A SIMULATION-BASED STUDY ON THE IMPACT OF TRACKING PERFORMANCE ON UTM FLIGHT SAFETY

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Abstract

Benefiting from the scientific achievements in recent years, autonomous unmanned aircraft systems (UAS) are rapidly maturing for use in various missions. The attempt to deploy UAS as an extension of the transportation system draws growing attention. One of the key challenges of deploying UAS traffic is to guarantee the safety of UAS flights, which becomes a focus of related research. The tracking system provides the location of airborne flights to support various UAS traffic management (UTM) technologies. Therefore the standardization of tracking system performance is crucial. In this study, a simulation-based study is carried out to analyze the impact of tracking performance on the safety of UTM flights. The indicators of the tracking system are reviewed and summarized. Flight safety is formulated as the probability of an accident, which leads to a design of a pair-wise aircraft encounter scenario. A UTM simulator is established to enable aircraft trajectories generation. Fast-time Monte Carlo simulations are performed with operational uncertainties implemented, which estimates the probability of safety violations. The results of sensitivity analysis on tracking performance indicators show that the sizing of the safety protection boundary affects the performance of the tracking system. In addition, a larger latency of tracking leads to an increase in the lag-time between violation and detection, which potentially affects successful deconfliction.

Keywords- Unmanned aircraft systems Traffic Management (UTM); Drones; Air Traffic Management (ATM); flight safety; Agent-Based Modeling and Simulation; Monte Carlo simulation; Tracking Performance

Introduction

Rapid developments in air vehicle technologies attract the attention of the public, and people started to investigate solutions to bring new air traffic paradigms in addition to traditional civil aviation to alleviate traffic congestion problems in road transportation, which leads to the emerging concepts of UAS traffic [1], [2], urban air mobility (UAM) [3], and advanced air mobility (AAM) [4]. Compared with UAM and AAM, the UAS traffic was earlier initiated. New promising advancements in air vehicular systems and onboard intelligence make UAS traffic a rapidly growing field [5].

Safety is paramount in air transportation. After decades of evolution, the current air traffic management (ATM) system has been operating with a very high level of safety performance. It is required that the introduction of UAS traffic to the national airspace system (NAS) will not impede the safety of the existing flight operations. There are several differences between emerging UAS traffic and traditional civil aviation [6]. On one hand, electrical vertical take-off and landing (eVTOL) aircraft are becoming a major aircraft type for UAS traffic, which differ from traditional fix-winged aircraft for its flexibility in maneuvering in small areas, independency on runway system, and utilization of electric power. On the other hand, compared with traditional civil aviation, higher flight operations density and higher environmental complexity in the urban airspace can be expected in UAS traffic. Due to these differences, existing ATM concepts and systems cannot be applied to UAS directly, which brings the need for the UTM system to guarantee safe UAS operations and promote the integration of unmanned and manned aviation in the NAS [7]–[9]. Civil Aviation Authorities (CAAs) and air navigation service providers (ANSPs) are working on UTM Concept of Operations (ConOps) development, which formulates the UTM services provided by UTM Service Providers (USSs) for flight operators.

The evolution of Communication, Navigation, and Surveillance (CNS) systems has driven the establishement of new concepts and strategies in civil aviation [10]. It is expected that CNS will likewise play a major role in various UTM concepts, with further technological improvements enabling scability to high traffic densities while preserving systemic safety. For example, researchers have attempted to extend the RNP concept to UTM operations [11], [12].

Tracking is a critical CNS function in UTM. Its main role is to locate airborne aircraft, with the collected data serving as the basis for various UTM services such as: conformance monitoring, centralized tactical deconfliction, dynamic capacity management, emergency management, etc. The performance of the tracking system thus has an impact on the safety of the UTM network; consequently, standardization of tracking service requirements serves as a preliminary to formulating and analyzing the requirements for other UTM services. Nevertheless, due to the complexity of UTM flight missions and the diversity of the configurations of UAS aerodynamics and avionics, limited studies were performed analyzing the impact of tracking service performances on the safety of UTM operations.

There are mainly three types of tracking techniques, namely active, broadcast, and networked tracking. Active tracking, like primary surveillance radar (PSR), does not need the cooperation of an onboard transponder and is able to detect flying objects actively. It has the advantage of monitoring non-cooperative drones, but its low accuracy and high sensitivity to obstacles as interferences make it unsuitable as the primary type of tracking for daily UTM operations. The other two types, broadcast, and networked tracking are all passive trackings: the system receives and decodes the message sent from the onboard transmitter, which contains location information. Normally, location information is a result of multi-sensor fusion combining the output of GNSS, IMU, altimeter, etc.; thus these two types of tracking are more accurate than active tracking. The difference between broadcast and networked tracking is that for the former, tracking information is transmitted with no specific destination or recipient and can be captured by any receiver (e.g. ADS-B), while for the latter, the tracking data is transmitted to an internet service, like using the cellular network. Considering the sufficient miniaturization of drone avionics, equipping onboard transmitters will not be a problem, therefore broadcast and networked tracking are presumed as the primary tracking method in UTM operations for their high reliabilities.

This study focuses on the mechanism of tracking system performance impacting the safety performance of UTM flight operations. The contribution of this study is threefold:

(a) A pair-wise aircraft encounter scenario is designed based on the formulation of accident probability and the summarization of tracking performance indicators.

