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Data Analysis on Track Deviation of UAS Operating under Visual Line of Sight (VLoS) Conditions

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The management of collision risk posed by recreational unmanned aerial systems (UAS) intruding into controlled airspace is becoming more critical with the surge in accessibility and popularity of these UAS. Risk mitigation actions that could be taken by the airport operators currently are limited by the lack of reliable UAS detection equipment, which limits their ability to track UAS positions over time and predict the collision risks posed by the UAS. While recent developments in airborne collision prevention of manned aircraft could utilize Markov Decision Process with state probabilities based on historical flight track records and processed using Bayesian Network, this method is not suitable for the off-nominal case of UAS intrusion into controlled airspace. Instead, the prediction of collision risk posed by non-cooperative recreational UAS have to rely on the assumption of worst-case intention, where the UAS aims for the aircraft operating within the aerodrome, and the Reich collision risk model to generate the probable distribution of future UAS positions. This paper documents a series of flight test to simulate such scenario with a UAS operating under visual line of sight condition while aiming for an imaginary three dimensional target in the air. The data was analyzed for the deviation in UAS positions at fixed time interval in the (horizontal) longitudinal and lateral direction, as well as the deviation in altitude. A comparison between the observed deviation and a Monte-Carlo based UAS path prediction following the UAS flight dynamic model were also conducted.

I. Introduction

Recent years have seen an increased instances of unmanned aerial systems (UAS) inside the airport airspace, either through intentional or accidental intrusion [1–3] by recreational pilots or permitted operations such as video survey or runway inspection [4]. As the higher density of air traffic within the aerodrome airspace meant a higher potential for the paths of UAS and manned aircraft aircraft to intersect, risk assessments would need to account for the collision risk posed by different types of UAS traffics.

The UAS traffic operating within the aerodrome airspace could be separated into two main categories: cooperative UAS operations, which maintain two-way communication with the air traffic controller, and non-cooperative operations, which do not. For the former, the collision risk could typically be managed by the ATC through issuing route assignment with sufficient temporal or spatial separations (tactical collision avoidance) and by dictating mitigation action for all traffics, manned and unmanned, if safe separation is lost (operational collision avoidance); for the latter, the management of collision risks depends on the information available to the ATC, e.g. the position, direction of travel, and speed of the intruding traffic. With non-cooperative intruders, the risk could be mitigated with the ATC moving cooperative traffic out of the way of the intruder using its last known position and predicted future path or, in the case of UAS intrusion into the aerodrome where the consequence of a collision is high, by shutting down air traffic operations within the airspace until the intruder no longer poses a threat.

Risk management for both cooperative and non-cooperative UAS traffic would require the ATC to have some method of estimating the airspace that could be occupied by the vehicles in near future. This could be achieved by using the available intent information of the vehicle, such as the declared destination by the operator or waypoint based on filed flight plans, and the possible deviation from the intended path, either through environmental factors or navigational

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errors. This paper presents a compilation of flight test data used to obtain the deviation from intended track for the case of visual line-of-sight UAS operation towards a virtual 3D target within the airspace.

II. Literature Review

The management of collision risk within the aerodrome airspace largely depends on the operation conditions and the associated airspace regulations. For example, collision avoidance in uncontrolled aerodrome between aircraft without ADS-B transponder would depend on radio call-outs from the pilots while maintaining visual separation; on the other hand, collision avoidance in controlled aerodrome under instrument flight rule (IFR) conditions would depend on the ATC prescribing safe separation distance based on navigation performance of each aircraft [5]. With the forecasting of increase in air traffic load in the coming years, however, the NextGen concept aims to remove many of the constraints from the current system while maintaining safety by leveraging advancement in navigation technology and collision prediction, as in the case of the Low Altitude Conflict Monitor (LACM) concept [6]. The LACM is based, conceptually, on the TCAS II implementation, though with significant changes in the data acquisition, collision prediction, and the type and threshold for alerts.

The collision prediction method used in the LACM concept and the TCAS II implementation is based on the ACAS II standard, which utilizes the closest point of approach (CPA) method to determine if a collision is expected to happen based on the current speed and heading of the traffics involved [7]. On the other hand, en-route separation requirements for flight corridor design were based on probabilistic collision risk analysis, i.e. the Reich Collision Risk Model, that estimate the aircraft deviation from nominal track using flight data derived distribution function [8]. More recently, collision probability contour inspired by LACM were constructed to inform the ATC of the threat level posed by an intruding, non-cooperative UAS, in which the probable track of the intruding UAS was modeled with Monte-Carlo simulation using the flight dynamics of the UAS, an assumed worst-case intention, and an assumed variance for a randomized input, e.g. thrust for Ref. [9] and target direction for Ref. [10].

