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2020

Pang, B., Ng, E. M. & Low, K. H. (2020). UAV trajectory estimation and deviation analysis for contingency management in urban environments. AIAA AVIATION 2020 FORUM, 1 PartF, 1-10. <https://dx.doi.org/10.2514/6.2020-2919>

<https://hdl.handle.net/10356/147357>

<https://doi.org/10.2514/6.2020-2919>

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UAV Trajectory Estimation and Deviation Analysis for Contingency Management in Urban Environments

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Contingency management of Unmanned Aircraft System (UAS) is an essential part of UAS Traffic Management (UTM). One of such contingencies is the loss of positional information due to weak or loss of Global Positioning System (GPS) signals, which will compromise the safety of the overall UTM system. This paper investigates the UAV trajectory estimation problem when GPS signal is weak or unavailable in urban environments. This research serves two purposes: Firstly, the study employed Extended Kalman Filter (EKF) to estimate the UAV true trajectory when GPS signal is intermittent or unavailable; Secondly, this work analyzed the deviations between pre-defined trajectory and estimated ones in different signal scenarios. The simulation results show that: (1) for uniform distribution of GPS signal, the estimated trajectory will deviate linearly with the decrease of signal density up until a density of 0.1hz and increase exponentially after that; and (2) for non-uniform distribution, the Gaussian distribution performed the worst, followed by random distribution and Sine distribution.

I. Introduction

The emergence of Unmanned Aircraft Vehicle (UAV) in urban environment is expected to fuel Urban Air Mobility (UAM) operations, transforming metropolitan airspace into a more complex airspace with myriad types of UAVs. In this regard, Unmanned Aircraft System (UAS) Traffic Management (UTM) will be essential for an ordered, safe and efficient operations of UAVs [1]. UAS contingency management, as a key part of UTM, plays an important role to deal with contingency situations (e.g. loss of control, communication and navigation lost, etc.) [2-5]. The contingency might be triggered by GPS signal loss, which the UAVs may encounter when the wireless satellite link in low urban airspace is blocked or interfered by physical obstacles or convective weather. Since onboard IMUs only provide rough navigation information for UAV operation, GPS signal loss may reduce the navigation accuracy of UAV, putting it in the risk of collision.

Currently, when a UAV experiences a contingency such as loss of telemetry, a pre-programmed procedure will be carried out by the UAV to either return to home position or land immediately. This procedure could be refined to land

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the UAV at the nearest available landing spot. However, in the event where GPS signal is weak or lost, it is very challenging to accurately predict the position of the landing spot relative to the UAV. To ensure that the UAV can fly to the landing point with an acceptable safety level, the trajectory estimation by the UAV should be carefully studied. More empirical research on the trajectory deviation of UAV under different GPS signal loss scenarios should also be conducted, so as to determine the safety boundaries for UAV contingency operations. This study can also support decision makers to determine the minimum density (amount and location) of contingency landing point required for safe operations. What's more, UTM system can also get information on occupation time period and airspace range that affected by this contingency, thus assisting decision making for airspace management, as well as rerouting or rescheduling for other UAV flight plans [6-7].

Current investigations on UAV trajectory estimation and deviation are fruitful. The UAV trajectory estimation for collision risk detection and resolution and also formation of UAV has been studied [8-9]. In their research, the assumption was made that GPS signal is available during all stages of flight. However, their assumption may not be tangible in urban environment, for GPS signal can be blocked by physical obstacles and interference. Weather is another important factor to interfere GPS signals, and it has been found that the GPS signal can be weak or completely lost when UAV encounter bad weathers [10-11]. To estimate the position of UAV when GPS signal is unavailable, there are few methods to do so. Kalman filter [12] as an effective method has been widely used for estimation problems, and extended Kalman filter method for dealing with non-linear estimation problems has also been explored in areas like state variables estimation [13-14], UAV location estimation [15], etc. Although existing research of UAV estimation have provided some good results, in urban environments, there are still research gaps which require further investigation.

The main contributions of this work are the UAV location estimation with different density of sample trajectory data and the analysis for the distribution of estimated trajectory deviation and error. This study will justify the allocation and distribution of contingency landing point for UAV in urban environment based on the deviation distribution of different signal loss scenarios, so as to satisfy the acceptable level of trajectory deviations and safety requirement.

The rest of the paper is structured as follows. The trajectory estimation problem is stated in Section II and Extended Kalman Filter method is formulated in Section III. Section IV presents the case study with several groups of simulation and results, followed by conclusions in Section V.

II. Problem Statement

GPS signal loss (intermittently or permanently) during drone operation in urban environment can be very dangerous. Without accurate navigation information, drones may have trouble in avoiding dense obstacles like high buildings and trees in urban airspace. GPS signal loss can happen due to many factors. Hence, accurately estimating the position of UAV and its trajectory becomes a pressing problem for safe drone operation, as well as for contingency management of UAS operations.