(b) A simulation tool is developed based on the research goal, enabling agent-based fast time UTM flight simulations. The tool includes the design of aircraft agent and aircraft controller agent, drag force estimation model, onboard navigator agent, and tracking system agent.

(c) Sensitivity analysis was performed by Monte Carlo simulations with various operational uncertainties, to achieve a quantitative analysis of the tracking performances. A major result shown in the preliminary analysis is the latency of the tracking system significantly affects the detection of an incident, which potentially influences the performance of deconfliction.

Methodology

In air transportation, like many other safety-critical industries, the cost of an accident is disastrous. Therefore, simulation tools are widely used in the assessment of safety performance before new concepts or procedures are implemented, to prohibit fatalities. In this study, Monte Carlo simulation, adopted by many safety studies in ATM [13]–[16], is used to perform quantitative sensitivity analysis aimed at uncovering the impact of the change in tracking performance on the safety of the UTM operations.

The workflow of this simulation-based study is illustrated in Figure 1. Firstly, the key performance indicators for tracking service are reviewed. Secondly, based on the formulation of the probability of an accident and the functionality of the tracking system, a pair-wise encounter scenario is designed. A simulation tool is developed for modeling the dynamics of rotorcraft. Monte Carlo simulations are carried out to analyze the sensitivity of the system's safety performance to each tracking performance indicator. Finally, discussions are made based on the simulation results.

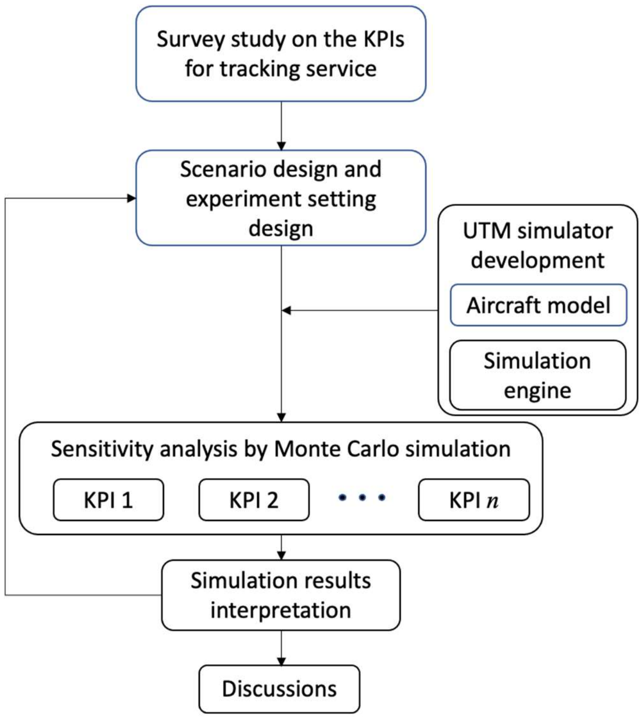


Figure 1. The workflow of the simulation-based study on the tracking service performance on UTM flight safety

Tracking Performance Indicators

A survey study has been carried out to identify the key performance indicators (KPI) for tracking in UTM. Due to the absence of comprehensive standardization in UTM, some KPIs are not fully developed and organized. Relevant materials for manned aviation published by the International Civil Aviation Organization are also referred to. A summary of tracking KPIs will be explained in this section.

Accuracy

Accuracy is the most fundamental performance indicator of tracking service. It is defined as the 95% error for those dimensions where an accuracy requirement is specified. Under the assumption that tracking is performed by either broadcast or networked methods, the accuracy of tracking is the same as the accuracy of the onboard navigation system. Specifically, the tracking information that the ground infrastructure receives is the same as the measurement of the onboard navigators.

Latency

The latency is described by the total delay of the tracking system, defined as:

$$l = t_{scan} + t_{relay} + t_{filter} + t_{publish} \qquad (1)$$

Where l is the total latency of the tracking system, t_{scan} is the max update interval, t_{relay} is the max time from the sensor to the processor, t_{filter} is the max time required by processing, and $t_{publish}$ is the max time after processing to present.

Availability

The concept of availability comes from performance-based navigation (PBN), where it is defined as the percentage of time that the services of the system are usable by the navigator. Availability is an indication of the ability of the system to provide usable service within the specified coverage area. Availability is the percentage of time that tracking signals transmitted from external sources are available for use. It is a function of both the physical characteristics of the environment and the technical capabilities of the transmitter facilities. It is calculated by mean time between failure (MTBF) and mean time to repair (MTTR) as:

$$p_{avail} = \frac{t_{MTBF}}{t_{MTBF}+t_{MTTR}} \qquad (2)$$

Update Rate

The update rate is defined as the frequency of the update of tracking information. A high update rate will challenge the information processing ability of the tracking system, and might make tracking system capacity a bottleneck when the flight density is high. On the other hand, when the update rate is low, the tracking system may not be able to detect flight conflicts in time and this may result in an accident.

Other Tracking Performance Indicators

Integrity and **continuity** are also conceptualized in PBN. Integrity is the measure of the trust that can be placed in the correctness of the information supplied by a navigation system. Integrity includes the ability of the system to provide timely warnings to users when the system should not be used for navigation. The continuity of a system is the ability of the total to perform its function without interruption during the intended operation. More specifically, continuity is the probability that the specified system performance will be maintained for the duration of a phase of operation, presuming that the system was available at the beginning of that phase of operation (this is sometimes known as reliability). Integrity and continuity thus describe the failure rate of the tracking system from different perspectives.

