UAV State Estimation Using IMU Vector with DNN.

Group 7

ITCS 5156

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Problem Statement

While there exist state estimators for Unmanned Aerial Vehicles, UAVs, in simulated environments few rely on strictly the raw data produced by inertial measurement units, IMUs. Most estimators that utilize machine learning models rely on, on/off-board optical sensors, and digital filters to train the models on state estimation. Our implementation aims to estimate the state by providing raw IMU data to a DNN with simulated data, using Micklisch et al.'s simulator, of 501 random quadrotor flights.

Motivation

One of the most difficult areas of designing a UAV is state estimation, especially with common off-the-shelf components. Current commercial IMU's are cheaply available but contain sensor error dynamics such as noise and drift. These error dynamics are usually resolved by the use of an extended Kalman filter (EKF), reviewed by Yang et al., but are complex to implement and require background knowledge of the Inertial body of the UAV. Al-Sharman et al. replaced the Kalman filter and fed the raw IMU data directly to the ML model. This resulted in an RMSEE score for the angular positions phi, theta, and psi of 0.00016, 0.00023, and 0.00200 respectively. We want to see if we can improve the accuracy of this model by sending the raw IMU data as a vector of recorded readings over a time period and predict not only the attitude, angular, position but the linear position as well.

Literature Survey - Summary of Related Approaches

As described by Yang et al. traditional State Estimation can be done using three core techniques, attitude estimation via an Inertial Measurement Unit (IMU), Pose estimation via extended Kalman filtering, and optimal state estimation. Outside of traditional works in state estimation Machine learning methods have been derived. Carrio et al. touched on the use of DNN and CNN for motion control with low-level control policies from imperfect optical sensor data in simulations implemented by Aznar et al. and Ross Girshick respectively. Jaradat and Hafez explored an integrated navigation solution, INS, that uses IMU sensors to provide data to a Neural Network which has been pre-trained with the sensors' error dynamics. This INS system characterizes the x, y, and z vector spaces individually. The INS was initially tested in a simulated environment and then run against real GPS/IMU data. Cheon et al. utilized Proportional Integral Derivative, PID, controller outputs to train a Deep Learning Controller on how to control a DC Motor System. Ibarra-Bonilla et al. developed a Kalman Filter with Neuro-Fuzzy logic for attitude estimation using the raw data of an IMU. Jin et al. proposed a relational graph network derived from a relational neural network to accurately predict a 6D pose of a quadrotor from optical sensors. Al-Sharman et al. implemented a deep learning framework to improve state estimation by identifying measurement noise and filtering it out.

Literature Survey - Criticize The Existing Approaches

Ibarra-Bonilla et. al's attitude estimation was only utilized with Pedestrian Dead Reckoning, PDR, and didn't compare the Neuro-Fuzzy adaptation of the Kalman Filter with the current UAV flight. The use of state estimation from optical sensors by Jin et al., Aznar et al., and Ross Girshick may be ineffective in foggy or low light situations. Jaradat and Hafez's use of GPS fusion will limit their Navigation System in Urban and indoor environments.

Literature Survey - What Are The Pros and Cons?

Pro: A deep neural network (DNN) can ensure identifying representative, fitted, and robust models for the unfiltered measurement noise. The deep-learning-based neural network (DLNN) attitude estimation results exhibit superiority over the conventional attitude estimates.

Con: The usage of DNN and DLNN models may only learn the error dynamics of the sensors it was trained against, limiting the models robustness against other sensors.

Literature Survey - How Do You Relate Them To Your Planned Approach

l-Sharman et al.'s approach to comparing the RMSEE scores of the DLNN model and the Kalman filter is appropriate for determining how well the DLNN compares to the Kalman filter introduced by Yang et al. We would like to adopt this approach by comparing the results of an Extended Kalman Filter to our DLNN model.

Approach (Summary)

To train a model that will produce the same output as an EKF we need to generate several hundred flights in random directions by utilizing a pre-existing simulator (Micklisch et al.). Each flight will be recorded as a CSV. An input target pair table will be generated by randomly selecting a flight recording, f, and a moment in the flight, i, and getting the next, x, rows from i. These x rows represent a stream of raw IMU readings that will be stored as a 6 DOF vector, this vector is the input. The difference in angular and linear positions from i to i+x will be the target. This dataset will then be trained and tested with a DNN Regression model. The RMSEE will then be compared to Al-Sharman et al.'s results.

Questions We Want To Answer From The Project

- Can we replace an extended Kalman filter with an ML model that can estimate the attitude of the quadrotor from a stream of raw IMU data?
- How large does a vector of IMU data need to be to accurately determine the state? Can a vector of size 1 with the accelerometer and gyroscope readings be enough or do we need at least 20 readings, 0.6 seconds of flight, to predict the linear and angular location?

Expectations of What We Will Be Able To Learn

- Data Preprocessing
- Preprocess timestamped simulation data into a vector format.
- Learn how to apply DNN Regression to a Vector of IMU data
- Learn Fast R-CNN for object detection

Plan / Tasks	Rohit Alavala	Saiphani Jasthi	Yuehan Lan	Christian Micklisch	Sai Nihanth Vanam
Survey of literature on DNN usage in determining attitude, pose and state estimation for unmanned vehicles	x		x		
Configure Simulator to output real state and IMU readings		x	x		x
Adjust simulator to alter dataset output for various different flights	x			x	
Pre-process the data, structure multiple train		x	x		
Research on which libraries to utilize for DNN Regression		x		x	x
Create a model that estimates the attitude (angular position)		x		x	
Compare Results from Al-Sharman et al.	x				
Write MidTerm Report	x	x	x	x	x
Create a model that estimates the state (linear and angular positions)		x		x	
Experiment with varying layer sizes and structures	x		x		x
Write up Final Report	x	x	x	x	x
Present the Final Report Slides	x	x	x	x	x

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