Interactive Multiple Model Filter for Inertial Sensor Drift Correction in GPS-Denied Target Drone Waypoint Flights

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Abstract

Target drones are smaller versions of military aircraft used to test air defense mechanisms and provide aid for manned aircraft during missions. One of the biggest threats to target drones is signal jamming and cyber hijacking. Tools like laser rangefinders, ground beacons, and occupancy-grid mappers have been used to supplement a GPS navigation system, but these solutions are not viable for target drones. Use of an inertial navigation system (INS) for navigation in GPS-denied areas has been suggested, but raw INS data is rather inaccurate due to drift error and sensor bias, especially in bodies experiencing large magnitudes of acceleration.

This project aimed to test and evaluate the accuracy of applying smoothing filters (Kalman filter, Extended Kalman Filter, and Unscented Kalman Filter) to the INS data using an Interactive Multiple Model (IMM). The IMM works by establishing x, y, and z drift rates from a series of acceleration and velocity inputs over time. These measurements were compared against the flight plan to identify and eliminate noisy and biased measurements in a process involving Bayesian statistics. The IMM is adaptive, as each estimation model is assigned a probability based on relative confidence that the filter would produce an accurate result. Data was collected with an INS on board a DJI Mavic Pro drone, which was flown according to pre-planned flight paths. Comparing the calculated trajectories using the INS data and a copy run through the IMM showed that using the IMM provided a displacement error reduction of about 75%.

Introduction

Military Drone Technology

Target drones are unmanned aerial vehicles (UAVs) built for the purpose of testing air-attack defense mechanisms or aiding manned aircraft in aerial missions. Target drones may replicate threat aircraft to test air-to-air or surface-to-air defense missiles and ensure that tracking systems are capable of identifying and targeting enemy aircraft (Elsayed Ahmed et al., 2015). In addition, US law requires that weapons systems demonstrate their lethality (Carter et al., 2011). The drones must have the ability to fly autonomously, mimic enemy maneuvers, and at times, carry out operations as if they were manned aircraft (Meyer, 2005). In some cases, target drones may be employed as a sort of wingman to larger, more expensive, manned fighters that cannot fly into risky situations (Fahlstrom & Gleason, 2012). UAVs are used because of their low cost, low potential for human endangerment and low complexity compared to traditional manned aircraft (Sharifi-Tehrani et al., 2016). Militaries around the world use target drones for testing and defense. Demand for newer and better target drones is abundant, as they play a crucial role in air defense (Hammes, 2019).

Target Drone Navigation

Target drones must possess onboard instrumentation to enable them to function like real aircraft or cruise missiles (Tahk et al., 2018). Perhaps the most important of on-board instruments is the navigation complex. Autonomous navigation is imperative for target drones, and there are several different navigation methods. The NASA AirSTAR software system has been designed for sub-scale target drones. It integrates multiple research control laws and anticipates system failures, safeguarding the drone against damage (Murch et al., 2009). However, the AirSTAR system requires a safety pilot to perform launch and landings, which is disadvantageous assuming the drone will not always engage in round-trip flights. Along with general navigation, target drones must also be able to carry out specific maneuvers. One of the most common is closing in on a target. An algorithm has been proposed to provide proper lateral acceleration commands that make the impact time error converge to zero by the time of impact for homing missiles (Tahk et al., 2018). The NASA AirSTAR system and the proposed homing algorithm depend on GPS for accurate navigation. However, GPS may be vulnerable to cyber-attacks and signal-loss (Hammes, 2019). In urban areas, buildings can block the GPS signal. Research suggests that it is necessary for a new means of navigation to replace or at least supplement the GPS-reliant navigation systems (Chowdhary et al., 2013).

Inertial Navigation Systems (INSs) are promising tools for navigation in GPS-denied areas. Loss of GPS signal can be caused by atmospheric disturbances, failure of the GPS antenna, electromagnetic interference, weather, GPS signal attack, or solar activity (Yao et al., 2016). While the INS is resistant to these, position estimation with information from INS accelerometers and tilt sensors are susceptible to error during the double integration process known as dead reckoning. Dead reckoning INS systems for mobile robots have been found to have a position drift rate ranging from 1 to 8 cm/s (Barshan & Durrant-Whyte, 1995). As such, an INS needs information from an absolute position-sensing mechanism. Some possibilities for absolute position mechanisms include ground laser trackers (Yang et al., 2020), on-board cameras (Chowdhary et al., 2013) (Brunner et al., 2018) (Shi et al., 2018), on-board planar laser range finders (Bry et al., 2012), and ground beacons (Barshan & Durrant-Whyte, 1995). However, laser trackers require direct line of sight, there aren't significant landmarks for vision-aided navigation at altitude, and radio-based map matching systems such as ground beacons are at risk of jamming for the same reason GPS systems are vulnerable.

