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Investigation and Modeling of Flight Technical Error (FTE) Associated with UAS Operating with and without Pilot Guidance

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Abstract—With the increasing interest in the utilization of urban airspace for unmanned aerial system (UAS) operations, be it for cargo delivery or passenger transportation, the future city sky could become quite a crowded place if all those visions become reality. In such case, the question of how close two operations could be conducted while sharing an airspace must be answered to ensure the safe and efficient use of the urban airspace. The lateral separation needed to prevent inadvertent intrusion by neighboring tracks is especially important when designing airspace corridors constrained by the urban landscape. This paper documents a series of flight tests conducted in open fields with the goal of assessing the along-track (longitudinal), cross-track (lateral), and altitude (height) deviation under two different flight conditions: operator guided operation within Visual Line of Sight (VLoS), and the waypoint-guided mission analogous to operating Beyond Visual Line of Sight (BVLoS). The flight test statistics were also compared to the Monte-Carlo based path prediction model that was used in earlier studies for collision prediction. The goal is to determine the Flight Technical Error (FTE) that forms a part of the Total System Error (TSE) for Performance Based Navigation (PBN) of UAS to support the establishment of separation requirements in urban airspace.

I. INTRODUCTION

With an increase in urban population and the associated increase in traffic congestion, people look upwards for the future of urban transportation. Major multinational companies such as Google [1], Uber [2], and even aviation giants like Boeing [3] and Airbus [4] have presented concepts for urban mobility or delivery solutions based on autonomous, vertical takeoff and landing (VTOL) capable, multi-rotor vehicles to navigate the confined urban airspace. With the expected increase in urban air traffic, the sophistication of the UAS Traffic Management (UTM) must also improve as well to ensure the safety of the vehicles, the goods and passengers, and the third-parties on the ground. In other words, the current system of offering limited airspace to commercial UAS operators and requires approval on a case-by-case basis otherwise, e.g. FAA Part 107 waivers, would no longer be feasible to cope with

the expected number of applications while providing timely approval.

Aircraft operations could be generally categorized under visual flight rules (VFR) and instrument flight rules (IFR), each requires different considerations when managing various airspace classifications. When translated to UAS, the detect and avoid (DAA) functionality has been proposed as a substitution under VFR for the role of the pilot to provide separation assurance (Well-Clear), while the wider (in terms of geographic area) application of UAS, e.g. for international flight, would fall under IFR as proposed in ICAO 2017 Concept of Operation (ConOps) [5], though the DAA system is still expected to perform automated collision avoidance in the case of failure, e.g. the loss of command and control (C2) link. The DAA technology is rapidly evolving and the definition for determining Well-Clear for both large [6]–[9] and small [10]–[12] UAS remains under intense research. On the other hand, there are relatively sparse research [13], [14] to support separation assurance criterion needed to conduct IFR-like operation in UTM airspace, which include the evaluation of separation requirements for same track, cross-track, and parallel track traffics.

One method of managing the risks associated with UAS operations is to utilize a waypoint based airspace corridor system [15], [16], similar to the ATS route for manned aviation. The separation requirements for these flight corridors in the highly constrained urban airspace as well as the manned-unmanned mix-use airspace near aerodromes would require a better understanding of the deviation associated with different type of UAS operations. The capabilities or performance of the DAA system meant as substitute for pilot in VFR would not be relevant under this IFR-like arrangement within normal operation conditions. Two types of currently practicable urban UTM operations are of particular interest: the human-guided visual line of sight (VLoS) operations, where the operator

maintain full control of the UAS movements from one point to another, and the satellite navigation-guided waypoint based operation that could be operated with or without human operator's direct supervision. The navigation-instruments guided operations without direct (line-of-sight) supervision by human operators could be considered as beyond visual line of sight (BVLoS), though the UAS track deviation should be identical to those under direct human supervision and did not involve operator intervention.

The total system error associated with the aircraft deviation from the desired track could be broken down into three components for the performance based navigation (PBN) concept [17]: the path definition error (PDE), the flight technical error (FTE), and the navigation system error (NSE). Flight test using two different guidance methods were carried out as a part of this paper, with the goal of measuring the UAS deviation between its reported positions and its desired positions, or more specifically the FTE. This is because the PDE stems from the difference between the desired path and the path traced from the published waypoints, which is not applicable to this study, and the NSE is based on the difference between the actual and the reported positions, specifically the error between the navigation data reported by the sensors and the actual position of the aircraft. An overview of the flight test location and flight conditions is presented in Sec. III, the UAS position traces from the flight test data presented in Sec. IV, which also contains the statistical analysis of the flight data. Sec. IV-C also presents the simulated probabilistic UAS distributions using the path prediction models from previous UAS collision risk assessment studies [18], with the results compared with the flight test data to determine future improvements for the models. Note that as evaluating the NSE component of the track deviation requires high accuracy instruments such as RTK, only the FTE component of track deviation is collected and analyzed. The VLoS flight data and some of the data analysis were presented in Ref. [19].

II. LITERATURE REVIEW

The determination and enforcement of separation minima to ensure the safe aircraft operation in a given airspace depends on three factors: how well can the aircraft identify its position on the air-chart, how well could the aircraft operators or the air traffic controllers (ATC) identifies traffics using the airspace, and how long it would take for the operators and/or ATC to communicate and mitigate a potential conflict in air traffic. Together, these three factors are known as the Communication, Navigation, and Surveillance (CNS) performance. For civil aviation operations with known surveillance and communication capabilities in a controlled airspace, where the tactical separation assurance (maintianance of separation minima) and collision prevention provided by the ATC with the TCAS system acting as a fail-safe [20], the minimum navigation capability that the aircraft must have is known as the Required Navigational Performance (RNP) in the Performance Based Navigation (PBN) concept [17].

