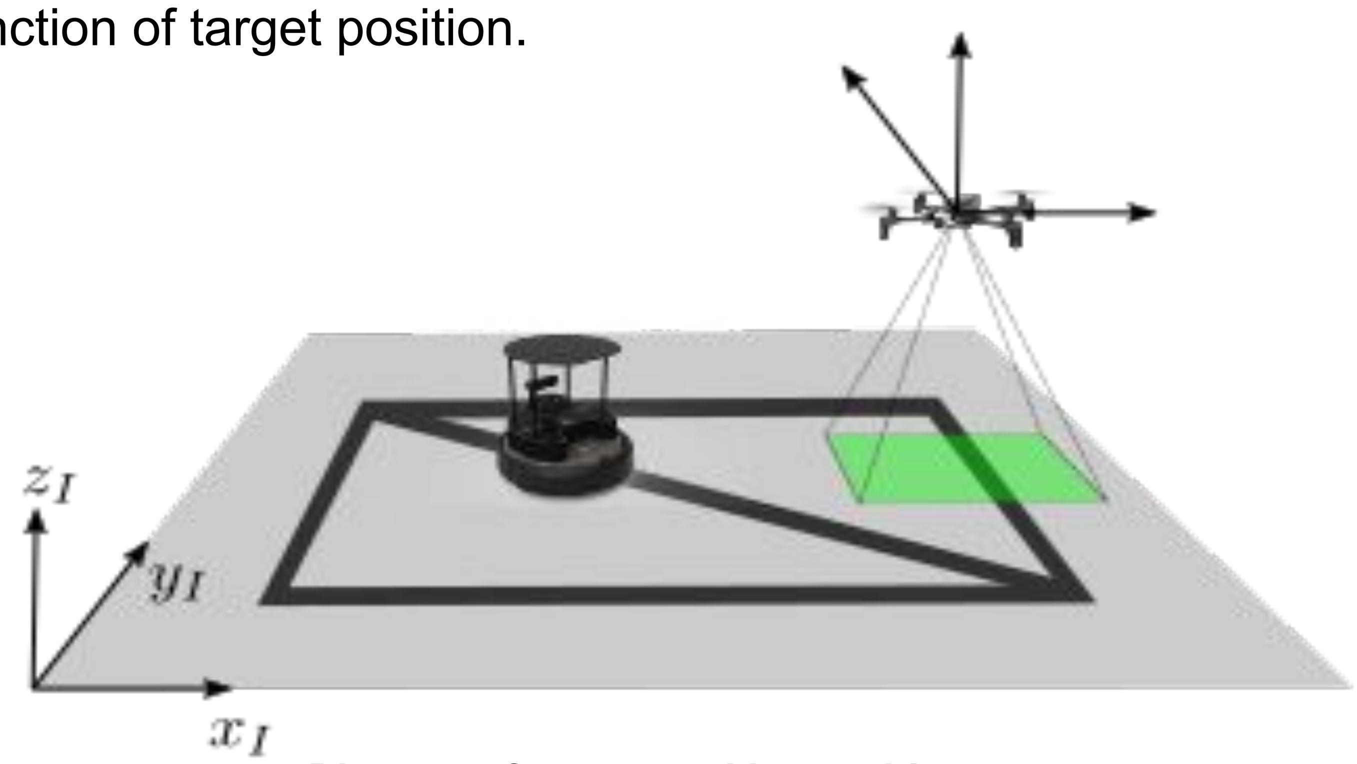
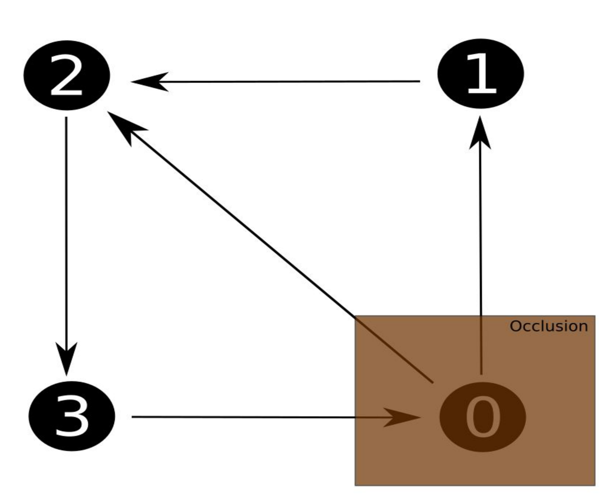