Capacity is defined as the maximum number of flights that the system can simultaneously track. For broadcast tracking, the capacity depends on the receiver, while for network tracking, the capacity depends on the bandwidth of the communication system.

Extrapolation (and its corresponding accuracy) may be used in the case that the tracking system is unable to detect an aircraft in its coverage range. The extrapolation should not consider flight plans, as the intention of the aircraft may change. The accuracy of the extrapolation shall be measured by different prediction times, e.g., in 5 seconds, 30 seconds, 60 seconds, etc. The longer the prediction time, the greater error can be expected. Quantitative definition of this measurement serves as an indicator of tracking system accuracy, i.e., 95% percentile of the prediction error.

The range of coverage applies to active and broadcast tracking. By repeated flying in the area near the border of coverage, measurement can be performed using the tracking data. The range is not an exact value. The larger distance, the smaller probability that the aircraft can be tracked. A threshold is required, e.g., 99%. This is associated with higher-level measures like availability.

Scenario Design

The measurement of UTM system safety performance is defined as the probability of an accident, which is formulated as a violation in conjunction with a failure by the tracking system to avert the conflict, as:

$$P(accident) = P(violation)P(\overline{STF}) \qquad (3)$$

where STF refers to successful tracking function, and $P(\overline{STF})$ is the probability of an unsuccessful tracking function.

In this study, a pair-wise encounter case was considered, where a crossing point exists between the straight-line flight segments of two flights, and it is assumed that there is no pre-flight deconfliction.

In this scenario, the first component of accident, violation, is defined as an operational status that violates the rule, including near mid-air collision (NMAC), well-clear violation (WCV), etc. The formulation of violation should be developed based on the purpose of analysis. In this study, we mainly consider NMAC and WCV: $violation \in \{NMAC, WCV\}$. The occurrence of a violation is majorly subject to the time difference between the two aircraft passing the crossing point, which is contributed by many factors, including aircraft dynamics, navigational error, and aircraft initial statuses like velocity, distance to the crossing point and the relative angle between two paths.

The second component, an unsuccessful tracking function, is defined as complementary to STF, which refers to the case that the tracking system detects the violation and provides successful deconfliction, as shown by

$$P(\overline{STF}) = 1 - P(detect|violation)P(resolve|detect) \qquad (4)$$

The development of conflict resolution algorithms is a popular research topic, and estimating a successful rate of conflict resolution is a complicated problem. In this study, we assume that the tracking system can successfully deconflict as long as the violation is detected, i.e. $P(resolve|detect) = 1$. This assumption allows us to focus on the quantification of $P(detect|violation)$, which is subject to the tracking performance measured by the indicators discussed before.

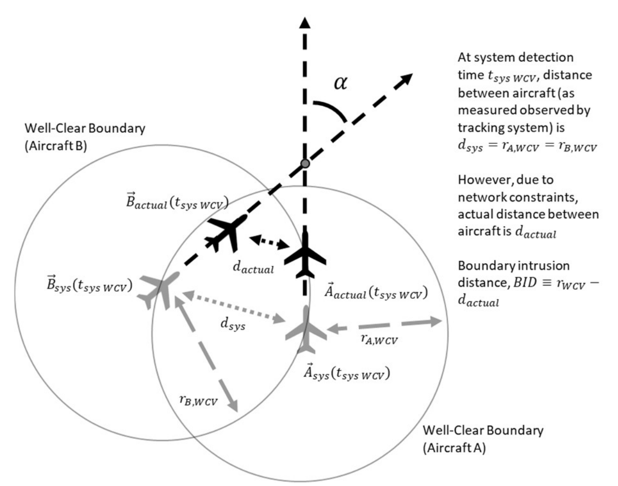


Figure 2. Pair-wise encounter scenario considered for simulation

An overall scenario design for the simulation is illustrated in Figure 2. In the definition of NMAC, the aircraft is approximated as a cylinder, where the diameter is the wingspan of the aircraft, and the height is the maximum height of the aircraft. The well-clear boundary (WCB) of an aircraft is also defined as a cylinder. However, there is not a widely accepted sizing of the WCB. In the scenario designed in this study, the horizontal separation-keeping between aircraft is more significant than vertical separation-keeping. Therefore an arbitrary height of 10 metres was selected for the WCB, while the radius of WCB was varied as part of the analysis.

UTM Simulator Development

For enabling the Monte Carlo simulations in this study, a software tool was developed specifically for eVTOL aircraft in the urban airspace.

Overall Design Principle

The scheme of Agent-Based Modeling and Simulation (ABMS) was employed in the development of the UTM simulator. The ABMS allows simulating the actions and interactions of heterogeneous autonomous agents to analyze the behavior of a system. It is widely used in socio-technical studies like transportation engineering.

In this research, ABMS is used to build the simulation environment. The agents include aircraft, aircraft controllers, onboard navigation systems, and tracking systems. In the design, the scalability of the simulation tool is emphasized. The simulator must be able to cope with the UTM traffic flow containing multiple aircraft types. The workflow of the simulation is illustrated in Figure 3.

Aircraft Agent and Controller Agent

The aircraft agent and controller agent were designed for computing the aircraft's movement in every time step with a given flight plan which includes a list of waypoints and the desired velocity.

