UNIVERSITY OF COLORADO - BOULDER

ADVANCED STATE ESTIMATION

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Project Proposal

Flying Object Tracking and ID

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I. Application and Context

Identifying and predicting flying objects is a key part of many defense systems. This project will design a system to track and identify (ID) flying objects via radar measurements from a static base station. The system will be tested with custom-built modeling software to generate trajectories for different systems (multi-rotor, fixed wing, bird, person), estimate and ID the systems, and then compare the resultant trajectory errors.

The radar system is approximated to measure the range, azimuth, elevation, and range velocity. Each of these measurements will have an associated noise, often non-Gaussian. The estimator will also use a simple kinematics physics model due to the wide variety of behaviors between different flying objects. This non-Gaussian noise in the estimator already presents a problem for traditional Kalman Filters (KFs) and they may not be able to track accurately with this noise. Instead, a Bayesian Estimation method would be more accurate because it could take into account non-Gaussian noises.

The flying objects will also be controllable. This allows them to behave linearly (flying in a straight line) or non-linearly (fast and tight maneuvering). The non-linearity in the generated trajectories will also be difficult for a traditional KF. Some approximations and extensions exist to the KF that help with the non-linearity, but when pulling tight maneuvers, they are expected to have inaccuracies. The Bayesian Estimation techniques like particle filters should provide more accurate estimations during the non-linear portions of the trajectory.

Overall, this is an interesting problem that should show off the usefulness of the advanced state estimation techniques learned in class.

II. Initial Problem Formulation

A. Sensor Model

The radar system is approximated to measure the elevation θ, azimuth ϕ, range r, and range velocity $\dot{r}$ of the object's center of mass. This avoids the complexity of point clouds and centroiding that more accurate radar models would have. Further into the project, we may add additional characterization info such as surface area to assist in the ID process. Figure 1 shows a graphical representation of these parameters and Equation 1 shows the measurement model.

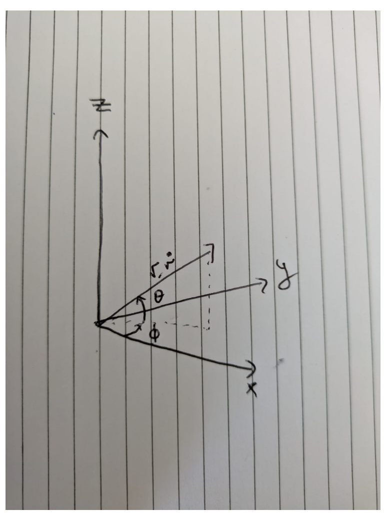

Fig. 1 Sensor measurement definitions

$$\mathbf{y} = \begin{pmatrix} \theta \\ \phi \\ r \\ \dot{r} \end{pmatrix} + \begin{pmatrix} U[a,b] \\ U[c,d] \\ R(\sigma_r) \\ \mathrm{T}(\nu, \sigma_{\dot{r}}) \end{pmatrix} \tag{1}$$

We will use uniform noise for the angle measurements, Rayleigh noise for the range and a Student's-t distribution for the range velocity noise. All specific noise parameters still have to be determined.

B. Dynamics Models

For the beginning of the project, all the models will be point mass models. This will work well with the sensor model returning the point mass info of the tracked objects. Farther into the project, this may be improved to return other characterizations such as surface area to improve the ID process.

1. Multi-Rotor

Standard linearized Multi-Rotor model with control inputs and noise. There will be normal noise on the motor forces representing motor errors and a students T noise for the velocities representing wind.

$$\begin{bmatrix} \dot{p} \\ \ddot{p} \\ \dot{w} \\ \ddot{w} \end{bmatrix} = \begin{bmatrix} \ddot{p} \\ F_{total}/m \\ \ddot{w} \\ T_{total}/I \end{bmatrix} + \begin{bmatrix} \mathcal{T} \\ \mathcal{N} \\ \mathcal{T} \\ \mathcal{N} \end{bmatrix}, \begin{array}{l} F_{total} = f(w_{motor}, \ldots) \\ T_{total} = f(w_{motor}, \ldots) \end{array} \tag{2}$$

where p is position, w is attitude, F is force, T is torque, and w is motor speed.

2. Fixed Wing

We are planning to use the following model in Julia: https://github.com/AlexS12/FlightMechanicsUtils.jl. We are planning to use this model to model the dynamics of a fixed-wing aircraft for discrete steps and add multiplicative noise on the velocities to model for wind.

3. Bird

Part of Objective 3.

4. Person

Part of Objective 3.

III. Objectives

This project is divided up into multiple levels of success with increasing difficulty.

Objective 1 Track a fixed wing and multi-rotor flying around steady level accelerated flight (SLUF):
- Make models for flying objects
  - Multi-rotor
  - Fixed wing
- Create a simulator to generate trajectories for models
  - Multi-rotor
  - Fixed wing
- Create a simulator to generate radar measurements given an object trajectory (may have simplified noise so that the EKF can work)
- Create an EKF (or similar) to estimate the state of the object given measurements and a standard kinematic model.
- Plot and compare estimated trajectory to actual trajectory.

Objective 2 Track a fixed wing and multi-rotor flying while preforming non-linear maneuvers:
- Change radar simulator to have more realistic non-Gaussian noise.
- Create trajectories from models that have highly non-linear maneuvers.
- Create a particle filter to estimate the state of the object given measurements.
- Plot and compare estimated trajectory to actual trajectory and EKF filter from Objective 1.

Objective 3 While tracking the targets, also preform classification to determine what they could be:
- Implement an estimator that takes in measurements and possible models, outputting an estimate for trajectory and type of object.

- Not sure what system would be used for classification (We talk about this later in class), but we are thinking something like the multiple model particle filter, where it tells you the likelihood of the data coming from the models.
- May have to implement other characteristics that the radar would return, such as surface area, to get accurate identification.

- Implement other models to test identification for (such as person and bird).

IV. Task and Milestone Roadmap

The objectives section does a good job outlining the sub-tasks needed to accomplish each objective.

A.

Major Milestones

1) Generate measurements for simulated trajectories.
2) Successfully estimate a trajectory from data. (Overall RMS error between points is lower than a tolerance)
3) Generate non-linear trajectories. (The trajectories have tight turns from controls).
4) Successfully estimate a non-linear trajectory from data. (Overall RMS error between points is lower than a tolerance).
5) Successfully classify a multi-rotor vs a fixed wing with some level of tolerance.

B.

Some potential ways to solve these problem are:

- LKF
- EKF
- Sequential Importance Sampling with Resampling
- linear/non-linear Gaussian sum filter

C. Work Distribution

1) Generate measurements for simulated trajectories.
    - **Ben**: Get the multi-rotor model to work and generate measurements
    - **Guido**: Get the fixed-wing model to work and generate measurements
2) Successfully estimate a trajectory from data. (Overall RMS error between points is lower than a tolerance)
    - **Ben**: LKF implementation
    - **Guido**: EKF implementation
3) Generate non-linear trajectories. (The trajectories have tight turns from controls).
    - **Ben**: Generate non-linear multi-rotor trajectories with appropriate dynamics noise
    - **Guido**: Generate non-linear fixed-wing trajectories with appropriate dynamics noise
4) Successfully estimate a non-linear trajectory from data. (Overall RMS error between points is lower than a tolerance).
    - **Ben**: Implement Sequential Importance Sampling with Resampling
    - **Guido**: linear/non-linear GSF
5) Successfully classify a multi-rotor vs a fixed wing with some level of tolerance.
    - **Ben & Guido**: Implement Multiple Model Filter (do it together because that seems hard)