Error Correction with Filters

When an INS is integrated as a position sensor, compensation must be made for the cumulative error. More accurate state estimations can be obtained using variants of the Bayes Filter. A Bayes Filter calculates the probabilities of multiple beliefs to allow a robot to infer its position and orientation. Variants including the Kalman Filter (KF), the Extended Kalman Filter (EKF), and the Unscented Kalman Filter (UKF) are widely used for trajectory optimization applications. A KF is an optimum observer that estimates the states of linear state-space models using a series of inputs over time for open-loop trajectory optimization. The KF and its variants are the most commonly used filtering techniques to integrate an INS as a position sensor. The difference between an EKF and a KF is that an EKF doesn't assume Gaussian noise distribution. Gaussian noise is statistical noise having a probability density function equal to that of the normal distribution. When state-space models are nonlinear, noise is not always Gaussian, which makes position estimations more complex. The Unscented Kalman Filter (UKF) is claimed to be an improved EKF. Both filters use a Gaussian Random Variable (GRV), which is the basis of the state distribution. The EKF propagates the GRV through first-order linearization of the non-linear system. The UKF, on the other hand, propagates the GRV directly through the non-linear system, producing estimates accurate to the third order via a Taylor series expansion. This strategy increases computational complexity, so instead of propagating the entire GRV, the UKF takes only a sample of the distribution. This way, the UKF achieves third-order accuracy while maintaining the same computational complexity as the EKF (Wan & van der Merwe, 2000).

It is currently unclear which of these strategies (or possibly a combination thereof) yields the most accurate GPS-free navigation for target drones. This can be tested using an interactive multiple model (IMM).

Interactive Multiple Model

The IMM is necessary for position estimation because, as previously mentioned, trajectory tracking using just inertial data results in drift error of several centimeters per second. After just 30 minutes of flight, the position estimate using an INS can be inaccurate by hundreds of meters. Drift error in the INS is a result of the integration process of acceleration and velocity. Small error accumulates over time, rendering the INS unreliable as a position estimator (Alaoi et al., 2016)

An IMM runs several filter system models in parallel (Akca & Efe, 2019). These filters are adaptive, for each estimation model is assigned a probability based on relative confidence that the filter will produce an accurate result. In this way, multiple filters along with weighted combinations can be tested at once. The weighted combination strategy allows for the model to iteratively update filter weights. Fusion of each of the filter outputs is designed to yield an estimate that isn't affected by drift error.

Statement of Purpose

Research Gap

Target drones lack an all-weather dead reckoning navigation method for long-range three-dimensional waypoint navigation that isn't subject to drift error. Previous studies tested the INS indoors, where small displacement and velocity yield very little drift error (Rehbinder & Hu, 2003). INSs have been tested outdoors, but they are often mounted on terrestrial robots, which don't experience as extreme periods of acceleration as target drones do (Aghili & Salerno, 2013), (Won, 2010). Algorithms have been proposed by Rehbinder & Hu (2003), Aghili & Salerno (2013), Won (2010), Lee et al. (2012) and Barshan & Durrant-Whyte (1995) to improve the accuracy of INSs. These algorithms use Kalman Filters, Extended Kalman Filters, and Particle Filters to track and adjust trajectory. However, none of these navigation methods can operate independently from a GPS or radar.

Research Question

Is it possible and reasonable to track the trajectory of a drone using just an INS and an IMM localization program?

Engineering Goals

1. Develop MATLAB code for flight trajectory tracking using data from an inertial measurement unit
2. Develop MATLAB code for an interactive multiple model filter for improved trajectory tracking of the drone
3. Determine through quantitative error analysis the optimal filtering strategy given flight type and conditions (trajectory from raw inertial data is treated as the control)

Methodology

Materials

Research was conducted using a DJI Mavic Pro drone. The Mavic drone was suitable for this project because it has a built-in inertial measurement unit (IMU) from which inertial data can be obtained. Microsoft Excel and MATLAB were also used in this project for trajectory plotting and tracking.