A. Determination of Separation Requirements

When applied to air operations, the RNP and communication interval length play important roles in the determination of the separation minima, the time or distance based requirements for tactical separation, for along-track or close-parallel tracks traffics [21], while the cross-track tolerance of the aircraft (identical to PBN Total System Error for GNSS-based navigation) would contribute to the determination of the spacing between parallel routes to meet strategic separation requirements [22]. For the former, the derivation of separation minima is conducted using the Reich collision risk model [23] using a combination of probabilistic analysis or Monte-Carlo simulation and historical air traffic trajectory data (Appendix 1, Ref. [21]); similar approach was initially used for the latter (Appendix 4, Ref. [21]), though more recent regulations on en-route track separation utilize the assigned RNP value for the airspace as basis for the separation requirement instead (Att A, 3.2, Ref. [22]).

Note that the collision risk modeling conducted by ICAO and the various civil aviation agencies typically use double-double-exponential function (though Gaussian-) to describe the position distribution of the aircraft from its assigned track. The two segment of the distribution functions could represent the variation in positions due to nominal and accidental cause [24], or more recently simply termed the core and tail/non-core) section [25], [26]. The distribution parameters are typically obtained by simple data fitting given the large number of position data available, though visual (via direct or quartile-quartile plot) and χ^2 tests has historically been used [24], [27], [28].

The original collision risk model developed by Marks [29] and Reich [23] were further combined with the 2D Gas model for randomized collision risk to form the 3D Gas Model [30] that was adapted into the MIT Lincoln Lab's aircraft encounter model [31], a building block for the ACAS X collision prediction and resolution algorithm [32]. More recently, this 3D Gas Model was adapted for the estimation of UAS collision in the BUBBLE project under SESAR [14]. The Reich collision risk model concept was also adapted, with the addition of kinematic limited randomized agent movements, for UAS collision risk studies under ATMRI [33], [34]. Ultimately, whether the probability distribution function for the traffic distribution in question is derived by data-driven distribution or randomized motion based distribution, the collection and evaluation or TSE for aircraft position distribution is essential to support the establishment of separation requirements be it at the strategic (route-design) or tactical (separation minima) level.

B. Performance Based Navigation (PBN) Errors in UTM

The total system error (TSE) as defined in the performance based navigation (PBN) ConOps could be further broken down into the Path Definition Error (PDE) for difference between defined route and route in the flight-computer, the Navigation System Error (NSE) for difference between the system reported position and the actual position, and the Flight Technical Error (FTE) for deviation due to operator

or autopilot. The TSE of an aircraft must be monitored and comply with the required navigation performance (RNP) of an airspace, a critical component in determination of separation requirement for strategic separation assurance (route-design).

The determination of outer bound for UAS distribution around its assigned track is especially important in urban airspace[35], where the combination of low allowable flight ceiling¹ and large number of man made buildings and obstacles greatly restricted the maneuverable spaces. While the utilization of air-highway type UAS network has been proposed and discussed [15], [16], no actual UAS air corridors has been implemented that could be used for PDE analysis. Further more, the utilization of Real Time Kinematic (RTK) technology has greatly improve the cost and workload associated with land survey, which would also limit the amount of expected PDE for UAS, as the UAS operating in very low altitude, well-mapped, airspace could quickly find land-based reference point to calibrate its positional set-point, or the position where the UAS aims to be at.

The NSE, on the other hand, depends on the type of navigation equipment available to the vehicle. For most off-the-shelf recreational and commercial multi-rotor UAS (e.g. DJI Inspire [37]), the navigation equipment consists of Global Navigation Satellite System (GNSS), e.g. Global Positioning System (GPS), Galileo, etc., and the Inertial Navigation System (INS). The GNSS shows particular weakness at very low altitude in dense urban area [38]–[41] where signal blockage by buildings and multipath error would lead to substantial dilution of precision, while INS is susceptible to external influences from the continuum, e.g. air, that the vehicle is operated in; the error from both instruments depends greatly on the model and the environment that the UAS is operating in.

Finally, the FTE very much depends on the type of external factors, e.g. wind gust, that caused the deviation, the navigation interface that is available to the operators, the response time between a deviation detection and implementation of corrective measures, and the dynamic response of the aircraft [42]–[44]. Given the dependence of PDE and NSE on the specific implementation of the UTM Concept of Operation (ConOps), which is still under intense discussion and development around the world, the current paper will concentrate on the FTE of UAS flights. In particular, the UAS operations in urban airspace could be conducted with two approaches, each with its associated FTE: the operator-guided visual-line-of-sight (VLoS) approach, and the waypoint-guided beyond-visual-line-of-sight (BVLoS) capable approach.

C. Visual Line of Sight (VLoS) Type Operations

The measurement of UAS track deviation under operator-guidance from the starting position near the operator towards a “virtual” waypoint in 3D space is similar to the measurement of deviation in human compensatory tracking task [45], [46], as oppose to the pursuit tracking task, where the target moves

independently from visual reference, using first-person view² [45], [47] as is typical in civil aviation [48]. However, the control of UAS also involves a time-lag associated with visual identification of UAS attitude and heading as well as the delay between operator command and UAS response due to the multi-rotor flight dynamics. As such, the task of controlling the UAS towards a target point is analogous to the compensatory tracking task of remote controlling and guiding a bomb towards a target [49], [50], though the vehicle dynamic is different. Experiments conducted with unaided radio-guided “AZON” bomb [49], which could only be controlled by changing the azimuth angle, showed that for a target 15,000 ft below the bomber aircraft (giving the bomb a travel time of ~ 20 s), a mean error ($n = 67$) of 1.7 micro-radian (mil) from the intended target with a mean oscillatory error of 1.65 mil was observed. A more recent study with wire-guided TOW missile [51], which could be controlled in both the azimuth and elevation directions, for a target that is 2,800 - 3,000 m away (for a controlled duration of ~ 15 s) the horizontal mean tracking errors ($n = 86$) is 0.612 mil with a standard deviation of 0.2566 mil and the vertical mean tracking error is 0.008 mil with a standard deviation of 0.0698 mil. The report also demonstrated that the operators’ lack of experience resulted in a azimuth deviation of up to 2.6 times larger than the baseline operator. Overall, one of the primary motivation for this study is the lack of data in literature on the TSE, specifically FTE, associated with UAS track deviations under VLoS conditions that could be used for collision risk modeling with UAS, whether with manned or unmanned traffic.

