Simultaneous State Estimation of UAV Trajectory Using Probabilistic Graph Models

Derek Chen, Grace Xingxin Gao

We present a new technique for sensor fusion and batch estimation of UAV trajectories. Traditionally, the goal of GPS UAV state estimation estimates current state and predicts a future state. Our technique not only estimates and predicts our current and future states, but also rectifies past states based on the current and future measurements through GPS and IMU sensor fusion allowing for a better mapping of a UAV's trajectory.

UAVs are commonly used for Intelligence, Surveillance, and Reconnaissance (ISR). Aerial platforms equipped with a variety of sensors such as imagers, radar, and SIGINT sensors can provide in-depth information across a vast region. Collected sensor data is commonly paired with corresponding GPS positions for reconstruction and correlation across an already survey map. An example application is ground feature reconstruction using airborne Synthetic Aperture Radar (SAR) Interferometry, where radar measurements taken from multiple positions combined with precise GPS data are post-processed to reconstruct geographical features [1]. Another application that precise positioning enables is reconstruction of 3D models in geo-registered locations from motion video [2]. Traditionally, the goal of aerial platform state estimation is to estimate its current state and predict its state at the next time step. Our goal is not only estimating and predicting our current and next states, but also rectifying our past estimates based on the current measurement through GPS and IMU sensor fusion and a UAV dynamics model. The improvement in accuracy of UAV positioning data allows for better reconstruction and mapping of sensor data.

In this paper, we propose to simultaneously estimate the trajectory states for a UAV flight. We use the probabilistic graph model by representing the set of UAV state estimates as a directed acyclic graph. We model the UAV state estimates of each time step as nodes, connected throughout the trajectory timespan. Each node is linked to its predecessor through a single edge. These edges represent the dependence of one node to its previous state provided by the dynamics model and the IMU measurements. Next, each GPS satellite visible across the timespan is designated as a different node. Each UAV state node is connected through edges to each visible satellite through the observed pseudoranges at each time step.

We then use iterative least squares to solve for the system states at the current and all previous time steps. The cost function is composed of two components: the measurement cost and the dynamics cost. The measurement cost is defined as the sum of differences between measured pseudoranges and distances calculated between each iterated position estimate to each respective satellite. The dynamics cost represents the error between each position's estimate versus each propagated position's estimate from each predecessor position through the dynamics model and IMU data. The observation Jacobian matrix is a combination of the matrix of line-of-sight unit vectors to each satellite for each state and the dynamics Jacobian which consists of the derivative velocity functions that allows for correlation between consecutive states. Although a vast Jacobian matrix is created with components from each time step, the resultant matrix is mostly a sparse matrix. We then explore the sparsity of the Jacobian matrix to reduce the computation load. Afterwards Gauss-Newton iteration steps are used until the system converges towards optimal estimate for the states in the trajectory so far. As each measurement is added on, past measurements are re-estimated and rectified. The optimal state estimates are achieved at the end of a trajectory where all pseudoranges and IMU data collected throughout the flight is used for a batch estimate for all states simultaneously.

To test our algorithm, we have equipped an Asctec Pelican Quadrotor with a u-blox LEA-6T receiver. Using the u-blox receiver as well as the onboard IMU, we implement our algorithm in post-processing and obtaining an optimal estimate of the quadrotor's trajectory. We show that through the use of probabilistic graph models and a smoothing approach, we are able to obtain a more accurate mapping of a UAV's trajectory than that through the use of traditional EKF techniques.

[1] Hensley S, Zebker H, Jones C, et al. "Use of airborne SAR interferometry for monitoring deformation of large-scale man-made features," International Workshop Spatial Information Technologies for Monitoring the Deformation of Large-Scale Man-made Linear Features, Jan 2010 Hong Kong, China.

[2] M. Pollefeys et al. Detailed real-time urban 3d reconstruction from video. IJCV, 78(2-3), 2008.