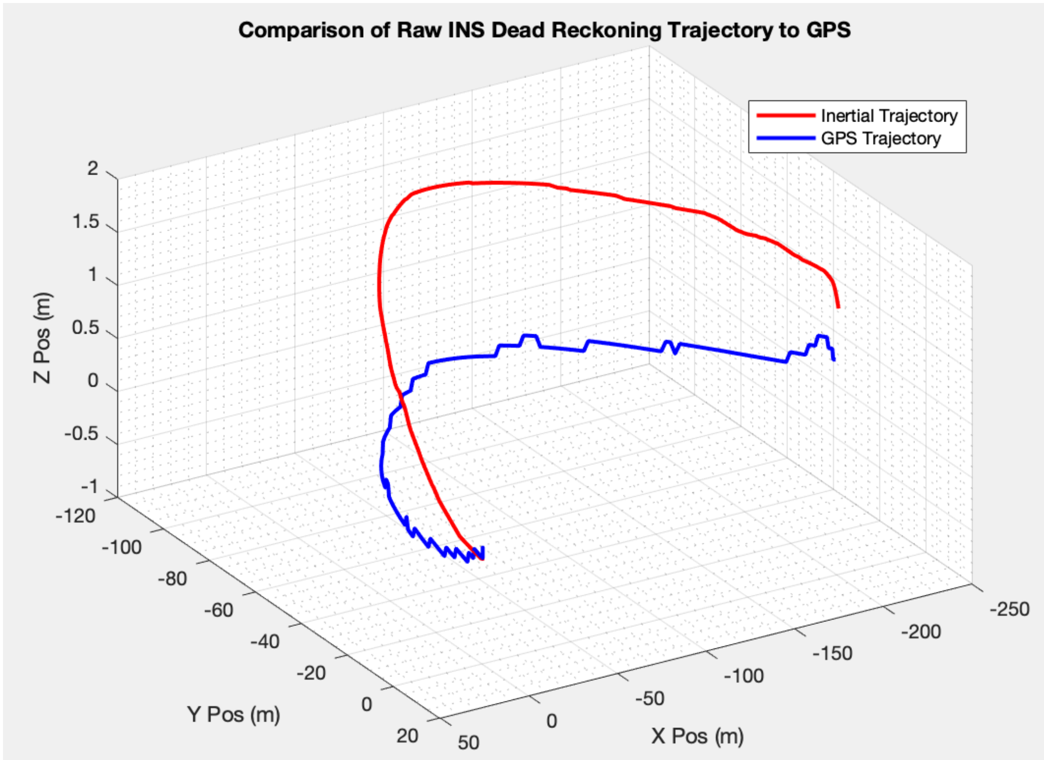
Collecting Inertial Data

Data were collected from 20 different drone flights. 3 of the 20 flights did not follow the flight plan; instead, they consisted of random maneuvers. Each of the 17 planned flights was conducted in the same location, 200 feet from the ground, or about 625 feet above sea level. Weather data such as temperature, humidity, air pressure, wind speed, gust speed, and wind direction with respect to drone orientation were collected to be controlled for during regression analysis. Each flight included 2 turns (one right, one left) of about 90 degrees, as well as 2 changes in altitude (one climb, one descent) of about 30 feet. After each flight, the flight record, containing all the flight data, was converted from a .txt file to a .csv using software from Airdata.com. Once in .csv format, the flight records were imported into MATLAB for inertial analysis.

Programs for Inertial Data Analysis

Four programs were required for proper analysis of the inertial data from the drone flight records. The first program integrates data from accelerometer readings to produce x, y, and z position matrices. Using acceleration and then velocity measurements, the recursive formula fills in subsequent positions by multiplying a higher derivative by a time step. The second program converts latitude/longitude coordinates and altitude to rectangular, (x, y, z) coordinates. It was necessary to perform calculations in a rectangular frame so displacement could be measured properly. The third program obtains displacement readings between the outputs of the first two programs. Error is collected in the form of absolute mean displacement, maximum displacement, end displacement as well as mean, max, and end displacement for each of the x, y, and z coordinates. The fourth and final program for the raw INS analysis plots overlapping trajectories of the positions derived from GPS and INS readings. Figure 1 shows such a plot.

Figure 1



Interactive Multiple Model Program

The IMM created and used for this research runs three Kalman Filter variants: KF, EKF and UKF. Each of the three filters contains and runs, in parallel, either two or three prescribed motion models: 3D constant velocity, 3D constant acceleration, and 3D constant turn for the EKF. Tracking filters like the KF and its variants use Bayesian statistics to generate more reliable position estimates. When applying Bayesian statistics to a problem of uncertain position, the region is divided into unit cubes. At first, each of the units is assigned an equal probability of containing a trajectory waypoint. Then, as each inertial measurement is processed, the probabilities are updated. The motion models act as a guide for the probability-associating process. This way, noisy and biased measurements are filtered out when the program determines that the probability of that being a true maneuver is low enough. The weight of any given motion model depends on the nature of the flight trajectory. For example, when the drone completes a turn and begins to slow down, the IMM will adjust the motion model weights such that the constant acceleration model is trusted more than the constant turn model. The IMM tests each of the three base filters as well as a combination thereof in order to maximize accuracy.

Results

Inertial Trajectory Tracking

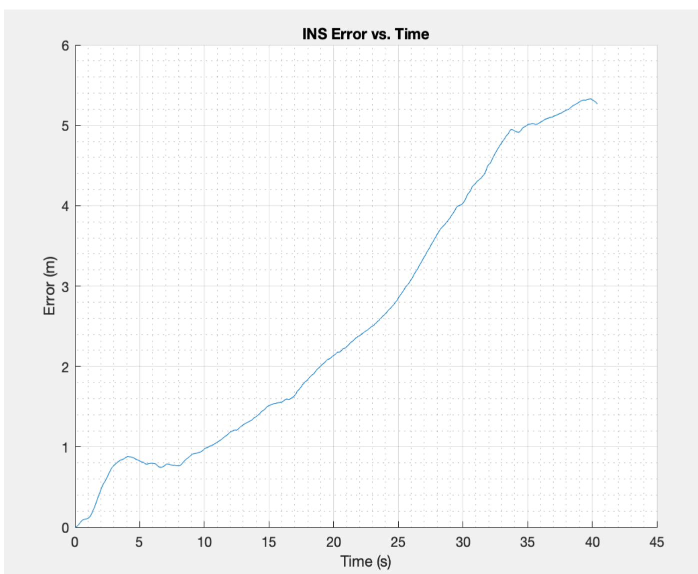
Inertial data from 68 total flight segments were analyzed using the three inertial analysis programs. The recursive algorithm successfully tracked the trajectory of the drone, but the position outputs were hindered by drift error. The average drift rates along with maximum error are displayed in Table 1. Barshan & Durrant-Whyte were the first to use inertial dead reckoning; they found an average drift rate of one to eight cm/s. For this project, the observed average drift rates were at the high end of that previously determined range. A likely explanation for the higher change in altitude segment average drift rate measurement is the volatility of barometric altimeters as altitude sensors.

Table 1

Segment Type	Avg Drift Rate (cm/s)	Avg X Drift Rate (cm/s)	Avg Y Drift Rate (cm/s)	Avg Z Drift Rate (cm/s)	Max Error (cm)	Max X Error (cm)	Max Y Error (cm)	Max Z Error (cm)
Turn	7.96	4.78	5.93	2.03	454.6	237.8	277.3	128.7
Altitude	9.95	5.12	5.16	6.63	226.6	131.5	138.4	152.17

The inertial analysis programs also tracked error over time. As expected, drift error accumulated at a relatively steady rate during the course of the flight, yielding error plots as shown in Figure 2.