D. Beyond Visual Line of Sight (BVLoS) Type Operations

The track deviation observed in airspace corridor based operation that is BVLoS-capable in absence of pre-defined RNAV-like network could be split into the NSE and FTE components [40], [52]–[54], while the contribution by PDE might not be insignificant depending on the accuracy of the published maps [54]. The NSE component of the error is largely related to the environment that the UAS is operating in, as urban airspace with tall buildings and narrow streets made getting accurate GPS readings difficult even with inertial sensor fusion [40], [55], whereas operations in open field will see the FTE having a greater contribution to TSE [53]. UAS operations in some urban airspace, therefore, could require the installation of navigational-aid infrastructure, e.g. beacons, or alternative positioning instruments on the UAS, e.g. SLAM camera. Flight test results for UAS waypoint-guided track deviation is relatively sparse, although data from previous study [53] with a octocopter in open field has shown that the mean TSE throughout a flight could range be up to 7.41 m with a standard deviation of up to 9.4 m; the standard deviation from FTE was reported to be as high as 9.85 m. The wind condition was found to be a major contributor to the FTE based on the difference in wind conditions between two sets of flight tests conducted on different dates. On the other hand, no significant changes were observed with the NSE between

¹Hard ceiling for day-time UAS operation under FAA’s LAANC is 400 ft, while commercial UAS could only be approved to operate below 200 ft above ground level in Singapore[36]

²While first-person view (FPV) control for UAS exists, the typical use case is for indoor “drone racing.”

the flight test data: as the current study is focused on the measurement of FTE over open field, this would support the minimal influence of NSE on TSE in these tests.

III. FLIGHT TESTS SETUP

The flight tests were conducted in stages over the course of a year from September 2019 to August 2020³, with one set conducted in January (Fig. 1(c)) while others took place in September 2019 (Figs. 1(a) and 1(b)) and July to August 2020 (Figs. 1(d) and 1(e)). The lack of wind energy resource in Singapore [56] appears as an advantage in this case, as the influence from, and changes in, wind speed and direction on UAS operations appears to be minimal (Fig. 1) across the different test dates. The wind-speed were obtained from the telemetry data as the difference between IMU velocity and GNSS velocity, and the wind statistics (Table I) were obtained using the Mitsuta method [57].

Fig. 1. Wind rose generated from the flight logs with 2 seconds sampling rate for the five test sessions.

The flight tests were conducted using two different models of multirotor UAS, in this case the DJI Mavic 2 Zoom

³With a gap of 6 months in between due to impact of COVID-19 restrictions

TABLE I
WIND STATISTICS FOR THE TEST FLIGHTS

	Magnitude (Mean, m/s)	Magnitude (σ , m/s)	Direction (Mean, $^{\circ}$)	Direction (σ , $^{\circ}$)
Mavic VLoS 1	0.698	0.532	182.2	52.3
Mavic VLoS 2	0.625	0.540	177.1	50.1
Mavic BVLs	0.002	0.039	174.6	102.4
Inspire VLoS	0.431	0.339	206.7	88.9
Inspire BVLs	0.311	0.207	186.9	101.9

($\sim 0.9\text{kg}$) and DJI Inspire 1 ($\sim 3\text{kg}$), for VLoS (human-guided) and BVLs equivalent (waypoint-guided) operations. The VLoS flights were conducted by flying the UAS towards a location 200 m away from the operator with a height of 20 m (based on the values shown on the controller display) in the direction of an easily identifiable background-feature, e.g. a particularly tall tree on the edge of the clearing. The UAS was flown with the highest speed that the operator were able to handle and was controlled primarily using the elevation and yaw control. The roll control were not used, as earlier flying experiences suggest utilization of roll control for this type of operation would change the heading angle and further complicates the corrections needed to stay on track.

With a take-off weight of 2.87kg, the Inspire 1 is significantly heavier than the Mavic 2 Zoom, which weights 0.905kg. While the two UAS possess similar thrust to weight ratio of ~ 2.5 , the propeller diameter for the Inspire 1 is much larger with a larger rotational inertia, resulting in a slower change in propeller RPM in response to user control inputs. The larger dimension of the Inspire 1 could also led to a greater influence by the wind. On the other hand, the larger dimension of the Inspire 1 provides the operator with better visual cue for the vehicle attitude and travel direction and allow the pilot to initiate track correction sooner.

The BVLs flights were conducted using the Waypoints Mode in the DJI Go mobile application (or DJI Pilot for Inspire), where the waypoints for the mission were chosen using touchscreen in the graphic user interface. Due to limitation with the DJI App, the latitude and longitude of the waypoints could not be prescribed precisely with numerical values while the coordinates of the chosen waypoints could not be exported. The BVLs missions were conducted following a quad pattern that consists of near-equal length sides of $\sim 140\text{m}$, resembling a square. Each flight around the quad pattern were split into four segments, one per side of the square. The flight speed of the UAS in Waypoints Mode is limited to 7m/s for Mavic and 15m/s for Inspire, with the flight tests performed at 7m/s for both the Mavic and the Inspire for better comparison. While the operator was holding the controller as fail-safe in all BVLs-like missions, no operator intervention were needed throughout the test flights.

