Kalman Filter-Based UAV Localization using RF Sensing

EECE 562 - Statistical Signal Processing - Project Report

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Marley Beckett
marleybeckett@ece.ubc.ca

Idan Roth
idanroth@ece.ubc.ca

Abstract

In this project, an Extended Kalman Filter (EKF) is implemented for the trajectory tracking and localization of an unmanned aerial vehicle (UAV). The EKF is designed to estimate the path of the UAV as it progresses through periods of constant velocity, constant acceleration, and constant turns kinematic motion models. By extending traditional linear Kalman filtering techniques, the EKF model is able to adapt to changes in the UAV's motion. UAV tracking was successfully implemented on a dataset containing GPS-based UAV location and *noisy* estimates from its corresponding Keysight N6854A radio frequency sensor.

1 Introduction

Unmanned aerial vehicles (UAV), otherwise called *drones*, are intended to be one of the key components in future wireless systems and smart cities [1]. The applications of UAVs include goods delivery, surveillance, aerial photography, meteorology, and agriculture; yet, UAVs' rising accessibility pose a significant threat to public privacy and the security of sensitive facilities. Therefore, detection, localization, and tracking UAVs is of upmost importance.

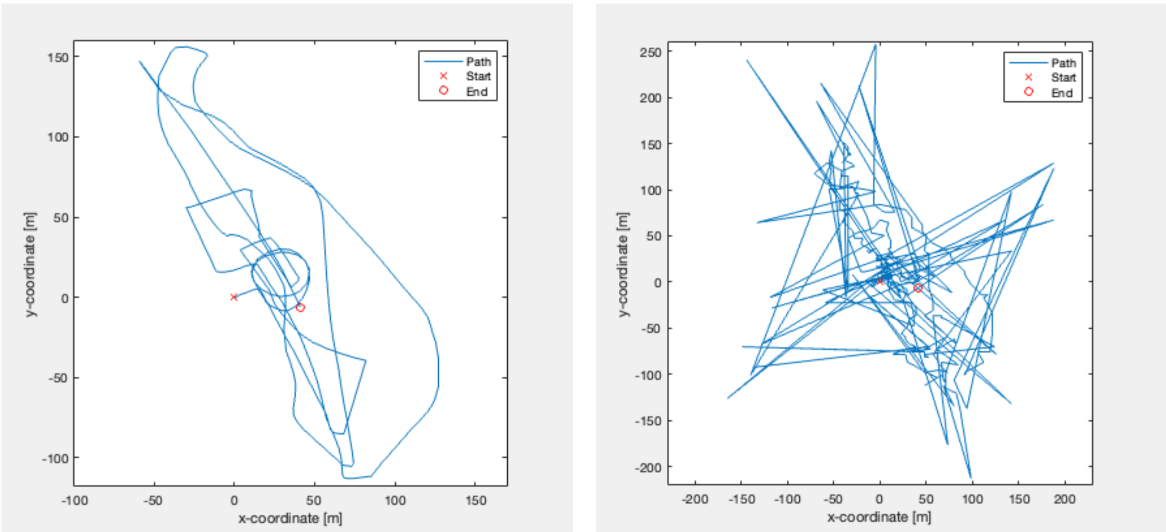
One of the most convenient and useful techniques for detecting and tracking drones, is by using inexpensive, passive radio frequency (RF) sensors for readily transmitted RF signal sources. The majority of consumer-level UAVs transmit in 2.4 GHz and 5.8 GHz ISM frequency bands to communicate with the remote controllers. Therefore, UAVs could be detected and localized using an RF sensor, which passively intercepts the RF signals. In real-world scenarios, RF sensors may preform poorly, resulting in high localization errors, hence, a method to improve tracking accuracy for GPS-denied environments is investigated.

In this project, we try to reproduce the results of a work [2], which proposed an extended Kalman filter (EKF) framework for the aforementioned problem. The authors conducted an outdoor experiment where the UAV's downlink RF signals were detected and the UAV was localized using the Keysight geolocation software N6854A with data collected by RF sensor N6841. Then, they improved the localization accuracy using an EKF. Their collected raw data was published by IEEE [2]. The EKF is a popular and effective approach use for tracking, and has a vast literature. The EKF performance relies mainly on the dynamics of the UAV trajectory. One of the ways to model a highly maneuvering UAV with an unknown pattern is to segment its trajectory into multiple motion models (MMs) that represents the possible maneuvering patterns for individual segments. The accuracy of the assumption that the UAV follows one of the possible MMs at each segment, will determine the overall performance of the EKF. A multi-MM framework models a UAV trajectory better, thus, provide better results then a single-MM framework. In [2], the authors adopted a multiple MM-based EKF framework which consist of three types of motions (kinematic models):

1. Constant velocity (CV) - moving on a straight line with constant velocity.
2. Constant acceleration (CV) - moving on a straight line with constant acceleration.
3. Constant turn (CT) - moving in a circular trajectory.

