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The Effect of Intent on Conflict Detection and Resolution at High Traffic Densities

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***Abstract*—The use of drones for applications such as package delivery, in an urban setting, would result in traffic densities that are orders of magnitude higher than any observed in manned aviation. Such densities not only make automated conflict detection and resolution a necessity, but it will also force a reevaluation of aspects such as centralised vs. distributed, coordination vs. priority, or state vs. intent. This paper investigates the use of intent in tactical conflict detection and resolution at high traffic densities in unmanned aviation. Experimental results show that combining both current state and future intent information improved overall safety. Adding intent enables the detection, in advance, of conflicts resulting from future changes of state. A conflict resolution maneuver is optimal for safety when all aircraft deviate only minimally from their current state to solve the conflict. Consequently, they could deviate from the broadcast intent information. Therefore, state projection into the future must still be kept to prevent very short-term conflicts when intruders do not follow their original intent.**

***Keywords*—Conflict Detection and Resolution (CD&R), Trajectory Intent, Space Solution Diagram (SSD), U-Space, Unmanned Traffic Management (UTM), Self-Separation, BlueSky ATM Simulator, ASAS, Sense & Avoid, Drones**

I. Introduction

The aviation field must prepare for the introduction of large numbers of mass-market drones. Safety automation within unmanned aviation is a priority, as drones must be capable of conflict detection and resolution (CD&R) without human intervention. The Federal Aviation Administration (FAA) ruled that an Unmanned Aerial Vehicle (UAV) must have Sense & Avoid capability in order to be allowed in the civil airspace [1]. The International Civil Aviation Organization (ICAO) requires UAV CD&R models to be capable of detection and avoidance in both static and non-static environments. Only after meeting this requirement, will civil-UAVs be allowed to fly beyond the operator's visual line-of-sight [2].

Most tactical conflict detection models rely on nominal state-based extrapolations to determine the closest point of approach (CPA) between aircraft. State-based methods assume a projection of the aircraft's current position and velocity vector. However, when future trajectory changes of all involved aircraft are not taken into account, false alarms may occur and future losses of separation (LoSs) may be overlooked. A state-based model can only adapt to a heading change once the aircraft completes the change and the new heading is the new state. An intent based model can compute this future heading change before it starts and, therefore, prevent last minute risk prone situations resulting from the change. When adding intent information, future trajectory change points (TCPs) will alter the detected conflicts:

- False positives are removed: by propagating the current state of an aircraft, we might be considering future LoSs expected to happen after a TCP. These are invalid as the aircraft will no longer have the state which would lead to the LoSs. We can now disregard (1) LoSs expected to occur after intruder's TCPs, and (2) LoSs expected to occur after the ownship's TCPs.
- False negatives are added: by considering future states resulting from TCPs, we can now add (3) LoSs expected to occur due to intruder's TCPs, and (4) LoSs expected to occur due to the ownship's TCPs.

Research performed for singular cases in the past identified the potential of using intent. Wing [3] explored how to depict the intent of an intruder in a primary flight display. Multiple works [4], [5], [6], [7] have used waypoint information to improve a single intruder's trajectory prediction. Using either state or intent information in high traffic densities was investigated for civil aviation [8], [9]. Yet, with drones even higher traffic densities are expected to occur. At such high densities, the emergent behaviour resulting from conflict avoidance is unpredictable and, therefore, the validity of intent cannot be assumed but must be tested.

This paper will analyse the effect of integrating intent information in conflict detection and resolution for unmanned aviation at high densities. In this work, we assume a situation similar to a package delivery setting, which is receiving wide attention in unmanned aviation research [10]. Aircraft must pass known delivery waypoints. During the flight, each aircraft is responsible for avoiding collision with other aircraft. Tactical conflict resolution models are of advantage in this situation: aircraft have free-flight and may continuously optimize their flight trajectory and next delivery points during flight; conflict avoidance intervention is kept to a short term and does not require change of delivery points. Data transmission includes the current state and future delivery points. All aircraft involved have the same priority.

For conflict detection and resolution, a velocity obstacle-based implementation called the Solution Space Diagram (SSD) model will be used [11]. Velasco [12] showed how intent information can be incorporated in a velocity obstacle representation to determine state-based constraints. The work herein performed considers only horizontal resolution, as we aim only at resolving conflicts between cruising aircraft. This is optimal when considering a layered airspace [13]. Future work may be performed to extend this model to 3D to consider other phases of the flight or different airspace structures.