A total of 22 VLoS missions with DJI Mavic 2 Zoom were performed, including 8 flights on September 10 and 14 and September 13 2019. Early analysis has shown that the two VLoS flight tests with Mavic produced comparable results [19] and the dataset were merged for analysis in this paper; a further 30 VLoS missions with DJI Inspire 1 were carried out on

July 23 2020. For the BVLoS-like missions, five square-pattern flights were performed on January 14 2020 using Mavic that yielded 20 total waypoint-guided segments, while 13 BVLoS missions were carried out with Inspire on August 21 2020 yielding 52 segments. The number of flights performed per test session was limited by the number of batteries available.

IV. TRACK DATA, ANALYSIS, AND DISCUSSION

The following sections presents the GNSS positions extracted from the flight logs for the flight tests conducted. The flight logs include, but not limited to, telemetries such as the GNSS longitude & latitude, IMU longitude & latitude using the takeoff point as reference, the height above ground reported by the ultra-sound height sensor (only valid up to 10m above ground level, AGL), and the flight altitude reported as barometric height using the pressure & WGS84 altitude at the takeoff point as reference.

The uncertainty associated with position reporting (e.g. navigation accuracy category - position, NACp, in ADS-B [58]) in civil aviation are typically derived from the 95% accuracy boundary (estimated position uncertainty, or EPU, for horizontal bound and vertical estimated vertical position uncertainty, or VEPU, for vertical bound). Similarly, the 95% uncertainty boundaries were used to describe the RNP needed to operate in a given airspace, which would then be used to form the probabilistic distribution of both aircraft to estimate the probability of horizontal overlap for a given aircraft pair. If the position distribution of the aircraft is normal (Gaussian), 2σ of that distribution would need to be under the RNP; if the distribution is double exponential, the scale parameter λ would need to be less than $-RNP/\ln(0.05)$ [21].

Thus, the first step of determining the separation minima for UTM is to obtain the position distribution of the multirotor flight track. For UAS operations in open field no predefined path the waypoints should adhere to, the NSE and PDE should be minimal with FTE dominating the position uncertainties. The flight data collected from the VLoS and BVLoS-like operations will be analyzed in Sec. IV-A and Sec. IV-B by first using descriptive statistics, i.e. mean (μ) and standard deviation (σ). Lilliefors normality test [59] would then be used to determine if the positional data fits the normal distribution, which would establish that 2σ is equal to the 95% uncertainty boundary for the FTE; this is essential as the number of flight test is not sufficient to establish the 95% bound using Bayesian inference. Some of the advantages of Lilliefors test includes the ability to perform the normality test without specifying distribution parameters (i.e. mean and standard deviation), the availability of the test package in the data processor, and the availability of critical values for small sample sizes; the Lilliefors test also showed similar statistical power as χ^2 test for small sample sizes such as the case of the current flight tests [60]. These statistics are further compared to UAS distribution predictions simulated using models from Ref. [18] in Sec. IV-C using the baseline distribution variance from that paper as well as variance from the test flights.

A. VLoS Track Data and Analysis

As mentioned in Sec. III, a total of 22 test flights were conducted with Mavic and 30 with Inspire to obtain the uncertainty measurements for VLoS operations. These tests were conducted for missions with a mission start point near the position of the pilot and an end point that is 200m away with 20m relative altitude (to the takeoff point). While the reported top horizontal speed is 20m/s and 22m/s for Mavic and Inspire, respectively, each flight mission lasted between 16 to 25 seconds. The pilot reported having to slow down the UAS near the end of the mission to check for distance and relative altitude. This is due to the operator reported difficulties judging the distance of the UAS from the starting position, a common issue with human tracking tasks [61], and is more sever with the smaller Mavic UAS. All data presented were cropped to $t = 15s$ for its variation over time instead of over distance traveled along the intended path. The mean and standard deviation reported at each timestamp (logged at 0.1s interval) along the longitudinal (along-track) lateral (cross-track) and height (vertical) dimensions are presented in Fig. 2. Note that the barometric sensor from the Inspire showed a near constant altitude drift of 0.02m/s downward based on the reported altitude when it was returned to the starting point, a correction factor was applied in post-processing of the height data..

Apart from the initial acceleration phase and some slow-down near the end point, the longitudinal position over time for both multirotor types showed similar slope, i.e. along-track speed. This is better visualized with box plot in Fig. 3(a), which shows the offset between the recorded longitudinal positions and the reference longitudinal position based on constant along-track speed of 10m/s for $t = 0, 5, 10, 15s$. Without the offset, the inter-quartile range would be too small relative to the mean reported longitudinal positions for visualization. Similar reference positions were used for the height distribution (Fig. 3(c)) using 1m/s and 0.8m/s climb speed for Mavic and Inspire, respectively. No offset was necessary to facilitate the visualization of the lateral position box plot. Interestingly, while both vehicles have similar thrust-to-weight ratio, the Mavic appears to reach its “cruise speed” faster than the Inspire, possibly due to the difference in inertia and drag.

Since the UAS starts each mission almost directly in front of the operator, the reported distribution of vehicle positions in both Fig. 2 and Fig 3 saw the smallest spread at $t = 0s$ in all three dimensions. The standard deviation of the reported positions showed an increasing trend over time, while the box plot showed that the inter-quartile distance does not necessary follow the same trend; the box plot also showed skewness in the distribution, especially in the lateral (cross-track) dimension. Some fluctuation in the lateral standard deviation and inter-quartile range for lateral distribution over time were also observed in the Inspire data, while a more consistent increase in both were observed in the Mavic data. This could be caused by the more consistent wind condition during the Inspire tests that led to similar corrective maneuvers, as the Mavic data was collect over two separate date with two different target

Fig. 2. Plots showing the mean (solid line) and the standard deviation (shaded) from the VLoS flight tests in the (a) longitudinal (along-track), (b) lateral (cross-track), and (c) height (vertical) directions.

headings; the larger mass and long propeller spool-up time for the Inspire could have also contributed to a lower oscillation frequency in the lateral position, resulting in standing-wave like pattern in Fig. 2(b). On the other hand, the height data from Mavic showed an abrupt increase in spread near $t = 9$ s while the Inspire data showed a more consistent increase over time. The difference between the mean height at $t = 15$ s could be related to the drift in displayed barometric altitude that led the operator to be less aggressive with height correction.