In terms of unmanned traffic management, similarities could be drawn between visual flight rule (VFR) traffic and cooperative UAS traffic if operating under visual-line-of-sight (VLoS) condition, while cooperative UAS equipped with the necessary transponders could be managed similarly to IFR traffic for VLoS or even beyond-visual-line-of-sight (BVLoS) operations. The collision risk prediction for the cooperative traffic would thus depend on the communication responsiveness of the operator and the navigation performance of the UAS. On the other hand, non-cooperative UAS, regardless of the detection capabilities available to the ATC, would need to be treated as airborne hazard (off-nominal operation), similar to an intruding bird flock, as the communication of operator intent is needed to determine if the traffic is performing nominal or off-nominal operations. In the case of off-nominal operations, either for non-cooperative UAS traffic or cooperative UAS operation where the operator no longer has control over the UAS, the path projection for the UAS could no longer depend on the previously stated/assumed intent nor could the track deviation derived from historical flight data be used. Instead, the worst-case assumption of the UAS intending to crash into other traffic via the most direct path would be needed to minimize collision risk.

The problem of measuring UAS deviation from intended track towards a virtual target in 3D space under visual-line-of-sight condition is analogous to the deviation measurement for the human compensatory tracking task [11], though with the added delay in visual-feedback due to the command transmission time and flight control response time more similar to that of human bombs [12, 13]. This is different from the measurement of deviation from track under first-person view (FPV) condition, which is more similar to the pursuit tracking task [11, 14]. The unaided radio-guided azimuth-only “AZON” bombs results reported by Anthony et al. [12] showed a mean aiming error of 1.7 mil (micro-radian) and a mean oscillatory error of 1.65 mil over a distance of 15,000 ft (with a total travel time of *sim*20 s), while tests with wire-guided TOW missile reported by Penetar et al. [13] showed a mean tracking error of 0.446 mil with horizontal and vertical standard deviation of 0.138 mil and 0.112 mil, respectively, over a distance of 2,000 m (with a total travel time of ~ 10 s).

III. Flight Test Setup

The flight test was conducted at the grass field between Old Holland Road and Holland Plain in Bukit Timah, Singapore (see Fig. 1) on September 10 and 13, 2019. The aerial vehicle used was a DJI Mavic 2 Zoom operated by a novice pilot, which might have contributed to the observed deviation from the intended track.

The flights were conducted by first identifying a target direction using visual landmark and fly the UAS in that direction for a distance of 200 meters and ascend to a height of 20 meters, as displayed on the remote-controller. This

position of the UAS would be memorized by the pilot as the target position for the subsequent, recorded, test flights. Each test flights were conducted close to the “Home” position in front of the pilot, and fly towards the target position as fast as possible using only the throttle, elevator, and yaw control. The roll control were not used as it made staying on track harder.

Fig. 1 Google map satellite image of the flight test site between Old Holland Road and Holland Plain in Singapore. Blue line is the intended track for Test 1 (Sept. 10, 2019) and red line marks the path for Test 2 (Sept. 13, 2019).

The GPS positions and velocity of the UAS were logged as a part of the DJI Go Mobile Application, and the reported GPS health were at level 5 (the highest level) for the entirety of the tests. The wind conditions on the day of the flight tests, derived from the difference between speed reported by GPS and IMU, are light with variable direction as shown in Table 1. A total of 22 flight tracks were recorded, with 8 on September 10, 2019 (Test 1), and 14 more on September 13, 2019 (Test 2). The processed track data are presented in Section IV. Note that tracks 1-4 from Test 1 were logged individually with the UAS powered down and reset between each flights, and tracks 5-8 on the same day were logged sequentially; all flight tracks from Test 2 were logged sequentially within a single takeoff/landing cycle. As a consequence, larger drift in reported positions could be expected in the flight data from Test 2.

Table 1 Wind Conditions

	Test 1	Test 2
Magnitude (Mean, m/s)	0.6975	0.6247
Magnitude (σ , m/s)	0.5323	0.5403
Direction (Mean, degree)	182.2002	177.1446
Direction (σ , degree)	52.2507	50.0753

IV. Track Data, Analysis, and Discussion

A. Track Data

The raw GPS output from the flight tracks are presented in Figs. 2(a) and 3(a), while the initial and final position from each flight is shown in Figs. 2(b) and 3(b).