II. Methods

A. Conflict Detection

Most of the existing CD&R models assume an extrapolation of the current state to detect potential conflicts. Based on the closest point of approach (CPA) calculation, conflicts with neighbouring aircraft are detected. Uncertainties (i.e. uncoordinated behaviour from other traffic, unknown wind or speed variation) are not considered although these affect the flight path. The addition of intent information may help reduce some of the uncertainty. For intent consideration, TCPs will be included in the process of conflict detection. When propagating an aircraft's position into the future, a possible approach is to consider the positions of all neighbouring aircraft at each incremental time step and calculate the horizontal and vertical distance between them. However, a robust prediction with this method involves reducing the increment between time steps to a minimum, greatly increasing computational time. A more efficient approach is to model the intent as a series of leg segments. Yang [4] has shown that reducing a non-linear trajectory to a series of straight lines trajectories allows for accurate computation of conflict states at speeds feasible in real-time complex scenarios. Naturally, this process is less efficient for turns which are initiated at bigger distances from the waypoints; points closest to the waypoint are thus incorrectly considered as future positions.

A leg represents a segment between TCPs. CPA is calculated for each leg until a LoS is encountered. However, if it occurs after the expected time for starting the next leg, then it is considered a false positive alarm and is removed. Once a future LoS is encountered, the aircraft enters 'conflict avoidance' mode, where it temporally adopts a new state computed by the conflict resolution model. The aircraft will exit this mode, once it is detected that it is past the previously calculated time to CPA (and no other conflict is expected between now and the look-ahead time). At this point, the aircraft will redirect its course to the next TCP.

B. Conflict Resolution

The SSD model used in this work is based on the velocity obstacle theory. Both these models are hereinafter described.

1) Velocity Obstacle (VO) Theory: Fig. 1 illustrates a situation in which the ownship (A) is in conflict with an intruder (B). A so-called collision cone (CC) can be defined by lines tangential to the intruder's PZ. A and B are in conflict when the relative velocity between these two aircraft lies inside the CC. By adding the intruder's velocity, the CC is translated forming the intruder's VO. This VO represents the set of ownship velocities which result in a loss of separation with the intruder. R represents the radius of the PZ. $P_{Ownship}(t_0)$ and $P_{Intruder}(t_0)$ denote the ownship's and the intruder's initial position, respectively. $P_{Intruder}(t_c)$ identifies the intruder's position at the moment of collision. Each intruder in the vicinity of an ownship results in a separate VO.

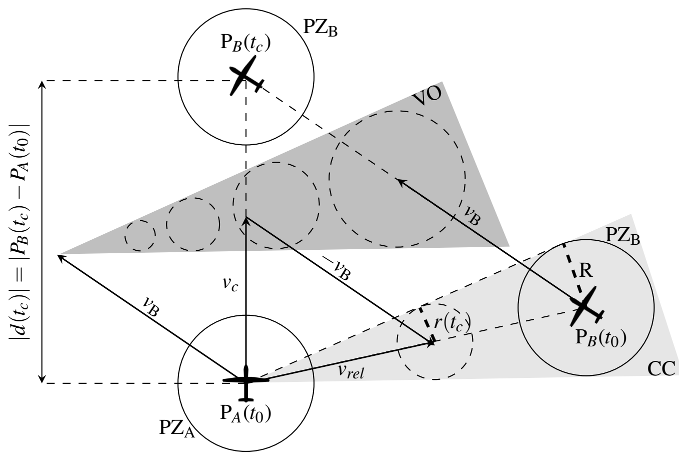

Figure 1. Representation of a VO imposed by intruder B, and the relationship between a circular velocity vector set and the PZ [12].

The velocity v_c which will make the ownship occupy the same position as the intruder at a given time t_c is equal to:

$$v_c(P_A(t_c) = P_B(t_c)) = \frac{P_B(t_c) - P_A(t_0)}{t_c - t_0} = \frac{d(t_c)}{t_c - t_0}, \quad (1)$$

where $d_c(t_c)$ represents the distance the ownship aircraft must travel in order to collide with the intruder at time t_c. In theory, the VO of an intruder can be built from $t_c = t_0$ to $t_c \to \infty$. For each t_c, the distance $d(t_c)$ that the ownship would have to travel, and the necessary velocity to do so within $t_c - t_0$, can be identified. As $|v_c|$ increases, t_c decreases from $t_c \to \infty$ towards $t_c = t_0$. However, in practice, the upper limit of the VO is set as the look-ahead time value for conflict detection. Given the symmetrical relationship in Fig. 1 between the radius of the circular set of velocities, r, and the radius of the protected zone, R, the former can be determined:

$$\frac{r(t_c)}{|v_c(t_c)|} = \frac{R}{d(t_c)}. \quad (2)$$

Given (1), (2) can be transformed into:

$$r(t_c) = \frac{R}{t_c - t_0}. \quad (3)$$

Intent can be added to a VO based on the work Velasco [12]. For a VO without intent, lines connecting all the circles in the VO will be straight, maintaining the same direction and size progression throughout time. However, when considering intent, circles will not follow the same progression. For each time to collision, t_c, a new VO circle can be calculated according to the predicted heading, velocity and acceleration of the intruder at that moment. The VO will then be formed by connecting these circles (see Fig. 2).