Several factors has been suggested to contribute to the widening distribution in the lateral and height dimensions of UAS positions over time as the UAS moves away from the operator: variable wind conditions, imprecise throttle control, and difficulties for operators to judge UAS travel distances. Of the three, the influence of wind is the easiest to quantify and the most obvious when viewed in the traced flight paths; the ebb and swell of the wind along the prevailing wind direction could have contributed to the gap observed in end-positions; the UAS heading changes needed to counter crosswinds could

Fig. 3. Box-plot of the positions reported from VLoS flight tests at 5 seconds interval, showing the (a) longitudinal (along-track), (b) lateral (cross-track), and (c) height (vertical) offsets from reference values.

also contribute to a lag in longitudinal distance traveled. The latter two factors are linked to track-correcting actions by the operator that might be mitigated with increasing awareness of vehicle state via additional visual or audio assistance, e.g. visual aid with markings for the desired track-normal positions and audio read-out of distance traveled.

The mean, standard deviation, and inter-quartile range of the position distribution by themselves would not be sufficient for use in the collision risk modeling, however. In fact, the standard deviation value would only be useful in the collision risk modeling if the position of the multirotor performing the mission follows the Gaussian (normal) distribution. This is especially true with small sample size that could not produce the desired probability bound through Bayesian inference, e.g. the 10^{-3} bound (1001 samples, or $\sim 3.3\sigma$ if following normal distribution) for each static aircraft to determine the separation distance to ensure 10^{-6} risk of collision. For longitudinal separation minim calculation for en-route traffic with a given RNP, even with known position distribution and velocity error

distribution for the aircraft the Monte-Carlo model with a sample size of up to 10^{11} would be needed [21], [62].

Fig. 4. Lilliefors test statistics from the (a) Mavic flight data and (b) Inspire flight data for VLoS operations compared to the critical values for normality test. The change in critical values are due to missing data point at the specific sample time.

The Lilliefors test for small sample size [59] is used to test if the flight data could be fitted to a distribution curve, in this case the Gaussian (normal) distribution. The results of the Lilliefors test statistics from flight data, along the three dimensions, comparison with normal distribution (at significance level of $\alpha = 0.05$) is shown in Fig. 4. The data could not be combined into a larger sample size due to its time-varying nature.

The results from the normality test showed that the positional distribution for both vehicles could be considered as following the normal distribution for the majority of the flights. This is despite of the variation observed in the standard deviation and box plots. The Mavic longitudinal distribution showed a larger skew in the direction of the end point, i.e. median being higher in the box in Fig. 3(a), but the distribution in all three dimensions falls back to normal-fitting by $t = 9$ s. The larger Inspire showed a better conformance to normal distribution throughout the flight apart from a few spikes in the number of outliers for very short duration. The positive normality test would allow the probable distribution of UAS track to be described using the mean and standard deviation with the expectation that the probability of UAS deviating further away from the mean path would follow the empirical rule (68-95-99.7 rule).

With the validity of standard deviation as descriptive static for the position distribution established, comparison could then be made between the observed mean and standard deviation and those modeled in earlier collision risk simulation from Ref. [18]. The heading-angle deviation used in the simulation

model from Ref. [18] is 20% of the full motion range, thus $\sigma_{sim} = 180 \times 0.2 = 36^\circ$, or a variance of $\sigma^2 = 7.2^\circ$. The lateral deviation results from the VLoS flight tests showed that the observed deviation is much smaller than the randomized deviation value used in previous collision risk model by up to a factor of 5 ($\sigma \sim 2$ m in lateral direction over ~ 80 m longitudinal travel distance at $t = 10$ s, or $\sim 1.43^\circ$ for Mavic.) A more detailed comparison with the simulation model is presented in Sec. IV-C.

B. BVLoS Track Data and Analysis

The waypoints-guided simulated BVLoS missions (referred to as BVLoS missions below) were carried out over a set of waypoints that traces out a roughly square route with sides of ~ 150 m in length and no change in the target altitude. Mission planning in DJI utilizes stop-and-turn for sharp turns, such as the ones in the square route pattern. The missions were setup so that the vehicle will hover and yaw towards the next waypoint at each vertex. As the waypoints were set using touchscreen with no option to export the coordinates, the mean latitude and longitude of the vertices where the vehicle perform the yawing maneuver were used as the start and end point for the tracks along each edge. The missions were conducted with target cruise-speed of 7m/s due to speed limit imposed on the mission mode with Mavic. The data from the four edges were combined by aircraft type and the mean and standard deviation from the flight tests are presented in Fig. 5. Flight track data were cropped to $t = 20$ s to accommodate for the variation in edge length and speed. Note that the Inspire missions were carried out at 30m AGL due to foliage height at the secondary test site.

The flight test data for both Mavic and Inspire showed a consistent, and near constant, mean and standard deviation throughout the flight in the longitudinal and height dimensions, while the lateral distribution saw a much larger impact from the initial acceleration from hover at the start of each flight segments. This is likely due to position modes prioritize altitude maintenance over horizontal motion, and reaching the speed set-point over maintaining cross-track position accuracy, similar to the control hierarchy shown in the PixHawk ⁴ multi-copter position mode source code [63]. The Inspire also showed a much larger standard deviation in reported height compared to the Mavic, possibly due to the larger mass and slower propeller ramp up for attitude and height correction. The effect of the larger size on longitudinal acceleration could also be seen with the longitudinal position plot, as the Inspire took longer ($\sim t = 4$ s to reach the speed set-point. As for the lateral distribution, the Mavic flights showed an initial leftward bias during the acceleration phase, but this initial deviation is mostly corrected by $t = 3$ s; the same cannot be said with the Inspire flights, where the mean never returned to the track-centerline and the standard deviation did not return to start-up level until $\sim t = 17$ s.