In the design of aircraft agents and controller agents, we need to balance the model's fidelity and its computational complexity. Using a full control model like the open-source drone controller API or even hardware-in-the-loop simulation will provide high fidelity simulations. However, considering the high safety standard that the aviation community is maintaining, e.g., 10^{-7} fatalities per flight hour, a very large number of simulation runs will be needed, which makes using a very complex model not realistic. On the other hand, a simple mass-point model will be computationally cheap, but it won't reflect the attitude-thrust correlated behavior of multi-rotorcrafts. To make a compromise between fidelity and computational efficiency, a position-velocity-informed thrust and torque dual-loop control model was developed with the following features:

- Flight plan input includes a waypoint list and the desired velocity, which meets the way of planning a mission for a drone flight operation.
- Following the behavior of rotorcrafts, the direction of thrust is governed by the attitude of the aircraft, to present the attitude-thrust correlating characteristics.
- Neglecting the specifications of propeller systems and directly controlling the torques generated allows easy implementation with multiple aircraft types while the users are free from acquiring detailed aircraft specifications.

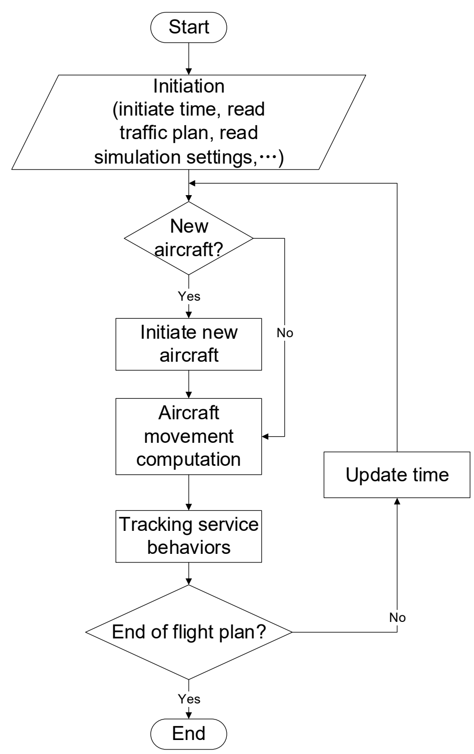


Figure 3. Workflow of UTM simulation

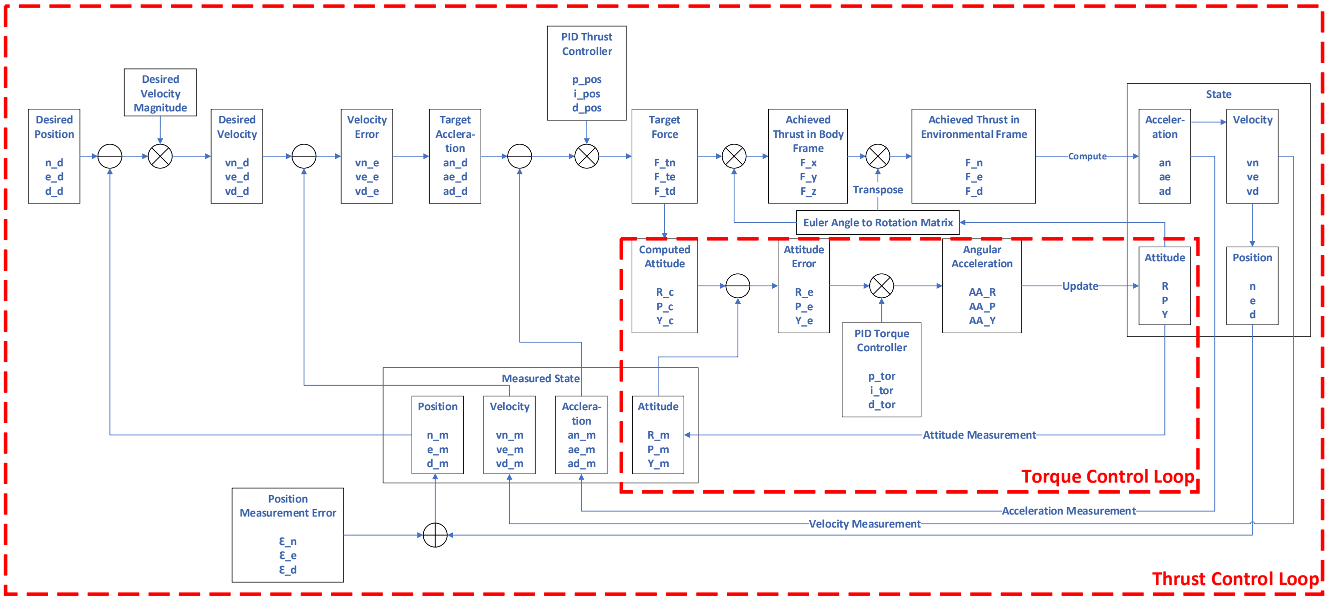


Figure 4. A position-velocity-informed thrust and torque dual-loop control model for aircraft and controller agents

The model allows the implementation of a navigator agent, which generates the navigational error as required in this research.