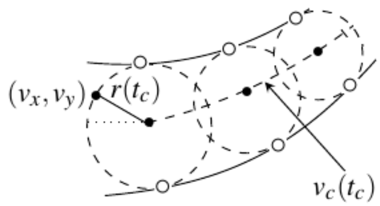

Figure 2. VO with intent. VO circles are centered at $v_c(tc)$.

Considering that time can be expressed along the bisector of the VO, the VO itself can be identified as a family of circular curves, with their center at $v_c(tc)$ along the VO bisector. The envelope of a family of curves is defined as [14]:

$$\begin{bmatrix} v_x \\ v_y \end{bmatrix} = v_c(t_c) + r_c(t_c) \begin{bmatrix} cos(\theta) \\ sin(\theta) \end{bmatrix}, \quad \forall\ \theta \in [-\pi, \pi], \quad t_c \in [t_c, \infty], \quad (4)$$

where v_x, v_y are the components of the velocity vector for each circle, and θ the angular coordinate. Deriving the envelope equation will result in the values of θ for which v_x, v_y are the tangent points on the envelope curve.

By assuming that the collision vectors are differentiable, the envelope of the family of circles define in (4), is [14]:

$$\begin{vmatrix} \frac{\partial v_x}{\partial t_c} & \frac{\partial v_x}{\partial \theta} \\ \frac{\partial v_y}{\partial t_c} & \frac{\partial v_y}{\partial \theta} \end{vmatrix} = 0. \quad (5)$$

By resorting to the following notation:

$$\dot{v}_{c_x} = \frac{\partial V_{c_x}}{\partial t_c}, \ \dot{v}_{c_y} = \frac{\partial V_{c_y}}{\partial t_c}, \quad \dot{r} = \frac{d_r}{dt_c} = \frac{-R}{(t_c - t_0)^2}, \ \Theta \equiv \tan\left(\frac{\theta}{2}\right), \quad (6)$$

we can rewrite (4) and (5):

$$\Theta^2(-\dot{v}_{c_y} + \dot{r}) + \Theta(2\dot{v}_{c_y}) + (\dot{v}_{c_x} + \dot{r}) = 0, \quad (7)$$

which can be solved as a second order polynomial. The solutions identify the values of Θ for the tangent points of the envelope. However, these are real coordinates only when the discriminant, $|\dot{v_c}|^2 - \dot{r}^2$, is greater than zero, i.e. $|\dot{v_c}| \geq \dot{r}$. As a result, VO circles can only be calculated when the variation of the radius of the VO circles is smaller than the variation of the center of the circles. Through (3), we can consider that VO circles are only possible when:

$$|\dot{v_c}| < \frac{R}{(t_c - t_0)^2}. \quad (8)$$

One important case to consider is that when minimum separation has already been lost, no tangent solutions are possible. Therefore, intent VOs are only possible before LoS.

2) Turn Estimation: For the design of a VO with intent, the positions of intruders during turns are considered, in order to guarantee that small LoSs do not occur during a turn. Fly-by TCPs for each turn are assumed. Note that turns were not considered for conflict detection due to the heavy computation that such would entail. However, in the resolution phase, a smaller set of aircraft which are in conflict is considered and, thus, calculating turns was deemed feasible and favourable to conflict resolution.

Turns are assumed to have a fixed bank angle, ϕ_{nom}, of 25°; aircraft remain at the same flight level and have constant speed throughout. In Fig. 3, the aircraft's TCPs are identified. As the heading post TCP_{i+1}, Ψ_{i+1} , is different than the current heading, Ψ_i, the aircraft initiates a turn assumed to start and end at a pre-determined distance, d, from TCP_{i+1}.

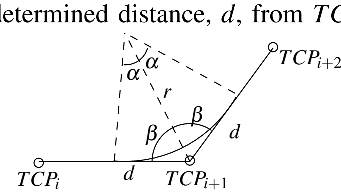

Figure 3. Geometry of a turn between TCPs. No wind assumed.

The radius of the turn, r , can be calculated by :

$$r = \frac{V^2}{g \times \tan(\phi_{nom})}, \quad (9)$$

where V represents the speed of the aircraft, and g the gravitational acceleration. Based on the geometry of Fig. 3, the total angle of the turn is defined by:

$$\beta = \frac{|\Psi_i - \Psi_{i+1}|}{2}, \quad (10)$$

and the distance from TCP_{i+1} at which the aircraft starts and ends the turn by:

$$d = r \times \tan(\beta). \quad (11)$$

The turn rate, $\dot{\Psi}$, can be determined by:

$$\dot{\Psi} = \frac{g \tan(\phi_{nom})}{V}. \quad (12)$$

3) Solution Space Diagram (SSD) resolution model: consists of finding the intersection between the VOs from all intruders and the performance limits of the ownship, in order to identify which sets of velocity vectors result in a future LoS with intruders. Each VO is in the same referential and, thus, these can be added. The main advantage of SSD is the possibility of avoiding conflicts in advance. For computation of this model, the VOs and the circles delimiting velocity performance are inserted into an existing polygon clipper library [15], which is responsible for finding the set of spaces within the velocity limits which do not intersect the VOs. Intent information can be added to the VOs considered in the SSD. Such will alter their shape, thus resulting in a different set of velocity vectors which do not intersect those VOs. Consequently, the decision of whether to use state or intent information has a direct effect on the avoidance maneuver generated by the model.