Further examination of the position distribution with the box-plots revealed that there is a lagging bias with the

⁴DJI flight controller is close-sourced and the control hierarchy cannot be analyzed.

Fig. 5. Plots showing the mean (solid line) and the standard deviation (shaded) from the BVLoS flight tests in the (a) longitudinal (along-track), (b) lateral (cross-track), and (c) height (vertical) directions.

longitudinal offsets (relative to the reference position based on a constant 10m/s cruise speed), which could be due to the position control hierarchy mentioned earlier, where the controller would actively try to match, but not exceed, the desired speed set-point. The box-plots also showed that both Mavic and Inspire reached the desired cruise speed by $t = 5$ s, ending the initial acceleration phase. On the other hand, an upward bias in height was observed in the Inspire dataset but not in the Mavic data. This could be caused by a combination of position control algorithm and the slower ramp-up speed with the larger propeller, as it would take more time for the vehicle to obtain sufficient thrust for the vehicle to reach the desired height after each deviation; the controller would not command the vehicle to exceed the desired height, and any overshoot would be corrected by the gravitational force.

Surprisingly, the biases observed in the longitudinal offset for Mavic flights did not lead to a rejection of normal fit at $\alpha = 0.05$. Instead, it's the height data, which showed small standard deviation and inter-quartile range with no obvious

Fig. 6. Box-plot of the positions reported from BVLoS flight tests at 5 seconds interval, showing the (a) longitudinal (along-track), (b) lateral (cross-track), and (c) height (vertical) offsets from reference values.

bias that did not conform to normal distribution. This could be due to the height data being reported at 0.1m accuracy, the same order of magnitude as the standard deviation. The lateral distribution for the Mavic tests showed good fit with normal except for the acceleration phase of flight. The variation in Lilliefors critical value for $\alpha = 0.05$ is due to patches of missing data from the flight logs that resulted in a reduction in sample size.

For the normality test with Inspire data, the biases observed in both longitudinal and height dimensions contributed to the rejection of normal distribution at $\alpha = 0.05$, while the lateral distribution saw a slow correction following the disturbance from the initial acceleration. Lilliefors test on lateral distribution after $t = 13$ s, after the initial disturbance has been corrected, showed a conformance to normal distribution. That it to say, the lateral distribution of the Inspire could fit normal distribution when cruising along a long, straight path, far away from the starting point of the track. The slow correction of the lateral disturbance could be a consequence of the PID

Fig. 7. Lilliefors test statistics from the (a) Mavic flight data and (b) Inspire flight data for BVLoS operations compared to the critical values for normality test. The change in critical values are due to missing data point at the specific sample time.

tuning for the positional controller to prevent the vehicle from becoming dynamically unstable; it is unlikely that there is insufficient residual thrust (after matching the height and cruise speed targets) as the DJI mission planner allows Inspire to operate with a cruise speed of up to 15m/s.

C. Comparison with Simulation Model

The Monte-Carlo based path prediction model for DJI Mavic 2 Zoom was adapted from the path-prediction module of the 3D collision risk assessment model described in Ref. [18] that simulate the UAS flight track distribution under VLoS condition while aiming for an incoming aircraft. For each simulation, Monte-Carlo samples were initialized at the point of origin with an initial heading angle, elevation angle, and speed. These three variables are randomized at each time-step using a Gaussian random number generator using the values from the previous time-step as mean and 20% of the full range (Eq. 4)⁵ for standard deviation. The motion of the UAS within each time step is further constrained by its kinematic model (Eq. 1) to ensure all movements are physically achievable.

$$\mathbf{a} = \frac{d\mathbf{V}}{dt} = \frac{(\mathbf{T}_{max} - m\mathbf{g} - \mathbf{D})}{m} \quad (1)$$

The motion of the vehicle is further constrained with the need to align velocity and drag vector of the vehicle:

$$\mathbf{D} = -\hat{v}[K_{da}(\mathbf{V} \cdot \hat{u})^2 + K_{dr}(\mathbf{V} \cdot (\hat{v} - (\hat{v} \cdot \hat{u})))^2], \quad (2)$$

⁵Full range of elevation angle is $-90^\circ \sim 90^\circ$, heading angles $-180^\circ \sim 180^\circ$, and $0 \sim 20$ m/s for velocity in this simulation

where $\mathbf{V}$ is the velocity vector, $\hat{v}$ is its unit vector, $\hat{u}$ is the attitude (thrust) unit vector of the vehicle, and K_{da} & K_{dr} the drag constant in the axial and radial direction of an axi-symmetric multirotor. The velocity unit vector is further related to the target direction via

$$\hat{v} = \begin{bmatrix} \sin \theta \cos \phi \\ \cos \theta \cos \phi \\ \sin \phi \end{bmatrix} \quad (3)$$

where the heading (θ) and elevation (ϕ) angles are randomized:

$$\begin{cases} \theta \sim \mathcal{N}(\theta_{target}, 0.04\theta_{max}), \theta_{max} = 180^\circ \\ \phi \sim \mathcal{N}(\phi_{target}, 0.04\phi_{max}), \phi_{max} = 90^\circ \end{cases} \quad (4)$$

The probabilistic distribution of heading angles follows the assumed values used in Ref. [33] and [18] for non-cooperative intruding UAS under VLoS condition with worst-case (aiming at a target aircraft) intention. These assumed values for θ and ϕ were chosen for the previous studies, due to a lack in track deviation data under VLoS conditions at the time, such that the lateral (cross-track) standard deviation by the end of the simulation (at $t = 70$ s) does not exceed the minimum protected volume radius (DMOD) defined in Airborne Collision Avoidance System (ACAS) II. While the DMOD value has no relevance to the current study on multirotor track separation requirements, the randomization ranges for θ and ϕ were retained due to lack of multirotor distribution data that states otherwise. One of the objectives for this study is to test the validity of these assumed θ and ϕ distributions ranges and provide a flight-data informed distribution modeling for use in future collision models.