As mentioned above, the authors collected the RF signals data using a commercially available RF sensor. The sensor system is accompanied by a localization software that is able to locate RF sources within a 2 km radius. Since the experiment took place outdoors, the software's time-difference-of-arrival

(TDoA)-based localization approach was used, which provides the latitude and longitude estimates of the UAV in decimal degrees. Furthermore, the GPS data collected by the UAV on was used to determine the accuracy of the modelling. The data collected by both sensors has been visualized in Figure 1. Since the EKF estimation was offline, the raw data was pre-processed and aligned. Next, a manual division of the the ground truth trajectory into MM segments took place based on a visual inspection of the trajectory and velocity information obtained from the UAV.



(a) (b)

Figure 1: (a) UAV's ground truth path. (b) UAV's path collected by the passive RF sensor.

2 Estimation Method-based EKF

2.1 Model Framework

Discrete EKF tracking methods aim to estimate the current state of the object given both previous states and current observations. EKF derivations are based on a discrete-time state-space model, where k denotes the state time index, s_k and z_k are the state and observation vectors at time k respectively, f_k is a time-varying vector valued state transition function, and H is the observation matrix.

$$\begin{aligned} s_k &= f_k(s_{k-1}, u_k) + w_{k-1}, \\ z_k &= H s_k + v_k, \end{aligned} \tag{1}$$

w_k and v_k are the process and observation noises, which are assumed to be zero-mean Gaussian distribution with a covariance matrix Q_k and R_k respectively.

2.2 Kinematic Motion Models

Observations are to be characterized into time-periods corresponding to one of three kinematic motion models described below. Previous studies have shown that UAV tracking can achieve high success when this approach is followed [3].

1. **CV-MM:** In this motion model, it is assumed that both the velocity and trajectory of the object is constant. Filtering relies on observations of the current position and velocity of the object.

$$s_k^{CV} = \begin{bmatrix} x \\ y \\ \dot{x} \\ \dot{y} \end{bmatrix}, \qquad F_k^{CV} = \begin{bmatrix} 1 & 0 & T_k & 0 \\ 0 & 1 & 0 & T_k \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$\dot{x}$, $\dot{y}$, T_k denote the velocity in x and y directions, and the time interval between time indices $k-1$ and k, respectively.

2. **CA-MM:** The constant acceleration motion model is used to describe the path of an object when the velocity changes with a constant rate. In addition to both position and velocity, this model relies on current acceleration observations.

$$s_k^{CA} = \begin{bmatrix} x \\ y \\ \dot{x} \\ \dot{y} \\ \ddot{x} \\ \ddot{y} \end{bmatrix}, \qquad F_k^{CA} = \begin{bmatrix} 1 & 0 & T_k & 0 & \frac{T_k^2}{2} & 0 \\ 0 & 1 & 0 & T_k & 0 & \frac{T_k^2}{2} \\ 0 & 0 & 1 & 0 & T_k & 0 \\ 0 & 0 & 0 & 1 & 0 & T_k \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

   $\ddot{x}$ and $\ddot{y}$ denote the acceleration in x and y directions, respectively.

   It is worth remarking, that in the prior mentioned MM, f_k is a linear function, i.e., a matrix multiplication between the state vector and a transition matrix $f_k(s_k, u_k) = F_k^{CV} s_k^{CV}$.

3. **CT-MM:** This motion model describes an object that is moving in a circular path with a constant angular velocity of ω (rad/sec). The state space equations in the Cartesian form is as follows:

$$s_k^{CT} = \begin{bmatrix} x \\ y \\ \dot{x} \\ \dot{y} \\ \phi \end{bmatrix}, \qquad \mathrm{f}_k^{CT}(s_k) = \begin{bmatrix} x + \frac{\dot{x}}{\omega} sin(\omega T_k) - \frac{\dot{y}}{\omega}(1 - cos(\omega T_k)) \\ \dot{x} cos(\omega T_k) - \dot{y} sin(\omega T_k) \\ y + \frac{\dot{x}}{\omega}(1 - cos(\omega T_k)) + \frac{\dot{y}}{\omega} sin(\omega T_k) \\ \dot{x} sin(\omega T_k + \dot{y} cos(\omega T_k) \\ \omega \end{bmatrix},$$

   ϕ denotes the angular velocity of the state vector. For this MM, $f_k(s_k, u_k) = \mathrm{f}_k^{CT}(s_k)$, and its gradient w.r.t. s_k is a matrix denoted as F_k^{CT} [4].