Figure 2



There is some deviation in the drift rate, due in large part to random error such as improper readings; overall, there is a clear accumulation of error when using the inertial algorithm to track trajectory.

Filter Performance

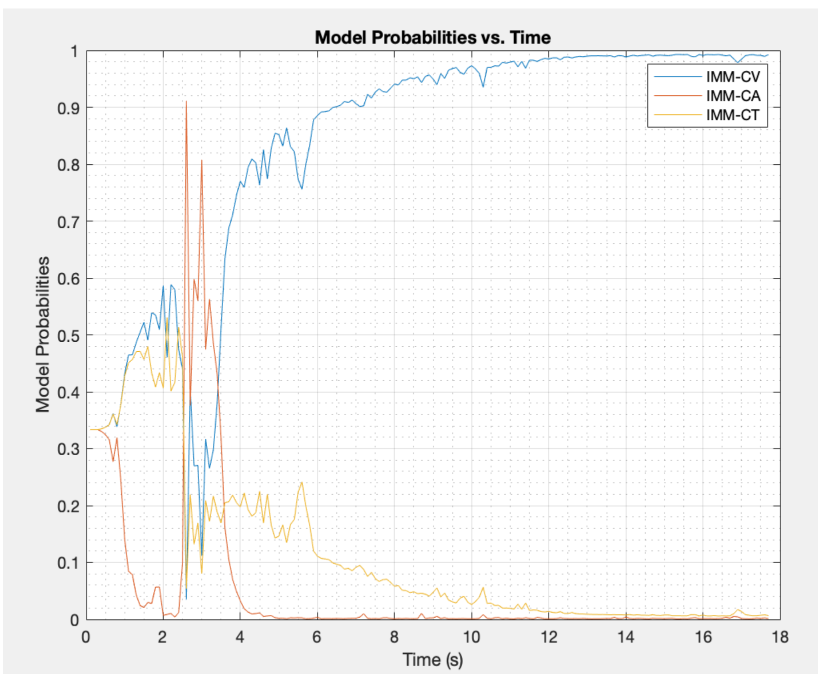
The IMMs were much better at trajectory tracking, providing error advantages summarized in the table below.

Table 2

Segment Type	Average Percent Error Decrease using KF IMM	Average Percent Error Decrease using EKF IMM	Average Percent Error Decrease using UKF IMM
Turn	56.8964	63.8371	63.2467
Altitude	53.4317	55.9277	49.4028

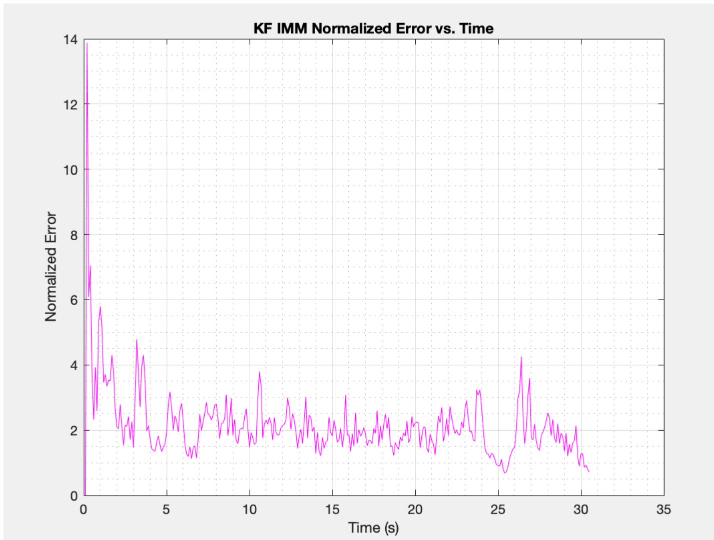
For the first few seconds of flight, the IMM adjusted its model weights to capture the combination most-suited for the nature of the flight. For example, the flight segment that yielded the data shown in Figure 3 was a straight descent segment, so the constant turn (CT) model approaches 0 and the constant velocity (CV) model approaches 1.

Figure 3



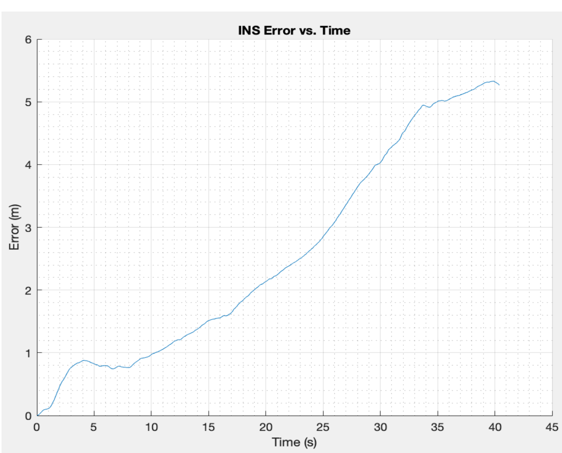
Because the IMM takes time to converge on the proper model, error is high in the beginning. However, error soon decreases and stays low for the remainder of the flight segment. Figure 3 shows a graph of normalized error over time for the Extended Kalman Filter IMM. Normalized error takes into account the covariance (uncertainty) of the predicted state and the measurement noise.