In order to simulate the track-keeping behavior of UAS operating under waypoint-guided operations, an additional track-correction module was created such that the UAS would be redirected towards the intended target waypoint if the distance between the UAS and its intended track exceeds a desired cross-track tolerance, in this case 5m is used. While track-keeping is generally handled by the PID controller for multi-rotor UAS [63], the history-independent random-number generation of the Monte-Carlo model would diminish the effects of integral and derivative controller. Thus, track-keeping in the simulation was enforced by setting the target heading and elevation angles to a point along the intended track with a distance of $V_{hor,max} \times dt$ from the current longitudinal (along-track) position⁶, i.e. the target angle is proportional to the distance between the UAS and the projected position on the intended track. The target angle is then used as the mean values to generate the randomized value for random heading and elevation angle generation based on normal distribution for the subsequent time-step. Fig. 8 shows the simulation results using the default deviation values with and without enabling the track correction modules for a duration of 20s, while the standard deviations reported at 5 s intervals are presented in Table II. The simulations were carried out with the worst-case intention setting where the UAS operates at the maximum achievable horizontal velocity of 20m/s.

⁶Often referred to as the position set-point in multi-rotor flight controller documentations.

Fig. 8. Monte-Carlo simulation output (5 s intervals) using DJI Mavic 2 Zoom kinematic modeling (a) with and (b) without 5m track correction enabled. The simulations were conducted with 200 samples with standard deviation of 20% maximum value for heading and elevation angles distribution at every time-step.

TABLE II

STANDARD DEVIATION OF THE SIMULATED UAS SAMPLES ($n = 200$) AT FIXED SAMPLE PERIOD OF 5s USING THE DEFAULT RANDOM VARIANCE UNDER WORST-CASE INTENTION SETTING.

Sample Time (s)	With Track Correction			Without Track Correction		
	Longitudinal	Lateral	Height	Longitudinal	Lateral	Height
5	3.1458	3.1458	2.1033	4.8889	4.6855	2.3423
10	7.5376	3.2125	2.3848	7.7481	7.3966	3.4243
15	9.3528	3.2695	2.8360	10.008	8.5218	4.2293

Note that the heading and elevation variances defined in the simulation are associated with the velocity vector, while standard deviation obtained from the flight tests are associated with the relative angle between the UAS position and the mean track, as defined by the vector from the mean starting position and the mean end position for the mission. Thus, while the inputted standard deviation values for heading and elevation angle generation appears high ($\sigma_{heading} = 0.2 \times 180^\circ = 36^\circ$, $\sigma_{elevation} = 0.2 \times 180^\circ = 18^\circ$), the resulting lateral deviation is only greater than the observed values from VLoS flight tests by a factor of two. The simulation result also support the flight test observation that the major limiting factor for cross-track flight technical error under waypoint-guided (BVL0S) operation is the positional control module of the flight controller, as any deviation exceeding the desired cross-track tolerance will be quickly corrected assuming that the motors do not exceed saturation. The difference between the simulated and observed longitudinal standard deviation is likely attributed to the more extreme instantaneous lateral maneuvers taken during the flight tests while operating near the maximum horizontal speed of the vehicle.

An additional set of simulation were carried out under the BVL0S flight setting to investigate the difference in longitudinal distribution with the more frequent corrective maneuvers by the flight controller at smaller magnitude. A cross-track

tolerance value of 1m was used for this simulation with a target horizontal velocity magnitude of 7m/s; the standard deviation for heading and elevation angles as well as the velocity magnitude remains the same. The simulation results are presented in Table III, showing a much closer match between the longitudinal deviation from the flight tests and the simulation.

TABLE III

STANDARD DEVIATION OF THE SIMULATED UAS SAMPLES ($n = 200$) AT FIXED SAMPLE PERIOD OF 5s USING THE DEFAULT RANDOM VARIANCE, TRACK-CORRECTION, AND TARGET VELOCITY OF 7m/s.

Sample Time (s)	Longitudinal	Lateral	Height
5	2.0675	1.1760	0.9441
10	2.8403	1.2529	0.9663
15	3.5834	1.1737	0.8646

The simulation results with the 1m tolerance exposed some issues with the above approach, however, as the mean travel distance by $t = 20$ s is 104m, lower than the flight test measurement of 134m. Possible contributing factors could include: the difference between the longitudinal component of the mean target velocity magnitude (i.e. desired velocity of 7m/s) and the mean longitudinal velocity after accounting for the randomized heading and elevation angles; the assigned

heading variance used in randomization that caused the UAS to bounce between the tolerance boundary on either side of the track, resulting in a shorter along-track travel distance; and the trailing nature of the track-correction module, which would lead to the observed lateral standard deviation exceeding the tolerance value. With some adjustments to the heading and elevation angle variance used in the randomization function, the issues mentioned could be reduced or mitigated. In fact, the simulation results could be made to match the longitudinal and lateral distribution from the Mavic 2 BVLoS flight test data by changing the variance to $\sigma_{heading}^2 = 0.02^2$ and $\sigma_{elevation}^2 = 0.05^2$ and the cross-track tolerance to 0.1m.