III. Experiment: Adding Intent to CD&R

A. Apparatus and Aircraft Model

The Open Air Traffic Simulator Bluesky [16] was used in order to test the effect of adding intent to the CR model SSD. Bluesky has an Airborne Separation Assurance System (ASAS) to which CD&R models can be added, allowing for different CD&R implementations to be tested under the same scenarios and conditions. A DJI Mavic Pro model was used for the simulations. Speed and mass were retrieved from the manufacturers data, and common values were assumed for turn rate (max: $15°/s$) and acceleration/breaking ($1.0\,kts/s$).

B. Independent Variables

Three independent variables are included in this experiment:

1) Traffic Density: varies from low to high as per Table I. High densities spend more than 10% of their flight time avoiding conflicts [17]. Each traffic density will be tested with three different repetitions, each with different trajectories.

TABLE I. Traffic volume used in simulation.

	Low	Medium	High
Traffic density [$ac/10000\,NM^2$]	3826	5000	6580
Number of instantaneous aircraft [-]	86	112	148
Number of spawned aircraft [-]	369	483	635

2) State/intent information usage: three different situations (see Table II) with using state and intent information will be tested in order to establish how to maximize the effect of using intent information:

(a) Only state (S) information; common application which will be used as performance baseline for comparison.

(b) State and intent information is used simultaneously ($S \wedge I$); conflicts are detected and resolved preparing for both situations: whether intruding aircraft continue their current state or follow their intent. This is a conservative approach, with aircraft working to prevent all possible risk situations. The disadvantage is that more VOs are included in the solution space and the amount of velocity vectors which can avoid all conflicts becomes smaller; it can potentially even reach a situation where no solution exists. In this case, a second iteration of conflict resolution was implemented; this will use state only to at least find one solution which will prevent part of the conflicts.

(c) Intent information is used when the aircraft is flying a nominal path ($S \vee I$). When it diverts from its nominal path, due to a conflict avoidance maneuver, then the intent conflict detection and resolution algorithm reverts to state projection. In this sense, this situation is a *hybrid* CD&R method. This approach is less conservative, but is optimal in terms of preventing solution space saturation. Symmetry in conflict is assumed, if the ownship is in conflict avoidance, it assumes that the intruder is as well.

TABLE II. Different state/intent information usages. Visual representation of the VOs included can be found in Fig. 4.

Experiment	VOs Included	Conditions
State (S)	(1)	Only state information
State AND Intent ($S \wedge I$)	(1) + (2)	State AND intent information simultaneously
State OR Intent ($S \vee I$)	(1) if intruder is in conflict avoidance (2) if intruder is following intent	State OR intent information whether the intruder is in conflict avoidance mode or not, respectively

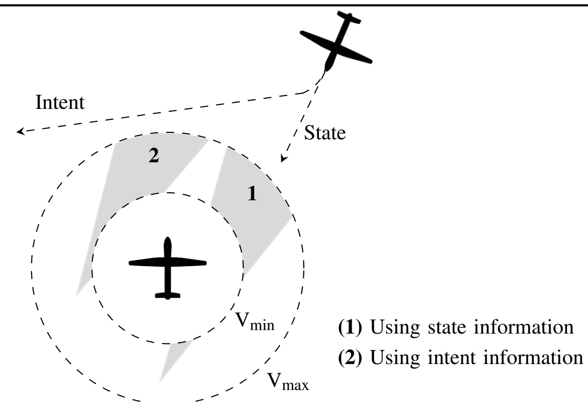

Figure 4. Shape of the VO depending on whether state or intent is used.

3) Conflict Resolution Strategy: different resolution strategies can be picked, based on which velocity vector is selected from the set of vectors which guarantee conflict avoidance. While most geometric CD methods work on basis of the (1) shortest way out, these have been mostly tested using linear trajectories. It is thus of relevance to test whether this strategy is still successful for a non-linear trajectory, or if having conflict resolution based on the intent (i.e. (2) shortest from destination) will enhance the potential of using intent in conflict detection and resolution. As a result, these resolution trajectories will be directly compared (see Fig. 5).

The shortest way out principle assures implicit coordination in one-to-one conflicts. As single conflicts are always geometrically symmetrical [11], both aircraft in a conflict will take (opposite) measures in order to evade the other. However, for shortest from destination, this is not guaranteed.