A pre-defined route (see **Fig. 1**) is determined at flight planning phase. The route can be seen as static trajectory of drone once it has been planned. GPS signal trajectory presents the full GPS signal is available, and intermittent GPS signal trajectory refers to drone trajectory with intermittent and discontinuous GPS signal availability. The lack of continuously accurate navigation information can give rise to situation such as drone deviating from pre-defined route, thus increasing risk of collision with obstacles. As Figure 1 shows that O-A segment is GPS trajectory which has little deviation with predefined one. Starting from point A, the signal becomes intermittent and its strength deteriorates progressively as the UAV moves to the emergency landing area.

In urban environment, the UAV may not be able to land immediately wherever and whenever the GPS signals are too weak to support operations, and the UAV will need to travel a distance passing non-landing area (see **Fig. 1**, red circle) (e.g. city square with crowded people, above road traffic, critical infrastructure, etc.) to arrive landing areas. The trajectory deviation (blue circle) will accumulate and rise as the distance travelled increases [16], and the risk will rise accordingly. Thus, it is important to investigate the trajectory deviation distribution characteristics and to find out the distance and time thresholds that the UAV can travel at an acceptable level of safety when GPS signal is intermittent or unavailable.

Fig. 1 Illustration of GPS signal lost in different scenarios

The deviation of EKF estimated trajectory from the predefined trajectory is mainly based on the quality of GPS data fed into the EKF method. Assuming an estimated trajectory consists of points of GPS data, it is reckoned that the higher density of data obtained will lead to less trajectory deviation. Thus, the UAV is able to travel longer and further at acceptable safety level, making the trajectory toward emergency landing point and “Home” point safer.

The trajectory deviation distribution depends mainly on the density of GPS data which may vary due to different situations in the urban environment. Basically, there are two types of intermittent data distribution: uniform distribution and non-uniform distribution. The uniform distribution of GPS data can be seen in situations such as constant poor GPS reception, intermittent satellite link, etc. **Fig. 2 (a)** demonstrates the uniform distribution of GPS signal. At time t , GPS signal will be available for a time interval of $f(t) = c$, followed by another interval of GPS unavailability of c , and the cycle repeats. The GPS signal may be obtained irregularly due to the uncertainties of physical blocks and interference; thus, the deviation distribution can be non-uniform. **Fig. 2 (b), (c), (d)** are Gaussian distribution, Sin distribution and random distribution respectively.

The EKF estimation results may be significantly influenced by the different types of distribution. To evaluate the influences, the estimation method will be first introduced, followed by simulations and experiments performed to verify the accuracy of estimation, and the influence of different distributions on trajectory deviation.

Fig. 2 Different distributions of GPS signal

III. Extended Kalman Filter Estimation Method

This section is to introduce the EKF estimation method and to analyze deviations between pre-defined trajectory and estimated one. Assuming the case uniformly intermittent GPS loss, the dataset of moving UAV's trajectory

is $\mathbf{P}_{Uni}$ and it contains the GPS position information $\mathbf{P}_t = (\mathbf{P}_t^{Lat}, \mathbf{P}_t^{Long})$ from $t = 1$ to $t = n$. Due to intermittent GPS signal, GPS data is only available uniformly at every odd moment of $t = 1, 3, \dots, t_n - 3, t_n - 1$ and unknown at even moment of $t = 2, \dots, t_n$ (Assume t_n is even). An assumption is made such that the position of drone remains constant during the absence of GPS data. Hence, the observed trajectory data will be $\widehat{\mathbf{P}}_{Uni} = \{\mathbf{P}_1, \widehat{\mathbf{P}}_2, \mathbf{P}_3, \widehat{\mathbf{P}}_4, \dots, \mathbf{P}_{t_n-1}, \widehat{\mathbf{P}}_{t_n}\} = \{\mathbf{P}_1, \mathbf{P}_1, \mathbf{P}_3, \mathbf{P}_3, \dots, \mathbf{P}_{t_n-1}, \mathbf{P}_{t_n-1}\}$.

The similar assumption is used for non-uniform distributions of trajectory set. E.g. in the case of Gaussian distribution, the unavailable GPS position will be regarded as same as the previous one, and the trajectory can be denoted as $\widehat{\mathbf{P}}_{Gau} = \{\mathbf{P}_1, \widehat{\mathbf{P}}_2, \widehat{\mathbf{P}}_3, \widehat{\mathbf{P}}_4, \mathbf{P}_5, \dots, \mathbf{P}_{t_n-1}, \widehat{\mathbf{P}}_{t_n}\} = \{\mathbf{P}_1, \mathbf{P}_1, \mathbf{P}_1, \mathbf{P}_1, \mathbf{P}_5, \dots, \mathbf{P}_{t_n-1}, \mathbf{P}_{t_n-1}\}$.