Drag Model

For better accuracy of aircraft movement computation, aircraft drag is estimated using a quasi-Newton method, by fitting cruise speed data from the study carried out by Theys, et al. [17], against angle-of-attack with a sinusoidal function:

$$v_{airspd}^2 = \frac{m_0\, g \tan\alpha}{\tilde{C_d}(\alpha)} \tag{5}$$

$$\tilde{C}_d(\alpha) = \beta + \gamma \sin^2\alpha \tag{6}$$

for parameters β and γ. Equation (5) models drag at cruising speed and is essentially the requirement that the forward thrust vector equals drag, with m_0 the mass of the test multirotor, v_{airpsd} the cruising airspeed and α the effective angle-of-attack between the plane of the multirotor's propellers and the incident air. The sinusoidal form chosen to model $\tilde{C}_d$ arises from the high degree of geometrical symmetry of typical multirotor designs, with drag expected to plateau at $\alpha = 90°$ and decrease thereafter. Figure 5 shows v_{airspd}^2 against α for the fitted parameters.

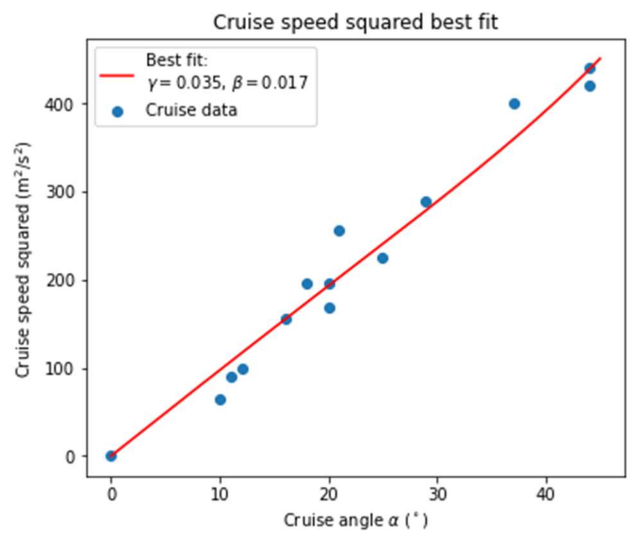


Figure 5. Parameters for $\tilde{C}_d$ as a function of cruising angle α are fitted to flight data

Drag is extrapolated to other simulated UAS sizes as given by

$$\vec{D} = -\hat{u}_{air}\, v_{airspd}^2 \left(\frac{s}{s_0}\right)^2 \tilde{C}_d(\alpha) \tag{7}$$

where $\hat{u}_{air}$ is the unit vector of the relative direction of airflow over the UAS in the earth frame and s/s_0 is the relative propeller diameter of the simulated UAS with respect to the reference UAS used fitting parameters in Equation (5).

Onboard Navigator Agent

The onboard navigator agent provides observations of aircraft position state with randomized error. An autoregressive model is used to model Navigational System Error (NSE); that is, positional errors sampled from GPS/IMU sensors separated by short time intervals are assumed to be correlated, with error given by

$$\epsilon_{n+1} = \alpha\epsilon_n + N\left(0;\, \sigma\sqrt{1-\alpha^2}\right) \tag{8}$$

where ϵ_n refers to the NSE at sample time t_n and $N(a, b)$ is a normally distributed random sample with mean a and standard deviation b. Over a long period, the parent distribution of such an autoregressive system tends toward zero mean with a standard deviation of σ [18].

An estimation for horizontal autocorrelation α_{ho} of ~0.994 was utilized. This estimation is compared against RTK flight test data from a Tarrot Ironman 650 kit, with the difference between reported RTK and onboard GPS positions utilized as a proxy for NSE. Figure 6 shows the simulated NSE versus flight data. The details of the flight tests were reported in another study by the research team [12].

NSE is updated at a 5 Hz rate (in line with current GPS systems), with σ_{hor} = 15 m selected to represent a worst-case scenario.

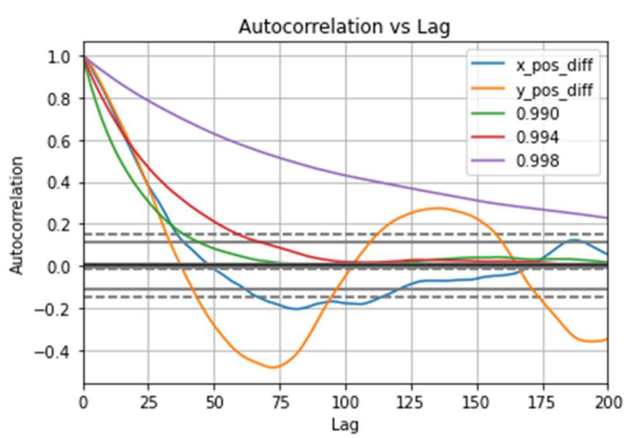


Figure 6. Autocorrelation v.s. lag for flight test data and various simulated α_{hor} values. Lag refers to the number of sampling intervals used to calculate the correlation value.

Tracking System Agent

A centralized tracking system responsible for receiving and recording critical aircraft parameters is implemented. It utilizes a self-reporting scheme akin to ADS-B/e-Reporting [19]. Under such a scheme, the central tracking system receives flight state information transmitted by the corresponding aircraft. The analysis of this study focuses on the tracking KPIs that have the potentially significant impact on safety, including update rate, latency, and availability.

As previously mentioned, since the system relies on UAS self-reporting, tracking system positional error is trivially equivalent to NSE. Hence the accuracy of tracking is not included in the sensitivity analysis.

For each simulated flight, data transmission is assumed to have a fixed latency l, and occurs and a fixed update rate f. In addition, at each transmission interval, a uniform probability of failure is modeled, with its complement probability denoted as p_{avail}. A one-factor-at-a-time sensitivity analysis was performed between WCV metrics and the aforementioned parameters, with explored values shown in Table 1.