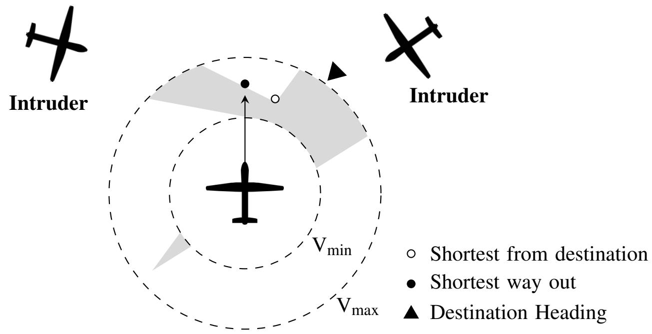

Figure 5. Representation of 'shortest way out' and 'shortest from destination' resolution strategies.

IV. Experimental Design and Procedure

All aircraft will fly at the same altitude of 300 ft. Each aircraft changes it heading five times; resulting in five different legs. Each heading is computed with a normal distribution random number generator, varying from 0° to 360°. Total flight distance is uniformly distributed between a pre-defined minimum and maximum value, 15 NM–20 NM, based on the minimum flight time and the average True Air Speed (TAS). No wind is considered. Each scenario lasts three hours.

Aircraft fly within a square data collection area, with an area of 250 NM^2. This dimension was defined based on the average True Air Speed (TAS) and average flight time. Aircraft are spawned just outside of the data collection area; this prevents the logging of very short term conflicts between just spawned aircraft and pre-existing cruising traffic. Spawn locations (origins) are spaced at a distance equal to the minimum separation distance plus a 10% margin, to avoid conflicts between spawn aircraft and aircraft arriving at their destination. The data collection area is inside a larger square area designated the simulation area. An aircraft is removed from the simulation once it exits this simulation area. This second area is used as we do not want to delete aircraft as soon as they leave the data collection area; they may temporary exit it in case a conflicting maneuver so demands.

A look-ahead time of five minutes is used for conflict detection. There is no pre-defined standard minimum separation distance for unmanned aviation. However, 50 m–400 m are values commonly used in research [18], [19] depending on the properties of the UAVs considered. For the DJI Mavic Pro, a value of 200 m will be used in these simulations.

A. Dependent Measures

Experimental results are compared based on measures in two categories: *safety* and *efficiency*.

In this study, *safety* is defined in terms of the number and duration of conflicts, and LOSs. Naturally, fewer conflicts and LOSs are expected to be safer. Additionally, the percentage of false positives and false negatives alarms in the baseline state only detection is analyzed; these will help interpret the changes in safety values once intent information is added. Finally, LOSs differ in severity according to how close aircraft get to each other:

$$LoS_{sev} = \frac{R - d_{CPA}}{R}. \qquad (13)$$

A low separation severity is naturally preferred.

Efficiency is evaluated in terms of distance travelled and duration of flight. CR models move aircraft out of their intended trajectory in order to avoid conflicts/LOSs, making the path longer. However, a CR model which results in considerable path deviations, significantly increasing the path travelled and/or the duration of the flight is considered inefficient.

V. Experiment Hypotheses

With smaller densities, Carreño [20] showed that intent can be used to reduce the number of false alarms. Intent also helps detecting future conflicts resulting from changes of state. With state only, these would only get detected once intruders have completed the change, which may be too late to prevent LoSs. It was hypothesized that intent would reduce the number of LoSs, as the ownship has more time to avoid them.

It was hypothesized that using both state and intent information simultaneously ($S \wedge I$) would increase the number of detected conflicts (i.e. false negatives are added and false positives are not discarded), but would prevent more LoSs with the 'shortest way out' resolution strategy. All possible future cases (i.e. intruder following intent or entering conflict avoidance) are defended for in advance. The state information is the best indication of the state during conflict avoidance as aircraft will try to differ from it as least as possible.

Finally, the *hybrid* solution ($S \vee I$) is hypothesized to have the most accurate conflict detection by removing false positive and adding false negative alarms. However, when intruders enter conflict avoidance mode near a TCP, switching from intent information to state information may be too late to avoid LoSs. Consequently, it was hypothesized that 'shortest from destination' would be the optimal resolution in this case, as state and intent information will differ the least.

VI. Experiment: Results

Fig. 6 displays the total number of conflicts. Traffic density has a direct effect on this number; the more aircraft within the same airspace, less maneuvering there is for each aircraft and more conflicts occur. Additionally, 'shortest from destination' resolution exhibits more conflicts when compared with 'shortest way out' in similar conditions; such is due to the fact the later used a bigger portion of the airspace during conflict avoidance. This effect is negligible at lower densities, where the space is divided between fewer aircraft; however, it is more evident as traffic density increases. In terms of information usage, as hypothesized, ($S \wedge I$) results in a higher number of conflicts. Additionally, there are more conflicts in the *hybrid* condition ($S \vee I$) in comparison with the baseline state only (S). The former is expected to have fewer false positive alarms than the latter, but will consider alarms resulting from state changes not included in (S) (i.e. false negatives). However, a direct interpretation of the number of false positives and false negatives alarms here is not possible, as these models have different conflict resolutions, which will create a different number of secondary conflicts.