Diagram of target tracking problem

Target Path

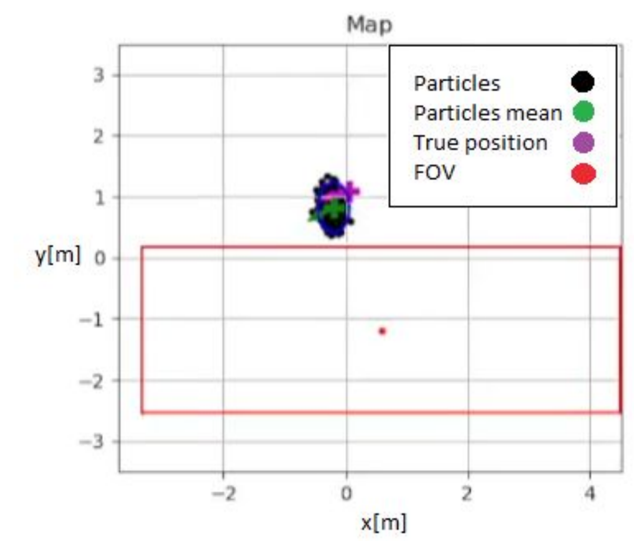
In this project, the trajectory of the mobile robot was designed to be a markov chain that mimics a road network. There are 4 way-points to track, and in which only state 0 has a stochastic transition of 50% probability of going to to state 1 and 50% probability of going to state 2. The road network is unknown to the quad-copter, and therefore it is learned from the pose history recovered while tracking.



Road Network

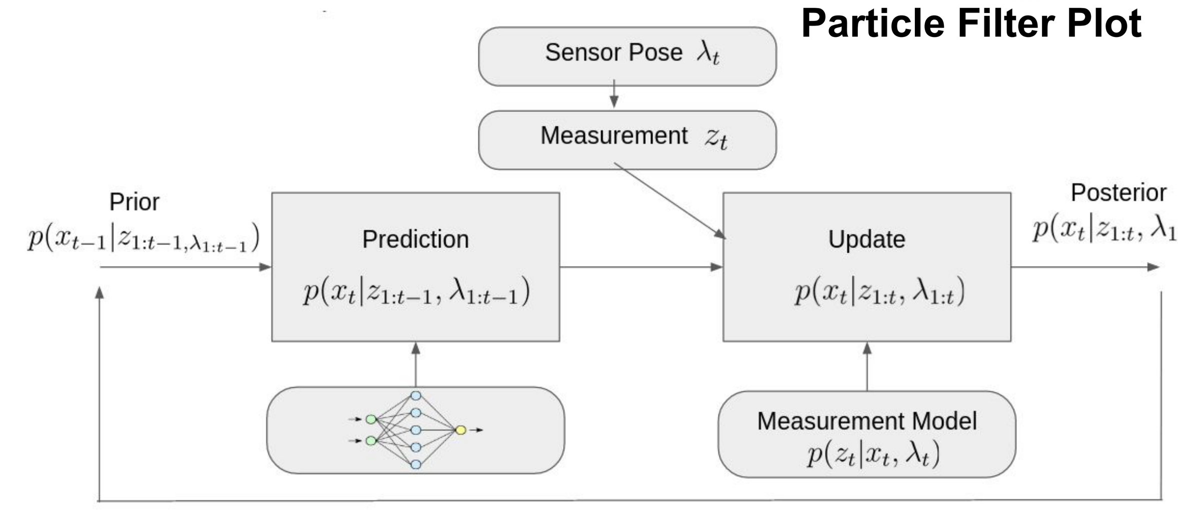
Target State Estimation

Particle Filter:
At each time step, a particle-based Bayes filter was used to approximate the target state as a distribution of weighted particles. The weights are updated based on gaussian distribution around the measured position by the camera



Particle Filter Plot

Motion Model Learning:
For the prediction step, we use a transformer based DNN to approximate the dynamics by feeding a history of target states and compute the future states.



Information Driven Guidance

This information-driven guidance law computes a sequence of waypoints that minimizes expected entropy based on the trained motion model. The entropy of the particle distribution was calculated according to [1]. Then, based on our motion model we propagate the particles in the future and compute the information gain

$$I(\hat{z}_{t+k}, \lambda_{t+k}) = H(p(x_t|z_{1:t}, \lambda_{1:t})) - H(p(\hat{x}_{t+k}|z_{1:t}, \hat{z}_{t+k}, \lambda_{1:t}, \lambda_{t+k}))$$

Then, the expected value over all the possible measurements give the Expected Entropy Reduction (EER).

$$EER(\lambda_{t+k}) = \mathbb{E}_{\hat{z}_{t+k}}[I(\hat{z}_{t+k}, \lambda_{t+k})]$$