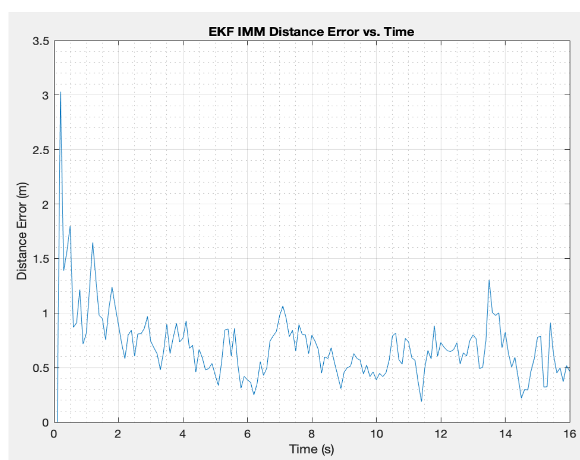
<u>Figure 4</u>



The IMM programs also produced true error (displacement) graphs, which can be compared to the Figure 2 - INS Error vs. Time graph. Figure 5 shows the graph of distance error using the EKF IMM. Error accumulates when using the inertial program, whereas error starts high and quickly drops when using an IMM. Maximum error is almost always greater when using an IMM, but the models adjust in just a few seconds, making the IMM advantageous.

<u>Figures 2 and 5</u>

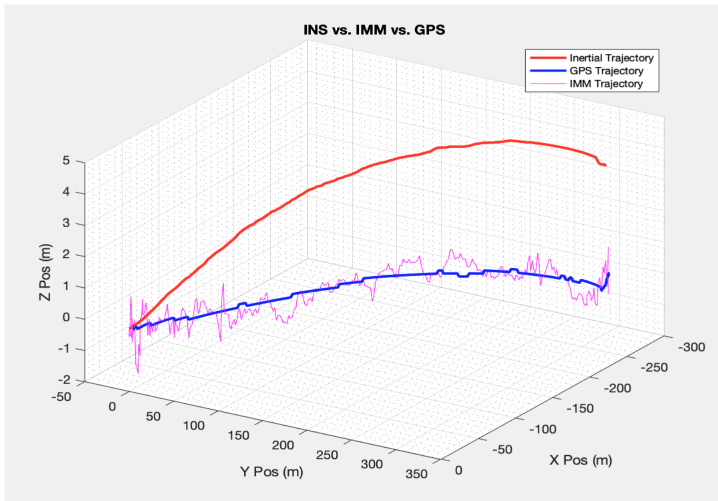




A visual comparison of the inertial and IMM trajectory-tracking algorithms can be seen from the 3D position graphs containing both of the calculated trajectories as well as the true GPS trajectory. Figure

6 shows such a comparison. As the inertial trajectory steadily deviates from the true state, the IMM trajectory holds to the truth.