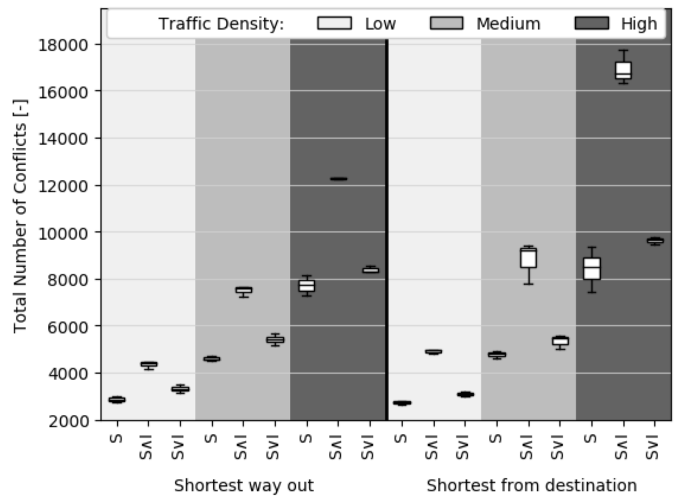

Figure 6. Number of conflicts per CD&R condition and resolution strategy.

Fig. 7 displays the results obtained from comparing conflicts detected by state only (S), with intent information. The average for all scenarios per traffic density is displayed. Within existing conflicts, true positives (i.e. conflicts detected both with state and intent information) and false negatives (i.e. conflicts resulting from state changes which are not detected by state only) are compared. On average, at any point in time during the simulations, state only is only able to detect about 10% of the existing conflicts. Regarding the conflicts detected by state only, a negligible amount are false positives (i.e. intruders and/or the ownship will change state before the predicted LoS); this is likely due to the short look-ahead period used. As a result, adding intent to conflict detection is expected to have a greater impact in terms of identifying, in advance, conflicts resulting from state change.

Fig. 8 shows the time each aircraft spends in conflict avoidance mode over the complete flight path. At higher traffic densities, although using a 'shortest from destination' resolution strategy results in more conflicts, the total duration of these conflicts is lower. While this resolution is less efficient in preventing less conflicts, it is able to resolve them faster.

Fig. 9 shows the total number of LoSs. As hypothesized, combining both state and intent reduces the number of LoSs ($S \wedge I$ vs S), albeit mostly for a 'shortest way out' resolution. Given the conflict detection analysis in Fig. 7, it is considered

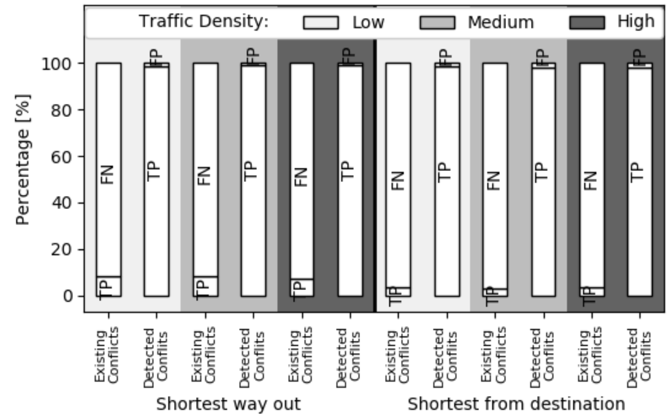

Figure 7. True positives (TP), false positives (FP), and false negatives (FN) resulting from a state only state detection algorithm per resolution strategy.

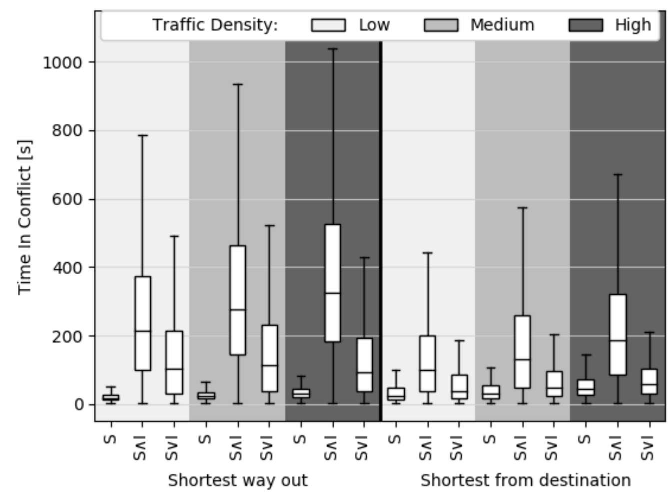

Figure 8. Time in conflict per CD&R condition and resolution strategy.

that this is due to alarms resulting from state change being detected in advance. Interestingly, the difference in LoSs is less than the difference in alarms detected, meaning that state detection is still able to prevent some of the alarms, although detecting them at a later point in time. With a 'shortest from destination' resolution, at the highest density, no improvement was achieved. For the *hybrid* solution ($S \vee I$), the 'shortest from destination' resolution is clearly the best option; however, even in this situation, adding intent does not reduce the number LoSs. Changing from intent to state projection only when intruders enter conflict avoidance is too late to avoid LoSs.