(a) Test 1, Tracks

(b) Test 1, Initial and Final Positions

Fig. 2 The (a) flight paths and (b) initial/final position for each tracks from Test 1.

The flight data from Test 1 showed two distinct groupings of the final positions with a gap of ~ 16 meters in the longitudinal direction between the closest end-positions: the group that traveled further consists of Tracks 2, 4, 6, and 7. The hypothesis that the different grouping is due to pilot mis-remembering the visual reference used for the target point was discounted as tracks 2 and 4 were flown independently from tracks 5-8, which were flown consecutively without landing the aircraft and reset the sensors. Another hypothesis is that the cluster of flights with shorter distance from the origin experienced stronger head or side winds, leading to more direction changes to remain on track. However, individual view of the track also did not show more zigzagging for the track with end-positions closer to the “Home” position comparing to the other group of tracks. Additionally, the difference between the maximum headwind (0.69 m/s along track) and tailwind (no wind) would result in a maximum difference of ~ 10.5 m over the 15 s flight time not accounting for the difference between mean wind direction (from 2.2°) and the track heading (37.5° from the North). The end positions could also be a part of a normal-random distribution, and the appearance of the gap is a consequence of the small number of sample size. Ultimately, the difference might be due to the cumulation of the above factors that could be categorized as “Navigational Errors.”

Fig. 3 The (a) flight paths and (b) initial/final position for each tracks from Test 2.

Similarly, the end-position data from the Test 2 flight showed a small, slanted gap of ~ 11 m running roughly along the mean wind direction. This dataset also showed a larger lateral track deviation closer to the $t = 15$ s end-time. Note that the pilot reported difficulties with identifying the orientation of the UAS at > 100 m from the origin, and would instead rely on the movement of the UAS to decide if controller-input is needed to return the UAS on track; the time delay between controller-input and UAS turning could have partially contributed to the deviation. Another contributing factor might be the direction of the wind, as the flight from Test 1 experienced mostly side-wind from a consistent direction (left of the track) while those in Test 2 experienced mostly tailwind with more variability in the directions that the UAS was being pushed.

The two sets of track data were consolidated by first setting the mean initial position as the point of origin and the mean final position as the target position, then rotate the tracks so the path to the target positions aligned. The histogram of the longitudinal (horizontal projection, along track direction), lateral (horizontal projection, normal to track direction), and height distribution from the flight tracks are presented in Fig. 4. Note that negative height values were reported by the UAS altimeter, which might have been caused by several factors: the “Home” position of the UAS were set at ~ 2 m above the takeoff point, while several tracks started out at knee level of the pilot; the test field slopes downward from the norther edge; and possible altimeter value drift for tracks that were taken consecutively instead of powering down the UAS and re-calibrate the instruments between each flights.

Fig. 4 Histogram distribution of the consolidated UAS positions at the start and end of each flight.

B. Normality of the UAS Track Deviations

The next step following the consolidation of the track data was to check for the normality of the UAS distributions at different time stamps. If these distribution fits a normal distribution, the track of the UAS over time could then be modeled using the mean and standard deviation (S.D. or σ). The Lilliefors test for normality for unknown mean and variance with revised table for critical value [15] were used due to the small sample size ($n = 22$) and the ease of implementation. A sample of the cumulative distribution function (CDF) fit between the flight data at $t = 15$ s and idealized normal distribution is presented in Fig. 5.

Fig. 5 Cumulative Distribution Function (CDF) of idealized normal distribution and the empirical distribution from the flight tests plotted against the corresponding Lilliefors Z-Score.

The Lilliefors test value $L = \max(|S_i - N_i|)$, where N_i is the CDF value for idealized normal distribution that corresponds to the Lilliefors Z-Score $Z_i = (X_i - \bar{X})/\sigma(X)$, and S_i is the empirical distribution of the Z_i . The Lilliefors test values for the UAS position distribution at $t = 0, 5, 10$, and 15 s are presented in Table 2.