Moreover, since we only have observations of the position information available from the RF sensor, the observation matrices of each MM are as follows

$$H^{CV} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}, \qquad H^{CA} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}, \qquad H^{CT} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}.$$

Regarding the model noise, they assumed that the process noise w_k is uncorrelated across its elements, and the covariance matrix Q_k is as described in [3]. The observation noise covariance matrix is characterized by the mean noise level errors of the RF sensor, $R_k = diag\{\sigma_x^2, \sigma_y^2\}$.

2.3 EKF Implementation

The EKF equations are described bellow. The process is composed of two consecutive steps, the prediction step and the update step, which are repeated recursively. In the prediction step, the object state $\bar{s}_k$ and the its covariance $\bar{P}_k$ at time k are predicted based on the kinematic process model and previous state estimation. These estimates are then used in the update step where the EKF updates the object state and the error in covariance based on the Kalman gain K_k and observations z_k. The Kalman gain acts as a weighting factor, which considers the trustworthiness between the predicted values and the observations.

Prediction	**Update**
1) $\bar{s}_k = f_k(\hat{s}_{k-1})$	1) $K_k = \bar{P}_k H^T (H \bar{P}_k H^T + R_k)^{-1}$
2) $\bar{P}_k = F_k \hat{P}_k F_k^T + Q_k$	2) $\hat{s}_k = \bar{s}_k + K_k(z_k - H\bar{s}_k)$
	3) $\hat{P}_k = (I - K_k H)\bar{P}_k$

3 Experimental Set-up

3.1 Data Pre-Processing

The original datasets used for this experiment varied significantly in size and accuracy of measurements. Prior to implementing the EKF, both datasets were matched for timestamps to millisecond accuracy, data points including duplicate timestamps were deleted. Additionally, measurements that contained extraneous data or empty values were removed. This resulted in a significant smaller dataset, as seen in Table 1 below.

Dataset	# Datapoints
UAV's GPS (original)	7912
Keysight N6854A RF Sensor (original)	480
Combined (processed)	301

Table 1: Comparison of dataset size before and after pre-processing.

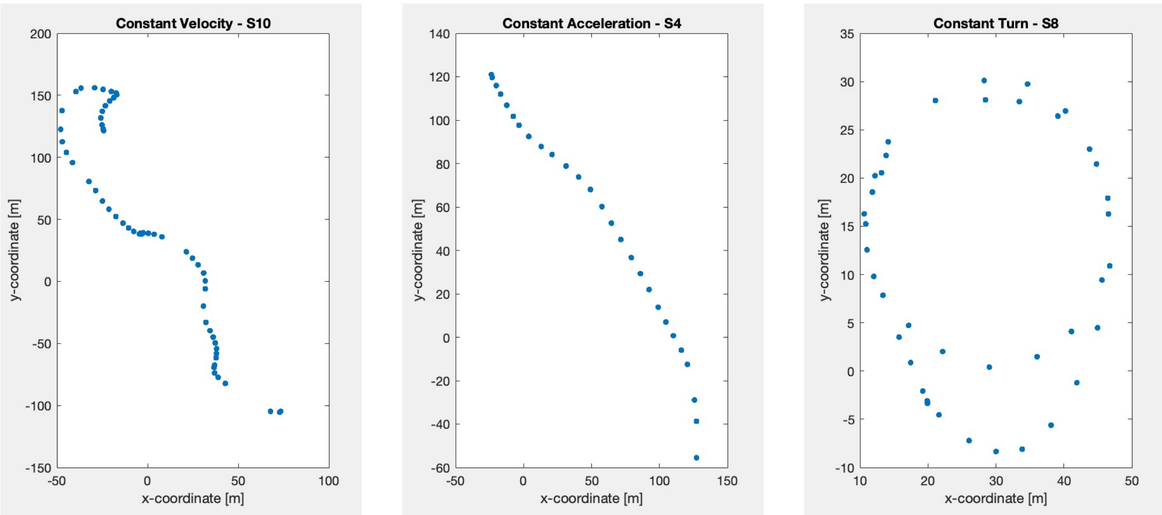
To ease computation and allow for accuracy in measurements, the original GPS data was converted to Cartesian coordinates using the MATLAB function *latlon2local* from the *Automated Driving* Toolbox.