Fig. 10 displays the separation severity for each case. This value does not seem to be dependent on either traffic density or state/intent detection and resolution. However, using 'shortest way out' resolution tends to maximize the distance between aircraft at the closest point of approach.

Figs. 11 and 12 display the percentage increase in flight distance and flight time, respectively. For situations ($S \vee I$) and ($S \wedge I$), 'shortest from destination' resolution minimizes deviation both in path and flight time. This was expected, as

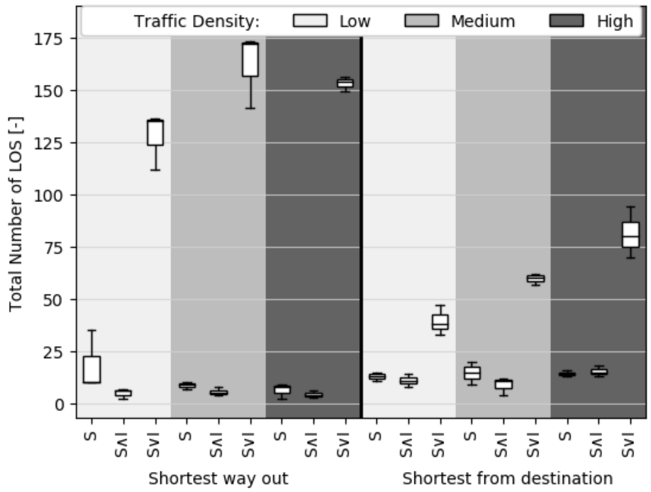

Figure 9. Number of LoSs per CD&R condition and resolution strategy.

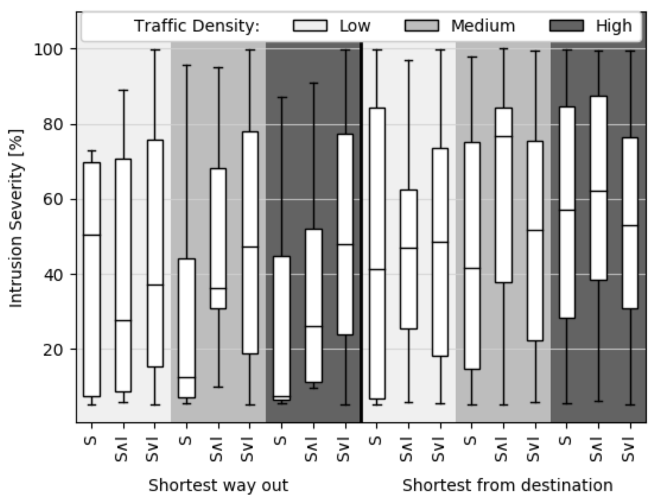

Figure 10. Intrusion severity per CD&R condition and resolution strategy.

aircraft opt for staying close to their destination heading as much as possible.

VII. Discussion

Combining intent and state information, although resulting in more false positives alarms, reduces the number of LoSs compared with using state information alone. The efficiency of this model is due to combining both information of the current state and intent which provides guidance regarding the future state. However, a disadvantage when using both intent and state information simultaneously with the SSD model, is that the solution space becomes saturated faster, specially as traffic density increases (see Table III). At high densities, most of the benefit of using intent results from including, in advance, alarms due to future state changes.

Regarding resolution strategies, 'shortest from destination' tries to deviate as little as possible from the intent trajectory and is, thus, a more efficient resolution by minimizing flight distance and time deviation. Nevertheless, 'shortest way out'

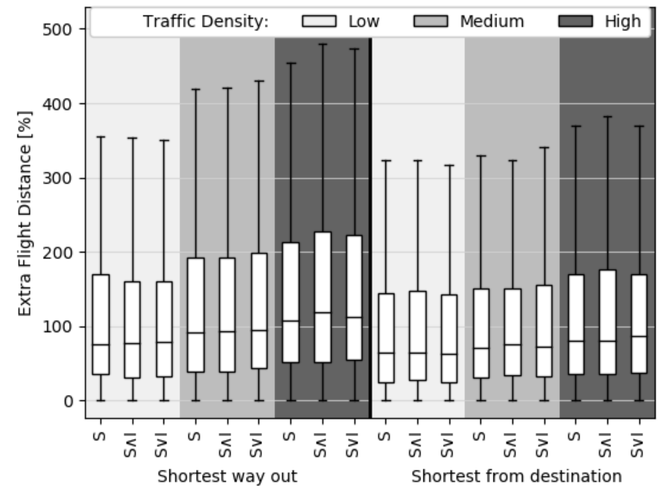

Figure 11. Extra flight distance per CD&R condition and resolution strategy.