Table 2 Lilliefors Test Values for UAS Distributions, the critical value for $n = 22$ and $\alpha = 0.05$ is 0.184

Sample Time (s)	Longitudinal	Lateral	Height
0	0.1596	0.1325	0.1839
5	0.1716	0.1461	0.2379
10	0.1734	0.1272	0.1359
15	0.1175	0.1385	0.1297

The results showed that the horizontal projection of the UAS positions could be treated as normally distributed to the confidence level of 0.05 based on the Lilliefors Test, while the use of normal distribution to represent the height distribution of the UAS for the first half of the flight would not be appropriate*. The mean values of the UAS horizontal positions at $t = 0, 5, 10$, and 15 s are shown in Fig. 6, while the standard deviation over time for the longitudinal and lateral positions are shown in Fig. 7. The mean and standard deviation of UAS height over mean longitudinal travel distance are shown in Fig. 8.

*The pilot reported that it is easier to follow visual reference along the tree line at the beginning of the flight before correcting for the elevation of the UAS.

Fig. 6 Mean value of the track in the longitudinal and lateral direction over time.

Fig. 7 Standard Deviation (S.D.) of the track in the longitudinal and lateral direction over time.

Fig. 8 Mean and Standard Deviation (S.D.) value of the UAS height over the mean longitudinal travel distance.

At first glance, the pilot appears to be much more proficient in maintaining the lateral deviation than originally assumed ($\sigma_{yaw}^2 = 0.2^2 * 180^\circ = 7.2^\circ$) in Ref. [9] and [10], at least for the distance tested. While simulation of the UAS position-distribution using the 3D CRM code from Ref. [10] showed a more concentrated distribution than the dotted line in Fig. 7(b) due to the inclusion of target waypoint, as shown in Fig. 9, the lateral standard deviation is still more than twice of those from the flight tests. The simulation was conducted using 100 samples with the target (intersect) position set to (200, 0) and the UAS starting from rest, and the longitudinal and lateral distribution for each of the output times were shown in Table 3. A wind field with $\bar{V}_{wind} = 0.01$ m/s, $\sigma_{wind} = 0.54$ m/s, $\bar{\theta}_{wind} = 198^\circ$, and $\sigma_{\theta_{wind}} = 50.15^\circ$ were also included.

Fig. 9 Horizontal projection of UAS (using Mavic 2 performance specifications) positions generated with the 3D CRM code from Ref. [10] for $t = 0, 5, 10, 15$ s (from left to right) with (square) and without (circle) target waypoint.

Table 3 Standard deviation of the simulated UAS samples at fixed sample period of 5 s.

Sample Time (s)	With Waypoint			Without Waypoint		
	Longitudinal	Lateral	Height	Longitudinal	Lateral	Height
5	5.7174	5.6929	2.5304	5.4092	5.6754	2.4105
10	6.4214	8.0560	3.2924	7.4430	7.7181	3.3061
15	5.2102	9.3581	3.1143	8.3434	9.3295	3.3154

The results suggests that it might be appropriate to further reduce the variance used to represent the navigational error, in both the lateral (yaw) and vertical (elevation) direction, by a factor of 0.5 in the simulation code, at least for this particular UAS model and the distance to target from the flight tests. It also showed that the mean longitudinal distance traveled by the UAS from simulation is mostly inline with the flight test data, suggesting that the travel distance might have been limited by the hardware and flight dynamics of the aircraft. It should be noted that the flight test only involved a single pilot, and pilot experience might contribute to the track deviation as in the case of [12].

V. Conclusion

Flight tests were performed with a DJI Mavic 2 Zoom for 15 seconds per track over two separate sessions to collect the track deviations associated with flying a UAS towards a virtual 3D target with the goal of intersecting said target point. The flight data were consolidated by aligning the mean flight paths, and the distribution of the UAS position at $t = 0, 5, 10$, and 15 s were collected and the Lilliefors test for normality was performed on the data. The resulting mean and standard deviation of the flight test data were than compared with the data generated using vehicle-performance based Monte-Carlo simulation using a “random navigational error” of $\sigma_{yaw}^2 = 7.2^\circ$ and $\sigma_{elevation}^2 = 3.6^\circ$. The results showed that the observed track deviation for flights under visual-line-of-sight condition towards a target in 3D space is much smaller than the expected values used in the simulation, though still larger than the deviation observed in human-guided missile or bomb (pursuit-tracking tasks) operated by experienced users. The difference in deviation from the flight tests and pursuit-tracking tasks could be due to differences in flight dynamics. While the flight test could be used to

provide some guidance for setting the variance for probabilistic deviation for the path prediction of UAS flights with the intention to intersect a 3D waypoint, the recorded deviation could be specific to the environmental conditions, ambient light level, and pilot experience level, thus limiting its generalizability.

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