Table 1. Test matrix for various tracking parameters

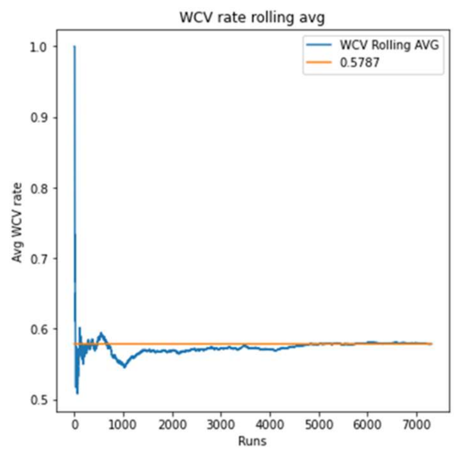
Update rate (f, Hz)	Latency (l, seconds)	Availability (p_{avail})
1, 2, 5, 10	0.1, 0.2, 0.5, 1	0.8, 0.9, 0.99

The selected update rates include the current ADS-B update rate of 2 Hz, and the ideal case of 10 Hz, corresponding to the e-Reporting recommendation for UAS equipped with 10 Hz-capable GPS units. Correspondingly, latency values are chosen reciprocally as $1/f$ [19].

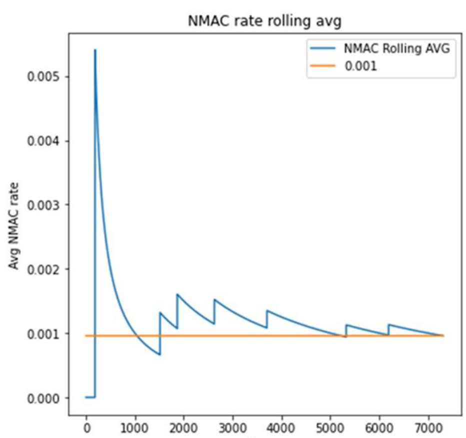
Studies performed by OpenSignal in 2019 indicate LTE network availability in Singapore in excess of 90% [20]. However, cellular networks may not be fully optimized for high altitude operation demanded by UAS. Nevertheless, the values selected represent near-term possible availabilities, when factoring in re-transmission protocols and fallbacks to other networks.

Simulation Results and Discussions

The size of the NMAC volume is much smaller than the WCV volume, so the probability of NMAC is much smaller than WCV. Hence estimation of the probability of NMAC requires a much larger number of simulations compared with estimating the probability of WCV. This statement is illustrated in Figure 7. The probability of WCV converges when the number of simulation runs reaches 5000, as shown in Figure 7(a). Comparatively, Figure 7(b) shows that with 7000 simulation runs, the probability of NMAC has yet to converge. To avoid the large computational burden associated with NMAC statistics, we focus on WCV analysis in the following part of this study.



(a) Number of simulations required for the convergence of the probability of WCV



(b) Number of simulations required for the convergence of the probability of NMAC

Figure 7. Estimation of the required number of simulations for WCV and NMAC analysis

STF v.s. WCV Radius

In the interpretation of STF, not only missed reporting, but also false reporting is important. The case that a violation happens but is not reported by the tracking system is a false negative case, while the case that the tracking system reports a violation while there is no violation happening is a false positive case, as shown in Table 2.

Table 2. Performance matrix for STF interpretation

	$Violation$	$\overline{Violation}$
$Report$	True Positive (TP)	False Positive (FP)
$\overline{Report}$	False Negative (FN)	True Negative (TN)

Figure 8 shows the true positive/false positive detection values for various WCV radii. These values provide an estimate for successful short-term conflict detection (i.e., STF) and nuisance alerts respectively.

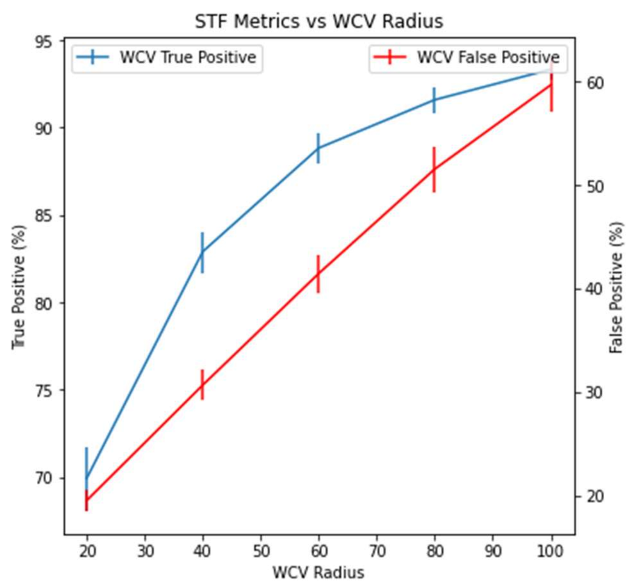


Figure 8. True/False Positive WCV Detection versus WCV radius

An increasing trend for both true positives and false positives is observed with increasing WCV radii. This is likely due to a larger conflict detection volume leading to a higher likelihood of reported aircraft positions being in conflict.

Interestingly, the detection lag between a WCV occurring and it is being registered by the tracking system changes with WCV radii. This is illustrated in Figure 9.