Notes:

[1] http://uavsar.jpl.nasa.gov/publications/hongKong2010_shensley.pdf
[2] http://graphics.stanford.edu/~pmerrell/Pollefeys_UrbanReconstruction07.pdf

http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=399626
http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=1294021
http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=5152678
http://repository.cmu.edu/cgi/viewcontent.cgi?article=1038&context=dissertations
https://www.princeton.edu/~ota/disk1/1991/9114/911405.PDF
http://repository.cmu.edu/cgi/viewcontent.cgi?article=1038&context=dissertations

Example applications are Synthetic Aperture Radar (SAR) where radar measurements are taken from multiple angles, and 3D reconstruction, where a 3D ground map is reconstructed from a set of images.

UAVs are commonly used for Intelligence, Surveillance, and Reconnaissance (ISR). Aerial platforms equipped with a variety of sensors such as imagers, radar, SIGINT sensors can provide in-depth information across a vast region. A common application for this is ground feature reconstruction. Using airborne Synthetic Aperture Radar (SAR) Interferometry, radar measurements taken from multiple positions can be combined with precise positioning data to reconstruct geographical features [1]. Precise positioning also allows for reconstruction of 3D models in geo-registered locations from video [2]. This combination of precise positioning with airborne sensor data allows for more accurate image reconstructions as well as a better correlation of sensor data to the surveyed world frame.

In this paper we refer to Unmanned Air Vehicle (UAV) state estimation as locating the position and velocities of a UAV at a particular time step. Traditionally, the goal of aerial platform state estimation is to estimate its current state and predict its state at the next time step. Our goal is not only estimating and predicting our current and next states, but also rectifying our past estimates based on the current measurement throughs GPS and IMU sensor fusion and a UAV dynamics model. This allows for better rectification of precise positioning of collected data throughout the entire timespan of the measurement trajectory.

We represent the set of UAV state estimates as a graphical model, specifically a directed acyclic graph where our goal is to estimate the states in its trajectory. We model the UAV state estimates of each time step as nodes, connected throughout the trajectory timespan. Each node is linked to its predecessor through a single edge. These edges represent the dependence of one node to its previous state and the constraint that the dynamics model and the IMU data place on possible states. Next, each GPS satellite visible across the timespan is designated as a different node. Each UAV state node is connected through edges to each visible satellite representing the observed pseudoranges at each time step.

Optimal nonlinear least squares is then used to solve for the system states at the current and all previous time steps. The cost function is composed of two components, the measurement cost and the dynamics cost. The measurement cost is defined as the sum of differences between measured pseudoranges and distances calculated between each iterated position estimate to each respective satellite.The dynamics cost represents the error between each position's estimate versus each propagated position's estimate from each predecessor position through the dynamics model. The observation Jacobian matrix is a combination of the matrix of line-of-sight unit vectors to each satellite for each state and the dynamics Jacobian which consists of the derivative velocity functions that allows for correlation between consecutive states.

Although a vast Jacobian matrix is created with components from each time step, the resultant matrix is mostly a sparse matrix. This allows for inexpensive computation and numerical solution. The Jacobian allows for calculation of a current iteration of the estimator. Afterwards Gauss-Newton iteration steps are used until the system converges towards optimal estimate for the states in the trajectory so far.

As opposed to using only the previous state estimate for a current state estimate, we estimate the UAV's state as well as all previous states. As each measurement is added on, past measurements are re-estimated and rectified.The optimal state estimates are achieved at the end of a trajectory where all pseudoranges and IMU data collected throughout the flight is used for a batch estimate for all states simultaneously.

To test our algorithm, we have equipped an Asctec Pelican Quadrotor with a uBlox LEA-6T receiver. Using the uBlox receiver as well as the onboard IMU, we test our algorithm in post-processing and obtaining an optimal estimate of the quadrotor's trajectory. We then compare our results between GPS with no filtering, GPS/IMU using the EKF as a state estimator, and finally our method of batch estimation formulated by the probabilistic graph model.

We show that through the use of probabilistic graph models and a smoothing approach, we are able to obtain a more accurate mapping of a UAV's trajectory than through the use of traditional processing techniques.