The action chosen is the one that maximizes the EER

$$\lambda_t = argmax\, EER(\lambda_{t+k})$$

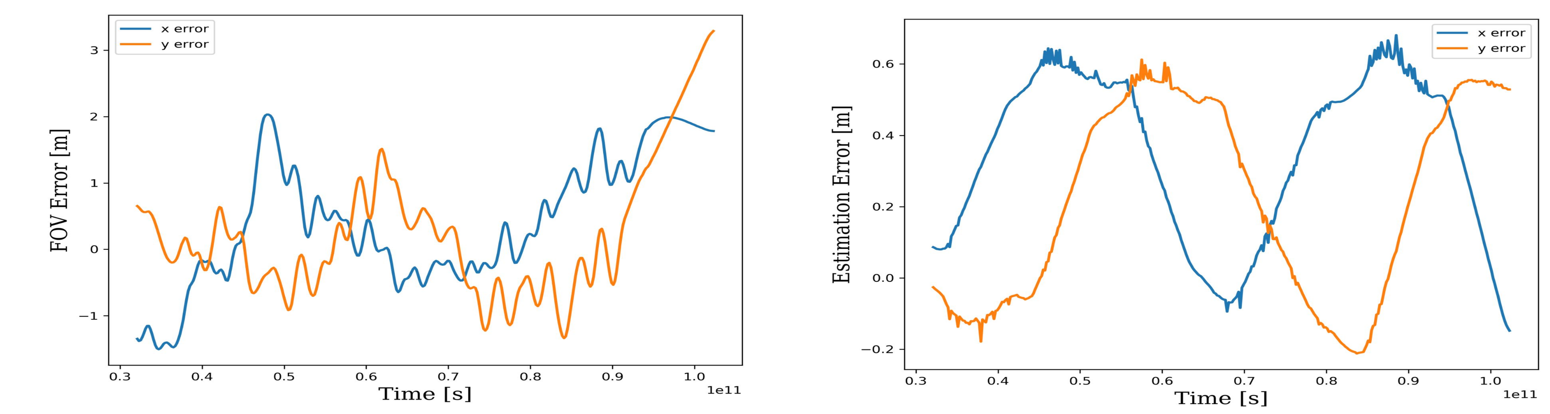
Preliminary Results

We compared RMS error of our guidance algorithm against two other guidance methods. The first one is going to the position of the weighted mean of the **particle** filter. The second is going to the position of the last target measurement, and if a measurement is not available perform a **lawnmower** path in the working area of the target

Method	Information	Particles	Lawnmower
X estimation error [m]	1.575	1.261	N/A
Y estimation error [m]	0.978	1.261	N/A
FOV X error [m]	1.177	1.871	1.329
FOV X error [m]	1.161	2.874	2.216

Preliminary Results Plots

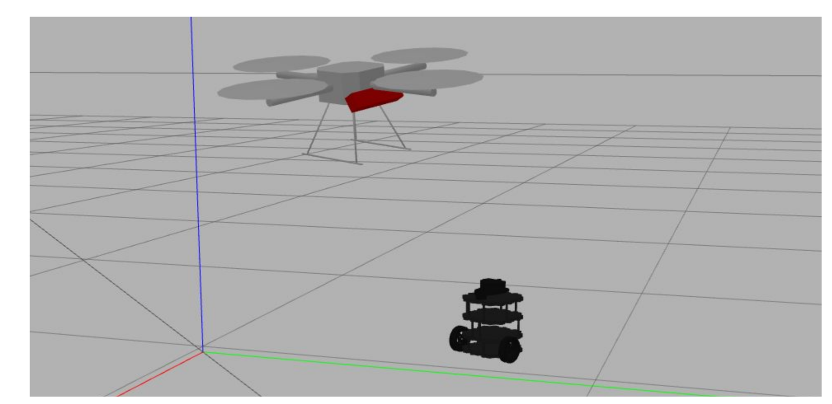
For all experiments the aim of the guidance algorithm is to reduce the tracking error when tracking the target (FOV Error, pictured below). The second plot below is the difference in position between he particle mean and the actual target.



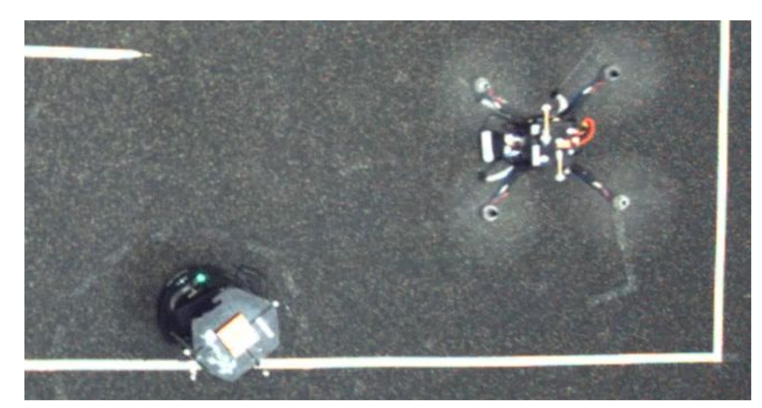
Errors in Information Guidance mode

Experiments

Simulation Experiments*:*
We used the Gazebo simulator to do the early development and the testing of the algorithm before deploying it on hardware.



Gazebo Simulation



Physical quadcopter and turtlebot in experiments

Hardware Experiments:
This work was validated on hardware platforms at the Autonomous Vehicles Lab (AVL) located at UF REEF. A 11mx5.5m flight space equipped a motion capture system with 12 cameras which helped to validate the true positions of the vehicles

Conclusion

This research presents a novel guidance law for target tracking applications where the target motion model is unknown and sensor measurements are intermittent. The target motion model is trained based on previous measurements and used in the prediction step of a particle filter. The information-driven guidance law estimates future target state based on the learned motion model and sensor measurement model and calculates the best next control input following the maximum expected entropy reduction of target state.

References

1) Y. Boers, H. Driessen, A. Bagchi, and P. Mandal, "Particle filter based entropy," in 2010 13th International Conference on Information Fusion, July 2010, pp. 1–8