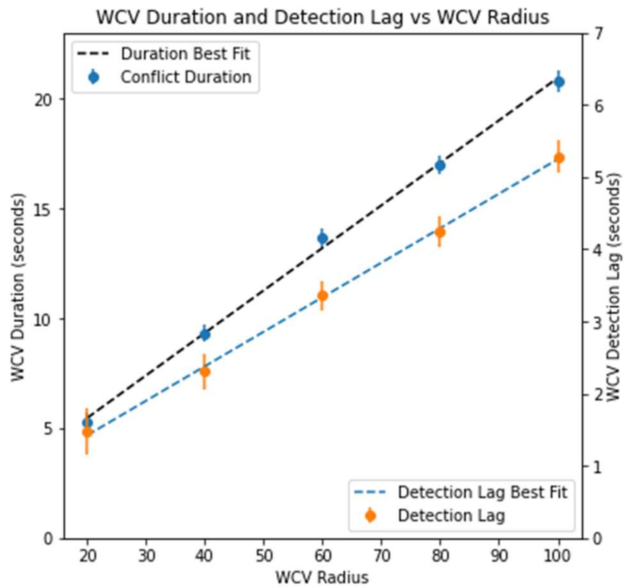


Figure 9. Conflict Duration and Detection Lag versus WCV radius

The following sections focus on STF sensitivity analysis with tracking-related parameters and adopt a WCV radius of 50 meters.

STF v.s. Update Rate (f)

In comparison to WCV radii, altering the tracking system update/transmission rate has a significantly lesser impact on overall conflict detection, as shown in Figure 10. This may be due to average conflicts lasting ≈11.4 seconds for the selected WCV radius, resulting in 11 transmission events per conflict even at the lowest update frequency of 1 Hz. Higher relative approach speeds with shorter conflict durations may, however, see a more significant degradation in detection capability.

STF v.s. Latency (l)

As shown in Figure 11, latency does not affect detection statistics directly. Rather, Figure 12 indicates the detection lag increasing with increasing latency, effectively reducing the available deconfliction time.

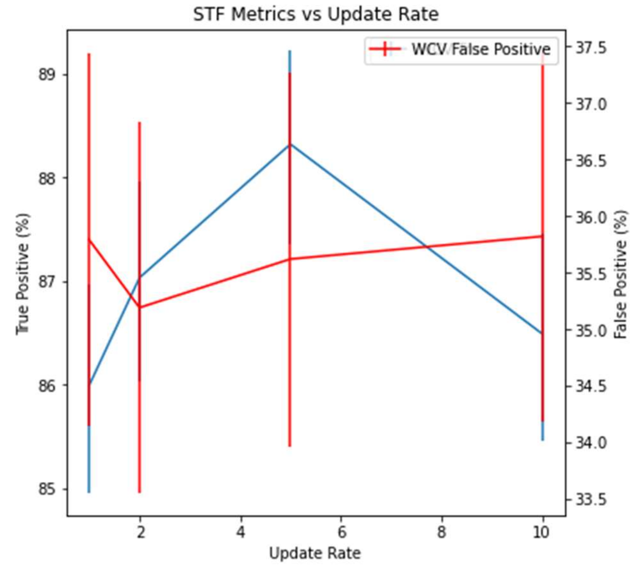


Figure 10. True/False Positive WCV Detection versus Update Rate (f)

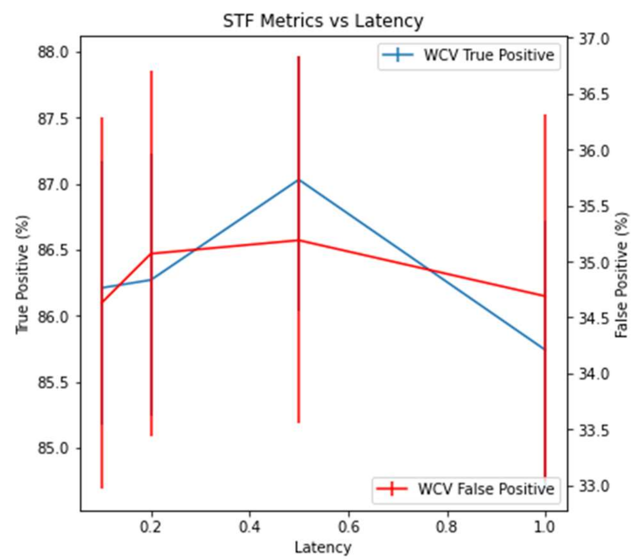


Figure 11. True/False Positive WCV Detection versus Latency (l)

STF v.s. Availability (p_{avail})

Over the considered parameter ranges, availability shows the weakest effect on WCV detection, nuisance rate and lag, as shown in Figures 13 and 14. This is likely as it serves to augment the effective update rate and latency.