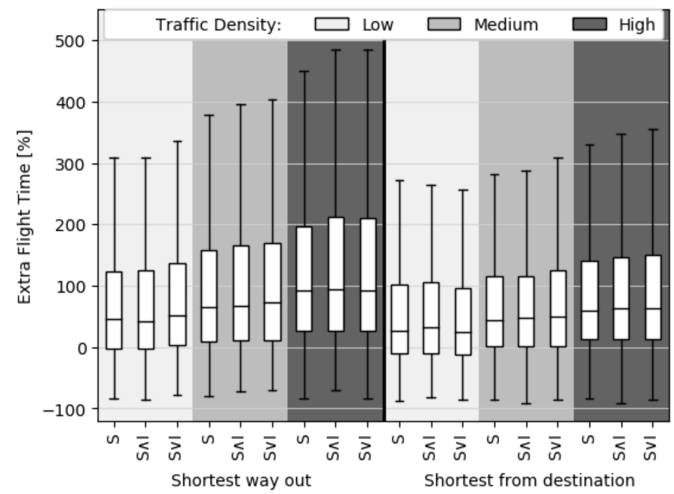

Figure 12. Extra flight time per CD&R condition and resolution strategy.

TABLE III. Solution space (SS) division during experimental simulations.

Resolution Strategy	Shortest way out			Shortest from destination		
Traffic Density	Low	Medium	High	Low	Medium	High
% SS not intersecting VOs (average)	41%	30%	23%	46%	38%	31%
% of SS computations without solution	4.6%	5%	12.7%	3%	2.1%	2.5%

resolution is preferred safety-wise; having minimum path deviations guarantees minimal LoSs. At high densities, tactical conflict resolutions can trigger conflict chain reactions due to the scarcity of airspace [21]. Not opting for the 'shortest path' resolution will potentially create a higher chain reaction as aircraft require a bigger portion of the airspace for conflict resolution. Additionally, given that 'shortest from destination' resolution does not guarantee implicit coordination, it may result in a higher time in conflict for neighboring destinations. Aircraft will initially resolve towards the same direction, and the conflict will have to be reevaluated. This was not observed in the experimental results (see Fig. 8), suggesting sufficient separation between destinations. However, this should be considered for scenarios with destinations in close proximity.

Surprisingly, state-based only always yields fewer LoSs than the *hybrid* solution ($S \vee I$). This was expected for a 'shortest way out' resolution as aircraft deviate as least as possible from their state during conflict avoidance. When an intruder, close to a TCP, enters conflict avoidance mode, only then considering a state projection may be too late to prevent the LoS. This effect was expected to be reduced with a 'shortest from destination' resolution; aircraft stay as close as possible to their destination heading during conflict avoidance, thus minimizing the differences between state and intent projection. However, this proved ineffective. In conclusion, state projection must still be used at all times.

Finally, an advantage of using state detection and resolution is that it is a fast prediction. Naturally, including intent, where information broadcast by neighbouring aircraft must be processed, requires more iterations. In a real case scenario, where computational speed is crucial, the potential of intent information must first be tested in terms of the available computational capacity, the desired minimum separation distance, and the expected traffic density. The latter is crucial: as traffic density increases, each aircraft will spend more time in conflict and will have to perform more deconflicting maneuvers. Additionally, each maneuver will have to consider more aircraft, leading to more complex solutions.

VIII. Conclusion

This work analysed the improvement in conflict detection and resolution at high densities in unmanned aviation by adding future trajectory intent. For conflict resolution, the Solution Space Diagram, based on the velocity obstacles theory, was used. Results were compared with a baseline detection and resolution model using state information alone. Fast-time simulations showed that combining state and intent information reduces the number of losses of separation, thus improving safety. Adding explicit intent improves conflict detection, as aircraft are informed, in advance, of future conflicts resulting from future state changes and can, thus, better avoid them.

A 'shortest way out' conflict resolution optimizes conflict avoidance. Choosing small deviations from the current state helps prevent conflict chain reactions which would result from occupying a bigger portion of the airspace. With this resolution, current state projection must also be used in conflict detection, so aircraft can prepare, in advance, for situations were intruders 'miss' trajectory changes points and instead remain close to their state for conflict avoidance.

For future research, simulation scenarios shall consider city-like obstacles with non-uniform patterns, which will likely create density 'hotspots', heavily increasing the number of conflicts as well as the number of heading changes.

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