To analyze the deviation between observed trajectory and estimated one, the trajectory dataset $\mathbf{P}$ of different signal density will be firstly input into EKF for trajectory estimation. Once we have the estimated trajectories of different signal densities, we will be able to analyze the deviation. By doing so, the relationship of how trajectory deviation will be affected by different GPS signal densities can be captured.

Kalman Filter is a linear system state equation and observation equation [17-18], which is widely used to estimate the status of a system. Extended Kalman Filter, as an advancement of KF method, is able to estimate nonlinear system status. This paper will employ EKF method to estimate the UAV position when GPS signal weak or unavailable during operations. The input will be the trajectories with inaccurate position information obtained from weak onboard GPS or IMU. The output will be the estimated trajectory. After that, the deviation will be studied to see how the frequency of getting accurate GPS signal (i.e. the density of useful GPS signal) will affect the estimation results. Main functions of EKF [19] are denoted as:

$$\mathbf{X}(k+1) = \mathbf{A}(k)\mathbf{X}(k) + \mathbf{T}(k)\mathbf{W}(k) \quad (1)$$

$$\mathbf{Z}(k) = \mathbf{H}(k)\mathbf{X}(k) + \mathbf{V}(k) \quad (2)$$

$$\mathbf{J} = \mathbf{E}[(x_{k+1} - x_{k+1}')](x_{k+1} - x_{k+1}')^T \quad (3)$$

$$\mathbf{X}(k+1, k+1) = \mathbf{X}(k+1, k) + \mathbf{K}(k+1)[\mathbf{Z}(k+1) - \mathbf{Z}(k+1, k)] \quad (4)$$

where $\mathbf{X}(k+1)$ represents the status value at $k+1$ moment; $\mathbf{X}(k)$ is the system state vector, representing the state vector of moving object at k moment. $\mathbf{A}(k)$ is the state-transition matrix, presenting state transition way from previous moment to current moment; $\mathbf{T}(k)$ is the interference transition matrix; $\mathbf{W}(k)$ is the state noise of dynamic model, assuming it aligns with Gaussian distribution. $\mathbf{Z}(k)$ stands for observation vector; $\mathbf{H}(k)$ presents observation matrix; $\mathbf{V}(k)$ is observation noise. x_{k+1}' means the best estimation value of this state. $\mathbf{K}(k+1)$ is the Kalman Gain at moment of $k+1$.

The estimation deviation between predefined trajectory and estimated trajectory can be denoted as:

$$D_{Lat(i)} = (Lat_i' - Lat_i) \quad (5)$$

$$D_{Long(i)} = (Long_i' - Long_i) \quad (6)$$

where, $D_{Lat(i)}$ is latitude estimation deviation; $D_{Long(i)}$ is longitude estimation deviation; $(Lat_i, Long_i)$ is the position of pre-defined trajectory; $(Lat_i', Long_i')$ is the position of estimated trajectory.

The estimation error then can be calculated by Root-Mean-Square Error (RMSE), denoted as:

$$RMSE = \frac{1}{K} \sum_i^K \sqrt{(x_i' - x_i)^2 + (y_i' - y_i)^2} \quad (7)$$

where (x_i, y_i) is the position in the predefined trajectory; (x_i', y_i') is the position in the estimated trajectory.

IV. Case Studies

In the previous sections, the workflow for estimating trajectory deviation and analyzing estimation error were presented. In this section, the feasibility and performance of proposed method will be validated by simulation studies.

A. Data Set

For the purpose of data collection, the author has flown an UAV through a set of predefined waypoints. The experiment was carried out at a big open plain at Old Holland Road, Singapore (Lat: 1.329285, Long: 103.785053), using a DJI Mavic 2 Zoom. Flight trajectory data was then extracted from the flight logs and used for analysis. **Fig. 3** shows the GPS-fused trajectory of the UAV.

Fig. 3 Historical GPS signal trajectory

To simulate the situation with weak GPS, the original GPS-fused trajectory data was down-sampled to obtain data with lower signal density. As mentioned in the previous section, different down-sampling distribution is done using uniform and non-uniform distribution. The UAV's true trajectory is then estimated using the down-sampled data. For comparison purposes, the original GPS-fused trajectory data is used as the reference value.

B. Uniform Distribution

For uniform distributed sampling, the data was down-sampled at fixed intervals. The respective trajectories and their deviation from the reference value are shown in **Fig. 4**, while detailed information of the deviation is presented in Table A1 (see Appendix A). This simulates a constant but weaker GPS signal strength, and hence a lower signal density. The original trajectory sampling rate is 10hz. The legend indicates the sampling ratio, i.e. 0.01 is 0.01 times the original sampling rate, which is 0.1hz.