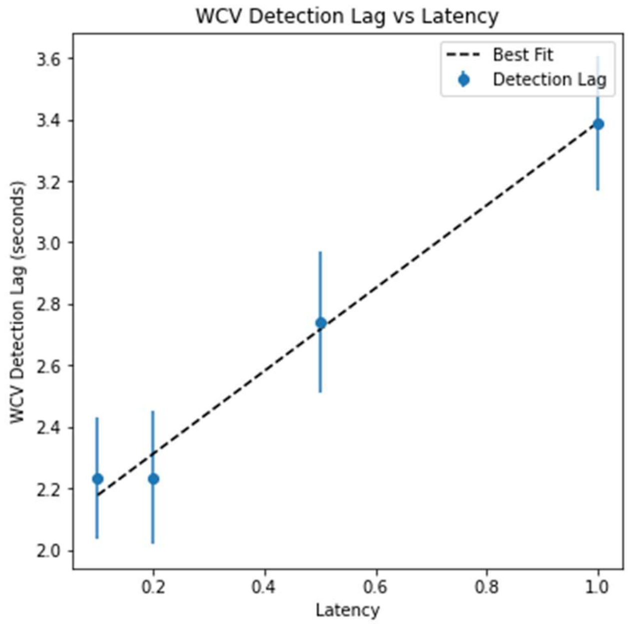


Figure 12. Detection Lag vs Latency (l)

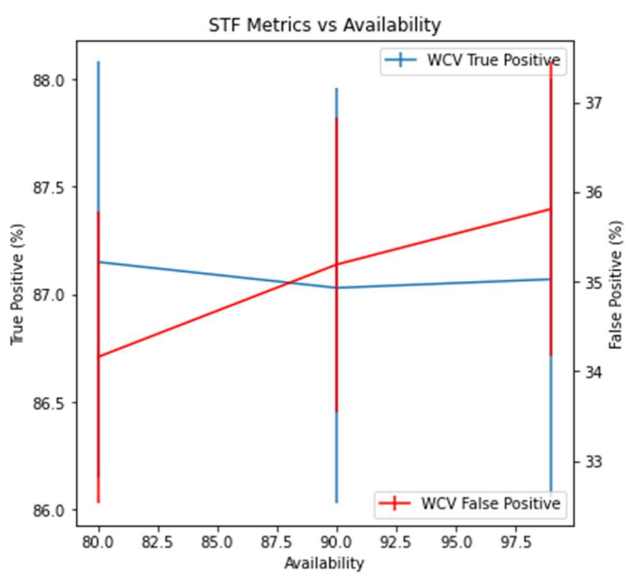


Figure 13. True/False Positive WCV Detection versus Availability (p_{avail})

Concluding Remarks

A simulator for collision risk evaluation was developed and implemented, with a sensitivity analysis for WCV performed. With a WCV radius fixed at 50 meters and a UAS speed range of (5, 10) m/s, overall true/false positive detection statistics are not strongly affected across the tested parameter ranges for update frequency, latency and availability. It should be noted that interaction effects may exist, e.g., in locations with poor reception, both latency and availability may suffer, leading to a reduction in effective update rate.

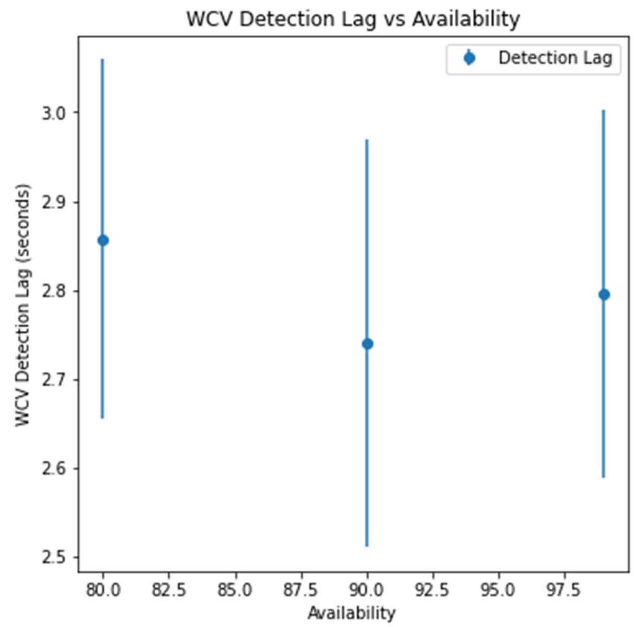


Figure 14. Detection Lag vs Availability (p_{avail})

While detection using fixed-radius boundaries centered around UAS may not show significant changes for the considered parameter ranges, nevertheless, the authors observe an unsurprising near 1-to-1 correlation between latency and detection lag. In the considered unaccelerated encounter scenario, the time to closest approach point from the start of the conflict is half of the average conflict duration, i.e., approximately 6.1 seconds. Thus, a latency of 1s represents a reduction in available deconfliction time by over 16%. Therefore, alternative metrics (beyond circular boundaries) should be employed for successful conflict tracking. Alternatively, airspace structures may be implemented to reduce relative approach speed and extend the average unmitigated conflict duration.

Future Works

Simulation results indicate the need for more robust metrics for a centralized tracking system to successfully fulfill the requirement of tactical deconfliction. Future studies may focus on sensitivity analysis using other airspace conflict detection metrics such as modified lookahead time τ_{mod}, as utilized by civil aviation in ACAS/TCAS logic.

Future sensitivity analysis may also include improved statistical latency modelling, and test scenarios containing flight plans with accelerated paths; both of which are especially useful considering that urban UAS use cases may see the confluence of elevated RF noise with complex flight trajectories featuring multiple heading changes for ground obstacle clearance.

By increasing the number of simulation runs, the a converged probability of NMAC can be acquired. Another focus of the future works will be analyzing the contribution of the successful rate of WCV detection to the probability of NMAC, to reveal the capability of tracking system in preventing flight accidents with given tracking performances.

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