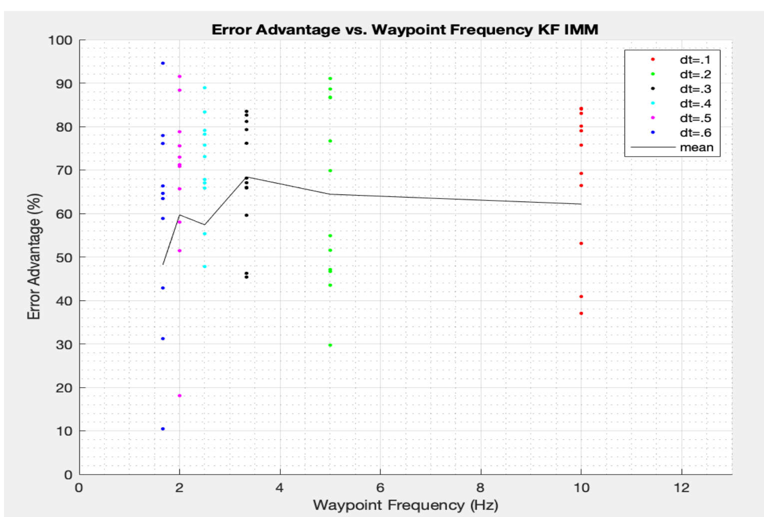
Figure 6

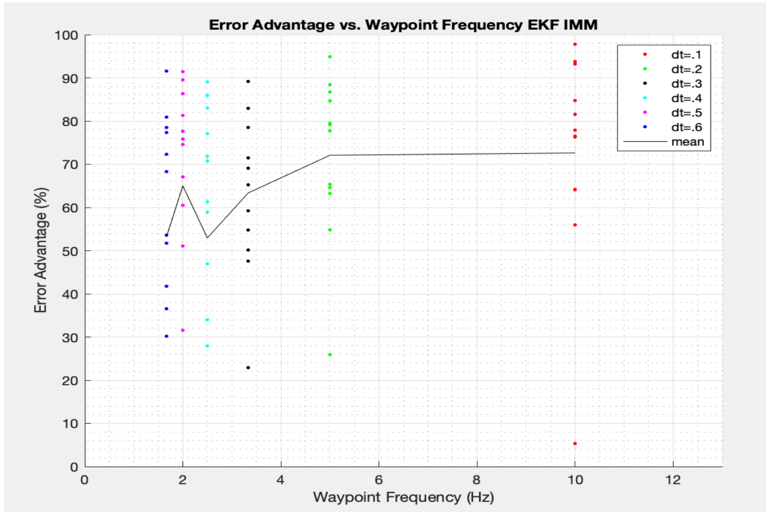


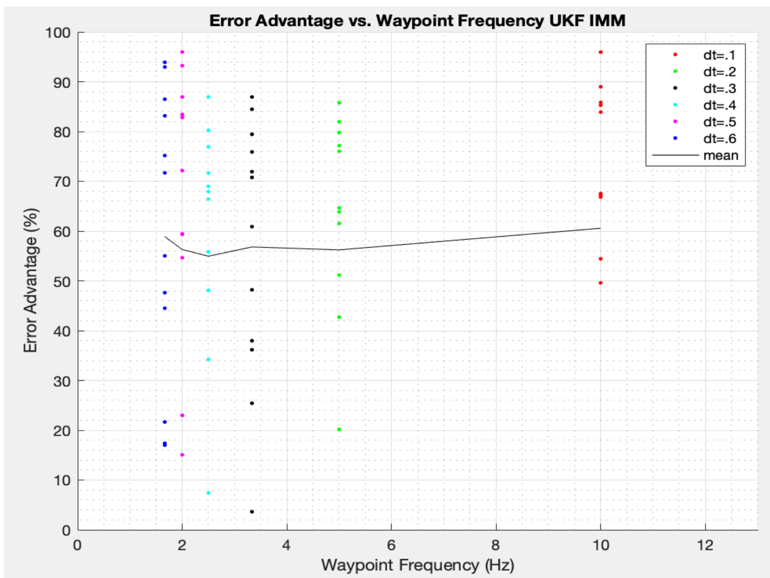
Waypoint Frequency Analysis

This project also tested the effect of waypoint frequency on the performance of the filters. A program ran the KF, EKF, and UKF IMMs while varying the time step of filtered predictions and corrections. Six frequencies were tested over 12 flight segments for each of the filters. The results from the optimal frequency test were taken into account when initializing the final IMM. Figures 7, 8, and 9 on the following page show the results of the waypoint frequency test.

Figures 7, 8, and 9







The intersection of a black line and vertical set of points is the average error advantage for the given waypoint frequency used for each iteration of that trial. The black line shows relative increases or decreases from trial to trial. While a waypoint frequency of 10 Hz (0.1 second time step in between measurements) provides the highest average error advantage over the 3 tracking filters, it comes at the cost of computational complexity. Reducing the waypoint frequency to 5 Hz (0.2 second time step) halves the required waypoints and only decreases average error advantage by 1.5%.

Regression Analysis of Flight Conditions

Before every flight, weather conditions were recorded to be used in a regression analysis. It was necessary to determine if specific conditions affected the incidence of sensor bias or drift error. Recorded conditions include temperature, pressure, wind speed, gust speed, humidity, and wind direction. For each flight segment, INS error and error advantage for each IMM were plotted against the recorded conditions. Microsoft Excel was used to generate least-squares regression lines to fit the data. An R^2 value close to 1 demonstrates a strong linear relationship, and a value close to 0 indicates a weak or nonexistent correlation. Table 3 summarizes the results. It can be seen that none of the R^2 values are greater than 0.1, indicating that there was no recognizable correlation between any of the weather variables and sensor or program performance. As such, no weather standardization adjustments to the final IMM are necessary.

Table 3

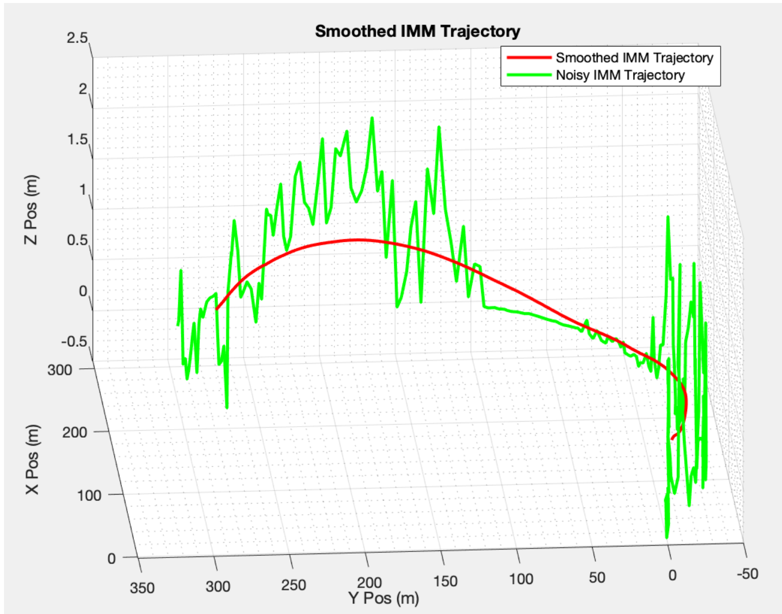
Flight Condition	Temper-ature (°F)	Pressure (inHg)	Wind Speed (mph)	Gust Speed (mph)	Humidity (%)	Head-wind Bearing (°)	Tail-wind Bearing (°)
R^2 for INS Error	0.0208	0.0996	0.0016	0.0712	0.0113	0.0022	0.0281
R^2 for KF IMM Error Advantage	0.0001	0.0134	0.0026	0.0164	0.0109	0.0502	0.0771
R^2 for EKF IMM Error Advantage	0.0117	0.0269	0.0213	0.0010	0.0100	0.0389	0.0291
R^2 for UKF IMM Error Advantage	0.0048	0.0110	0.0226	0.0000	0.0047	0.0018	0.1151

Final IMM

The final IMM program is a culmination of the aforementioned analyses of this project. It contains 7 different motion models: constant velocity KF, EKF, and UKF, constant acceleration KF, EKF, and UKF, and a constant turn EKF. The only inputs for the program are a 3D waypoint trajectory matrix and inertial data from the drone. The program first analyzes the inertial data for sensor bias and drift. Then, during the IMM prediction and correction loop process, the model iteratively accounts for inertial error. The output position matrix is smoothed to get rid of noisy estimates, and the result is the accurate trajectory of the drone. Waypoint analysis showed that a waypoint frequency of 5 Hz was ideal for each of the 3 filters, and regression analysis showed that weather conditions, even wind, have no significant effect on program accuracy.