3.2 Segmentation

Following the approach for segmentation in [2], we plotted the dataset in Cartesian coordinates, and manually labeled all segments as *CV*, *CA*, and *CT* to match the previously described kinematic MMs. The labels for the 12 segments are shown in Table 2. Figure 2 presents three examples of MM segments.

S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
1-15	16-28	29-37	38-46	47-53	54-58	59-99	100-140	141-201	202-259	260-264	265-301
CV	CA	CV	CA	CV	CA	CV	CT	CA	CV	CA	CV

Table 2: Segment labels for datapoints for the CV, CA, and CT motion models.



(a) (b) (c)

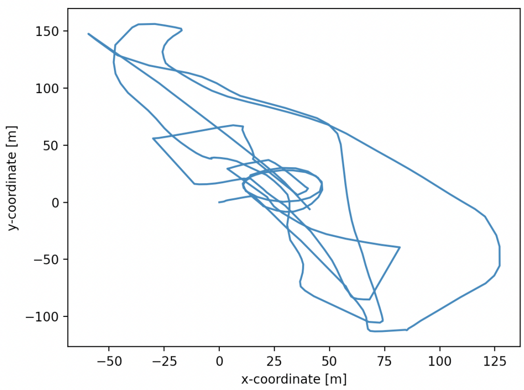
Figure 2: Example plots of segments for EKF motion models (a) CV. (b) CA. (c) CT.

Previous work using this dataset made use of the readily available MATLAB *TrackingEKF* function from the *Sensor Function and Tracking* toolbox [2]. We have chosen to implement pre-processing in MATLAB, and the EKF model, without the use of a filtering toolbox or library, in PYTHON.

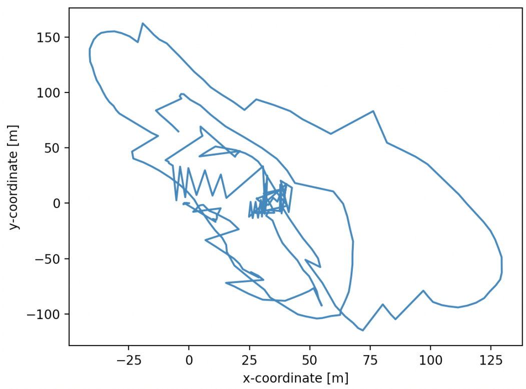
4 Results

The EKF was applied accordingly to each of the 12 labeled segments. Figure 3 illustrates our filtered path result compared to the ground truth path. Table 3 shows a comparison of the results obtained from our results versus the baseline model [2].

Our model preformed significantly better than the baseline model in all categories. The error for the segments with CV MMs was significantly lower than that in the reference paper. We believe that this discrepancy is due to the usage of a larger post-processed dataset, or different error measurements



(a)



(b)

Figure 3: (a) UAV's ground truth path. (b) UAV's estimated path using EKF.

	Model Accuracy (m)			
	CV	CA	CT	Total
Our Model	3.70	5.65	4.26	**4.38**
Bhattacherjee [2]	9.97	7.69	7.39	**8.38**

Table 3: Comparison of accuracy between UAV GPS position EKF tracking.

used. We reported the MSE error, however, the method used in the reference paper was not specified. The equation for the MSE in Cartesian coordinates is as follows,

$$MSE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2},$$

where $\hat{x_i}$ and $\hat{y_i}$ are the estimated positions in the x and y directions respectively.

5 Conclusion

In this report, an EKF based method for tracking the position of UAVs using data obtained from a commercially avalible RF sensor is proposed. Initial results show that EKF based tracking methods are accurate within an average of 4.38m for UAVs flying at constant altitude. Segmentation of the UAV trajectory was done manually, and therefore is subject to interpretation. In future work, results could be validated by recording additional data for a UAV path with specific trajectories in mind (i.e. flying the UAV in a straight line at a constant velocity to create accurately labelled data). Overall, the approach of segmentation and fitting multiple EKF models to different motion paths is successful approach for tracking UAVs.

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References

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