Given the consistent lateral deviation observed throughout the flight test and supported by the simulation results, the buffer airspace needed between closely spaced parallel tracks could be estimated using a multiple, depending on the acceptable risk, of the maximum cross-track tolerance of the UAS traffic using that airspace. For example, parallel tracks with UAS operating with $EPH_{max} = 5\text{m}$ would need a buffer distance of 30m in between to maintain a 9×10^{-6} collision risk. On the other hand, the observed longitudinal distribution did not consistently follow a normal distribution, which coupled with the wide motion range of the multi-rotor vehicle would greatly affect the positional distribution of the leading vehicle (as shown in Ref. [34]) and the buffer distance needed. The longitudinal distribution could further deviate from normal if the mission involves multiple acceleration/deceleration phases.

V. CONCLUDING REMARKS

The present work is aimed to investigate the navigational error associated with human-guided visual-line-of-sight (VLoS) and waypoints-guided simulated beyond-visual-line-of-sight (BVLoS) operations. To understand the problems, flight tests using DJI Mavic 2 Zoom and DJI Inspire 1 UAS were performed in an open field for both VLoS and BVLoS-like conditions. The navigational errors measurements could help determine the buffer airspace (horizontal separation) necessary for closely spaced UTM corridors in the confined urban airspace. The flight test data primarily examines the flight technical error (FTE) component of the total system error (TSE) associated with the performance based navigation. This is due to the lack of high precision navigation unit, such as the real-time kinematic (RTK) unit, that could be used to determine the difference between the actual and sensor-reported positions in the flight logs (i.e. navigation system error, NSE, component of the TSE).

A. VLoS Flight Tests

The VLoS flight tests were conducted by performing flight mission from the controller towards a virtual target. Flight track data showed a cross-track error (lateral deviation from the intended track) that is $\sim 50\%$ of the allocated deviation from kinematic-based Monte-Carlo simulation model from Ref. [18] that assumed a random heading and elevation variance at 20% of the maximum value. Comparing to the results from previous human-guided tests using different vehicles, i.e. AZON guided bombs and TOW wire-guided missiles,

the observed lateral and height deviation in the VLoS flight tests are much larger when normalized by flight time. The difference between the flight test deviation and the previous experimental works on human-pursuit track could be attributed to difference in vehicle flight dynamics, especially given the lack of responsiveness associated with multirotor yaw control, as well as operator experience level. The role of vehicle flight dynamics on observed track deviation is further investigated by repeating the flight tests using the heavier DJI Inspire 1, which showed similar track deviation in all three dimensions throughout. Overall, the VLoS flights showed surprisingly good lateral accuracy with following the intended track, while the overall longitudinal standard deviation is up to 30m over a mean travel distance of 130m.

B. Flight Tests with BVLoS Conditions

As for the flight tests conducted with Mavic under BVLoS conditions, the results showed a relatively high consistency in deviation from intended track regardless of the relative wind directions, given the conformance to normal distribution with the near-square flight pattern. For the Mavic flights, the initial acceleration from the start of the track did not appear to contribute significantly to the longitudinal (along track) standard deviation, and its impact on lateral (cross-track) error quickly disappeared as the flight controller corrected the initial offset; all data, apart from the initial 2 seconds of acceleration, along both dimensions conforms to normal distribution based on Lilliefors test at $\alpha = 0.05$. The height data, on the other hand, rejects the normal fit at the desired significance level of $\alpha = 0.05$, possibly due to the standard deviation of the height data being close to its reported accuracy (rounded to the closet 0.1m). Compared to Mavic, the Inspire flights showed much larger deviation and skewness in the longitudinal and height data, likely due to a combination of the position controller logic, the larger mass, and the slower thrust change associated with larger propeller with higher inertia. While the initial acceleration for the Inspire only lasted for $\sim 4\text{s}$, the resulting shift in the lateral distribution was not corrected until $t = 13\text{s}$, after which the normal distribution for lateral position could be assumed. The slower correction in the lateral offset could be due to the larger mass of the vehicle or the controller tuning necessary to maintain dynamic stability of the vehicle. The results suggest that the lateral distribution of the multirotor positions while cruising along a track could only be treated as normal distribution if it is sufficiently far away (in terms of distance or time, and depends on vehicle size) from the last acceleration event. There is insufficient sample size to suggest a distribution for the acceleration phase, and further data collection would be needed to support the establishment of buffer requirement near waypoints. For operation in confined airspace, it might be necessary to prioritize track keeping along the lateral and height dimensions in the flight controller setup.

C. Simulation Results, UTM Separation, and Limitations

The simulation results showed that the path propagation model from Ref. [18] could be modified to reflect the standard deviation observed in the flight test data, but only by

modifying the heading and elevation deviation empirically. The current model is unable to generate the correct UAS distribution through specifying the variance in heading and elevation angles by simply using the performance data of the guidance instruments. This is due to the way those variances were measured, with former relative to the track and latter relative to the vehicle frame. Overall, the simulation results support the observation that the deviation of the UAS track under waypoint-guided operations is bounded by the prescribed cross-track tolerance and the tuning of the flight controller. This, along with the observation that cross-track deviation from BVLoS operation follows the normal distribution, would allow the estimation of buffer distance needed between closely spaced parallel tracks using the empirical rule. For longitudinal separation requirement, the current flight controller implementation only enforces the ground speed of the vehicle and not the travel distance over time, thus allowing inconsistency during the acceleration phase to be carried over throughout the flight. Thus, larger UAS that require longer time to accelerate to the enforced cruise-speed would see larger longitudinal distribution that is not consistent with a normal distribution, making it more difficult to estimate the longitudinal separation distance needed to prevent collision for two multi-rotors traveling along the same route. It should be noted that there is ongoing research on flight controller for multi-rotor UAS missions that would allow for smoother transition between waypoints and time-accurate trajectory management (e.g. Ref. [64]), but a more generous longitudinal separation would be necessary for UAS until those can be widely implemented.

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