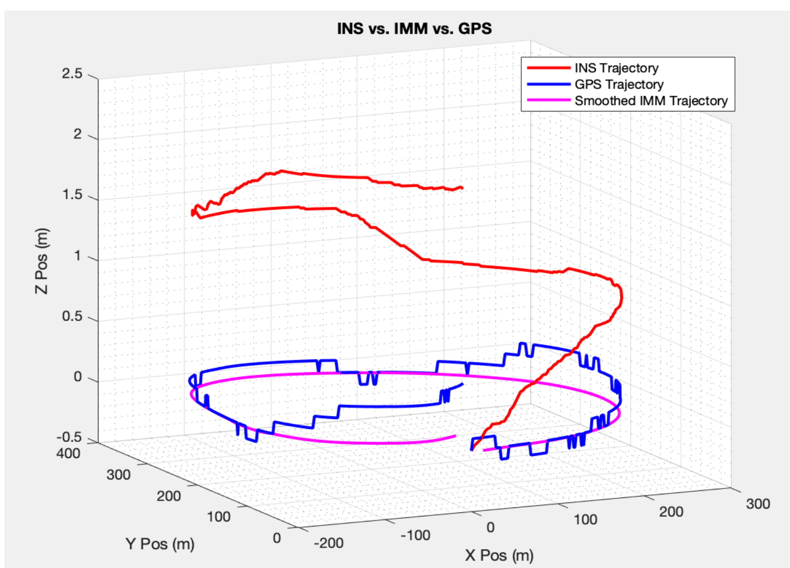
The program performed significantly better than the separate filter IMMs. There was an average error reduction of over 75% compared to the inertial trajectory (preliminary IMMs provided an average error reduction of about 57%). Furthermore, smoothing of the IMM estimated positions yields a reasonable trajectory. Figure 10 shows the effect of smoothing on the trajectory. The smoothing function takes a moving average of the position estimates, which removes noise from the estimates and improves the accuracy of the trajectory.

Figure 10



There is a considerable amount of noise in the GPS *z* axis measurements because they are taken with a barometric altimeter. This random variation is excluded when the IMM is smoothed, making the IMM *z* estimates more accurate than those of the GPS.

Figure 11



As expected, the INS trajectory steadily deviates over time due to drift error. Meanwhile, the IMM trajectory not only holds to the truth (GPS trajectory) but also improves upon it by not including the *z* axis noise.

Discussion

Summary

This research created a program to accurately track the trajectory of a drone in a GPS-denied environment. As long as a waypoint flight plan and inertial data are available, the designed IMM will determine the position of the drone. The original strategy for GPS-free navigation was by dead-reckoning, or integration of inertial data to produce position estimates. This method is unreliable because of the accumulation of drift error. The IMM created for this project fixes that problem by applying tracking filters that iteratively correct drift error. The program also constructs visual representations of the data, including Displacement vs. Time graphs, Normalized Error vs. Time graphs, INS, IMM and GPS Trajectory graphs, and Model Probabilities vs. Time graphs. Data used in these graphs come from output MATLAB matrices of the program.

Significance

This program can be used in the onboard navigation complexes of target drones in case of loss of GPS signal. Losing GPS signal is quite common, especially when drones are being used for military purposes. Signal jammers are often used to disrupt the GPS of aircraft, and the best solution is frequency hopping. However, synchronizing the transmitter and receiver is a major challenge for this strategy, so it is necessary for the drone to have a reliable GPS-free navigation method for instances of signal jamming or loss. Position accuracy for these drones is of paramount importance. They often fly close to manned aircraft to provide protection or in tight formation with other drones. Cole (2019) reported that there were over 250 Class II (150-600 kg) and Class III (600+ kg) drone crashes between 2009 and 2018. Safety is a big risk when drones are flying in civilian airspace. The program developed in this project will improve the safety of target drones, thus decreasing concern over their use. Target drones are incredibly beneficial to an air force because they are used for testing and help protect pilots of manned aircraft. It is necessary to make target drones safer so they can make the skies safer.

Limitations

The major limitation for this project is that inertial data was collected using a DJI Mavic Pro, a Class I (less than 150 kg) drone, because there was no access to a legitimate target drone. Target drones are almost always Class II and Class III, and bigger, stronger drones will undergo larger magnitudes of acceleration. As long as the inertial measurement unit on the drone can capture that acceleration, the program should still perform as well as it did in this project. Because the IMM runs 7 different motion models, it takes time for the model weights to adjust to fit the nature of the flight. When considering the Model Probability graphs (ex. Figure 3), it doesn’t take more than a few seconds for the IMM to converge on the proper model, which in turn makes the position estimate converge on the truth. So, even for larger drones with the capability of maneuvers with more extreme acceleration, as long as the drone isn't changing the nature of the flight (ex. acceleration, constant velocity, turning) over and over every few seconds, the IMM will shortly converge on the true position. Additionally, it's possible that there is correlation between weather conditions and sensor accuracy or program performance. This project didn't capture a wide range of weather conditions because all of the flights were performed in the same place at the same time of year. Research into the effects of more extreme weather conditions is necessary for the improvement of the program this project created.