(a). Latitude trajectories and deviations

Fig. 4 Estimated trajectories and deviations by uniform distribution of data

C. Non-uniform Distribution

For non-uniform distribution, the data was sampled at varying intervals. The respective trajectories and their deviation from the reference value are shown in **Fig. 5**, and detailed information of the deviation is showed in Table A2 (see Appendix A). This simulates a varying GPS-signal strength, where signal density is either random or dependent on stage of flight. The legend indicates the different distribution used for the sampling intervals.

Fig. 5 Estimated trajectories and deviations by non-uniform distribution of data

From latitude and longitude perspectives, **Fig. 4** and **Fig. 5** show that the estimated trajectories and deviations in terms of uniform and non-uniform GPS signal distribution. **Fig. 6** presents pre-defined GPS trajectory and trajectories estimated by receiving different GPS signal data distribution. It also shows that the deviation of estimated trajectory will be greater in these status changing points (e.g. turning point), compared with straight-route flight.

Fig. 6 Trajectories with different GPS signal distribution

D. Result Analysis and Discussion

Based on the preliminary results, the deviation of the UAV's estimated trajectory has been determined. Fig. 7 and Table 1 show the means and standard deviations of the estimated UAV's longitudinal and latitudinal position of the trajectory. For uniform distribution, the standard deviation is low up until the sampling ratio of 0.05. For non-uniform distribution, the standard deviations of all cases are high, and performed worse than the uniform distribution at sampling ratio of 0.05.

The preliminary results suggest that the UAV estimated trajectory will be relatively accurate up as long as it received more than 5% of the GPS signal, provided that the GPS-signal are uniformly distributed.

Fig. 7 Average deviation of latitude and longitude

Table 1. RSME results of different data densities

Type	Density	RSME (10^{-5})
Uniform Distribution	1.00	0.4517
	0.70	1.8187
	0.50	1.9798
	0.30	2.1645
	0.10	3.0112
	0.05	3.3251
	0.03	5.4256
	0.02	8.7995
	0.01	12.8216
Non-uniform Distribution	Gaussian	6.7695
	Sine	5.5511
	Random	5.5718

V. Concluding Remarks

This paper is concerned with the problems of UAV trajectory estimation and deviation analysis. Different distribution patterns of intermittent GPS signal have been considered and presented as uniform and non-uniform. Extended Kalman Filter model was then developed and employed for UAV trajectory estimations in terms of the different patterns obtained. Simulation results show that the proposed method is able to predict UAV's trajectory in a tolerable level when it receives more than 5% of the original GPS signal, provided that the GPS-signal is uniformly distributed over time. While the performance of the method will deteriorate when non-uniform distributed GPS signals are ingested into the method over time. This study will help to determine geo-fencing area range and duration caused by UAV contingency of GPS signal lost.

Appendix: Tabulated results of Fig. 3 and Fig. 4

Table A1. Deviation of UAV position for uniform distribution

Density	Latitude		Longitude	
	Mean	Standard Dev.	Mean	Standard Dev.
	10^{-5}	10^{-5}	10^{-5}	10^{-5}
1	1.3547	1.2053	1.4479	1.1365
0.7	1.4668	1.2156	1.6696	1.237
0.5	1.524	1.4176	1.6697	1.2351
0.3	1.5174	1.5731	1.9038	1.4461
0.1	2.1461	2.4027	2.3992	1.7868
0.05	3.0001	3.2712	2.459	1.9065
0.03	5.2677	4.3548	4.2132	3.024
0.02	8.7705	4.7255	7.2988	4.9076
0.01	12.1695	6.4671	10.1618	7.0796
Average	4.1352	2.9592	3.6914	2.6399

Table A2. Deviation of UAV position for non-uniform distribution

Density	Latitude		Longitude	
	Mean	Standard Dev.	Mean	Standard Dev.
	10^{-5}	10^{-5}	10^{-5}	10^{-5}
0.03	5.2677	4.3548	4.2132	3.024
Gaussian	5.3833	3.4613	6.1153	5.2223
Sin	5.2567	3.5095	3.8948	3.4373
Random	5.2158	3.5297	3.895	3.4994
Average	5.3026	3.7752	4.7411	3.8945

Acknowledgments

The authors would like to thank Mr. Chan Yang Jie Elliot and Dr. Wang Chung-Hung John for their valuable advice and technical support during the data collection process. The authors would also like to convey their gratitude for other research staff in the UAS Programme at the NTU's ATMRI for their valuable feedbacks and suggestions. The support by the ATMRI's UAS Programme throughout the tenure of the present work is greatly appreciated.

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