Future Research

This research has the potential to be a useful tool in the aeronautical field. However, the IMM program should first be tested in target drones.

Beyond that, similar programs can be created that use other estimation filters such as the Alpha-Beta filter, Cubature Kalman filter, Gaussian-sum filter, or Particle filter. These filters required inputs that were not available in this research. Furthermore, fusion of other sensor measurements can be incorporated into the program to produce more accurate estimates.

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STUDENT

Certification

The Student, Teacher and Scientist Certifications are the last pages of the research paper.

Student Name: Jack Sendek School Name: Briarcliff High School

Please be as specific as possible in answering the following questions.

1. What steps led you to your hypothesis (where did you get the idea for your research)?

I got the idea on a call with my mentor. We were talking about signal jamming and he explained to me that aircraft use frequency hopping but that it's very difficult to sync the transmitter and receiver. I had read literature that discussed ways to trajectory track without GPS, and most of the proposed solutions required instruments like lasers that require line of sight or relied heavily on beacons or landmarks from the ground. I wanted to design a tool to track trajectory from the drone with no external aid.

2. Where did you conduct the major part of your work (home, school, other institutional setting, university lab, medical center, etc.)?

I conducted my research at home.

3. If you worked in an institutional setting, did you work on your project as part of a team/group? If YES, who was on the team (students, adult researchers, etc.) and what was your role?

N/A

4. Describe the parts of the research you did on your own and where you received help (literature search, hypothesis, experimental design, use of special equipment, gathering data, evaluation of data, statistical analysis, conclusions and preparation of written report (abstract and/or paper).

I found and read literature mostly on my own. My mentor sent me a few articles he thought I should read. I came up with my research questions and engineering goals with some guidance from my mentor. I gathered data, evaluated the data, wrote the program, drew conclusions and wrote the report on my own.

5. If this is a continuation of an investigation that was previously submitted to a Sub-Regional JSHS describe how you have expanded your investigation?

N/A

Student Signature (hand written) Jack Sendek

Date 11/9/2020

TEACHER
Certification

The Student, Teacher and Scientist Certifications are the last pages of the research paper.

Student Name: Jack Sendek

School Name: Briarcliff HS

Specific comments will help judges understand the student's motivation, independence, overall performance and your input in the selection process of this student's research.

1. **Originality, Motivation, Creativity, Ingenuity**: Discuss the student's role in identification and selection of the project; where he/she received help; i.e., literature search, hypothesis, experimental design, use of special equipment, gathering data, evaluation of data, statistical analysis, conclusions and preparation of written report – abstract and/or paper.

Jack was largely independent for his project. He spent a few months reading literature to narrow down his specific research topic: GPS-free navigation for drones. On calls with his mentor, Jack worked out his research question and engineering goals. He wrote his research plan, which was reviewed by me and his mentor. Jack performed data collection and analysis by himself at his house. Jack used the data he collected to optimize the MATLAB programs he wrote for his project. He taught himself MATLAB and wrote his own programs, which were reviewed by his mentor. He drew conclusions from his project and wrote his research paper

2. **Initiative:** The student's role if this was a team project, the nature of that team, i.e., other participants and the student's role on that team.

Individual project. Student completed all his own work.

3. **Other comments**: Regarding the student's investigation, independence, overall performance and motivation. This is your opportunity to give judges a ranking of your student versus other students.

Jack was very independent, and his work is excellent. He was self motivated and ranks in the top 10% of students that I have taught.

Teacher Name: Michael Inglis

Signature (hand written)

Date 11/13/2020

SCIENTIST MENTOR

Certification

The Student, Teacher and Scientist Certifications are the last pages of the research paper.

Student Name: Jack Sendek

School Name: Briarcliff High School

Your sharing of information reflects strongly on the student's performance.

1. State the origin of the project idea: Was it an assignment, chosen from a list of possibilities, the student's suggestion, or did it arise from discussion, continuation of previous work?

Jack's project was his suggestion. The origin of the project came after brainstorming over several areas of interest to Jack. Jack is interested in drones and unmanned technologies.

2. Did the student work on the project as a team member? If yes, please state the make-up of the team; i.e., whether they were students, professional researchers, etc. Please describe the student's role on the team.

Jack produced this project himself.

3. Estimate the student's level of dependence (0%) versus independence (100%) on each part of the project listed below. Example: For a student on a three member team who worked as a fully participating member, the answer would be 30-35%.

Experimental design	100 %	Gathering data	100 %
Choice of techniques	100 %	Evaluation of data	100 %
Use of special equipment	100 %	Results/discussion	100 %
Construction of equipment	100 %		

4. How many weeks was the student's research project at your institution? ~~52~~ 0

Jack did the project at home.

5. Indicate whether or not the student received a salary or other compensation for this research

☐ yes ☒ no If yes - dollar amount

6. Other comments

It was a pleasure mentoring Jack through this research.

Supervising Scientist: Brendan Rhatigan
Brendan Rhatigan

Email: rhatiganbt@gmail.com

Affiliation: Family Friend
Kratos Defense

Phone: 805-235-1152

Signature (hand-written):

Date: 11/16/2020