Autonomous Separation in U-Space
Assessing the Impact of Position Uncertainty

Rahman, Muhammad Fazlur; Vlaskin, Aleksandr; Ellerbroek, Joost; Hoekstra, Jacco

Publication date
2024

Document Version
Final published version

Published in
14th SESAR Innovation Days, SIDS 2024

Citation (APA)
Rahman, M. F., Vlaskin, A., Ellerbroek, J., & Hoekstra, J. (2024). Autonomous Separation in U-Space: Assessing the Impact of Position Uncertainty. In *14th SESAR Innovation Days, SIDS 2024* (SESAR Innovation Days).

Autonomous Separation in U-Space: Assessing the Impact of Position Uncertainty

Muhammad Fazlur Rahman, Aleksandr Vlaskin, Joost Ellerbroek and Jacco Hoekstra
Faculty of Aerospace Engineering
Delft University of Technology
Delft, The Netherlands

***Abstract*—With the rapid increase in the use of Unmanned Aerial Systems (UAS) for commercial applications such as medical and parcel delivery, the need for safe airborne separation in airspace has become critical. This paper examines the impact of position uncertainty on autonomous separation methods within U-Space, a European Union initiative for managing drone traffic. The study focuses on evaluating various conflict resolution algorithms—specifically, Modified Voltage Potential (MVP) and Velocity Obstacle (VO) variations—under conditions of navigational uncertainty. Through Monte Carlo simulations using the BlueSky ATM simulator, position uncertainty stemming from Global Navigation Satellite Systems (GNSS) errors is modelled and analysed. The research compares the effectiveness of different conflict resolution strategies in preventing conflicts between UAS, measuring intrusion prevention rates and the closest point of approach during encounters. The results indicate that MVP provides superior performance in handling positional uncertainty, offering more robust conflict resolution capabilities than VO-based methods especially at shallow angles conflict situation. These findings are critical for ensuring the safe integration of UAS into increasingly congested airspace environments, guiding future developments in U-Space operations.**

***Keywords*—Position Uncertainty, Autonomous Separation, UAS, U-Space, Conflict Detection and Resolution, BlueSky, Drones**

I. Introduction

Commercial applications that involve Unmanned Aerial Systems (UAS), commonly known as drones, are on the verge of rapid growth. With applications such as medical delivery, parcel delivery, and remote monitoring for infrastructure and emergency response, the commercial drone sector is expected to grow to unprecedented levels in the coming decades. The EU drone outlook study [1] estimates some 500,000 commercial drones in EU airspace alone by 2050. This, of course, requires an extra effort to allow drones to fly safely among existing air traffic.

The CORUS project proposes a U-Space concept of operations (CONOPS) to allow UAS to fly safely in the airspace [2]. Several services will be available in U-Space to enable safe operations, such as registration, remote identification, and separation management. Any aircraft, both crewed and uncrewed, flying in the U-Space is expected to be registered. Next to it, remote identification provides situational awareness by communicating all aircraft positions by radio or through the internet. Most crucially, the U-Space concept relies on autonomy - since the traffic numbers are expected to be too high for human operators to effectively manage, all of the separation management is to be performed by an autonomous separation management system. Such a system will be comprised of multiple layers [3], namely a strategic (pre-flight) component that manages planning and flows, a tactical in-flight component that will avoid conflicts when they occur, and a collision avoidance (detect-and-avoid) system. This paper investigates possible implementations for the Tactical Layer, which will be crucial to enable UAS flight and fulfill the mandatory self-separation requirement set in the U-Space CONOPS [2].

In literature, numerous conflict resolution algorithms for tactical separation have been proposed. Geometric methods have proven to be especially effective in terms of safety and low computational demand. Velocity Obstacle (VO) [4], a geometry-based algorithm, enables UAS to find the shortest way out of the conflict. Several variations of VO are also available [5]–[8], with each proven to perform better than the original VO. Another conflict resolution algorithm is Modified Voltage Potential (MVP) [9], using the distance at the closest point of approach (CPA) vector to determine the direction of the resolution velocity. Although numerous scenarios have been conducted to compare these algorithms [10], [11], the accurate modelling of uncertainty aspect is often still missing.

Uncertainty in U-Space is an imminent problem. Position information is typically obtained from Global Navigation Satellite Systems (GNSS). This is then transmitted through the radio-based or internet-based service called Automatic Dependent Surveillance - Light (ADS-L) [12]. There are two types of uncertainty that affect these position data: one related to communication and the other to navigational uncertainty. These types of uncertainty are inherent to communication, navigation, and surveillance systems [13]. The navigational uncertainty can be modelled using a Gaussian Distribution, while the communication uncertainty is defined in terms of update rate and reception probability.

The aim of this work is to evaluate several Conflict Resolution methods under navigational uncertainty and determine how they perform in terms of safety. To this end, an ADS-L model is developed as a plugin for the BlueSky ATC [14] simulator. This plugin is designed to include positional error due to GNSS as variables, allowing for the simulation of the uncertainties that drones will experience when performing conflict resolution with communication loss and positioning

SESAR Innovation Days 2024
12 - 15 November 2024. Rome

error. Then, Monte Carlo simulations are run for three different Velocity Obstacle-based methods: Modified Voltage Potential (MVP), priority-based Velocity Obstacle (VO), and cooperative optimal VO. The Monte Carlo simulations consider a range of relative headings and speeds. The methods will be compared in terms of intrusion prevention rate (IPR) and distance at the closest point of approach (CPA).

II. State-Based Autonomous Separation

In state-based autonomous separation, the positions, ground speeds, and headings of conflicting aircraft are used to perform conflict resolution. Each aircraft considers itself the ownship and others as intruders, with the ownship's state determined through internal measurements. The states of intruders, however, are obtained via ADS-L communication, introducing both navigation and communication uncertainties. These uncertainties can lead to inaccuracies in state measurements and potentially delay conflict detection or resolution. Since ADS-L broadcasts aircraft states every second, reception delays due to range limitations or interference can result in outdated information, causing asymmetry in conflict detection.

Given these uncertainties, effective coordination among UAS becomes essential to maintain safe separation. To achieve self-separation, UAS must coordinate during flight. Many studies outline three forms of coordination: explicit, implicit, and uncoordinated. Explicit coordination involves direct communication of resolution maneuvers, while implicit coordination relies on common rules that all UAS follow without direct communication. In this research, implicit coordination is selected due to its simplicity in implementation. Moreover, ADS-L, the primary communication and surveillance system, does not support explicit coordination, reinforcing the need for a rule-based approach in U-Space.

Building on this framework, we selected three state-based conflict resolution methods for comparison, chosen for their ability to operate in continuous space, lower computational complexity, and ease of implementation. The first method is the original Velocity Obstacle (VO) [4], a geometry-based approach for conflict resolution. The second is Modified Voltage Potential (MVP) [9], which draws inspiration from the behavior of charged particles repelling each other when in close proximity. Both VO and MVP require cooperation between ownship and intruders to avoid conflicts. In contrast, the third method, Selective Velocity Obstacle (SVO) [8], integrates priority-based rules from the rules of the air [15], allowing it to manage conflicts based on established right-of-way guidelines. The details of these algorithms will be discussed in the following paragraphs.

To construct VO, a triangle is first drawn using the two tangent lines to the protected zone of the intruder. This triangle is called the collision cone (CC). Then, the triangle is translated in the direction of the intruder's velocity. This new triangle represents the set of velocity vectors that will evolve into conflict with the intruder. The solution to the conflict is to select a new velocity vector, which is the closest point between the current velocity and the side of the VO. Figure 1 illustrates

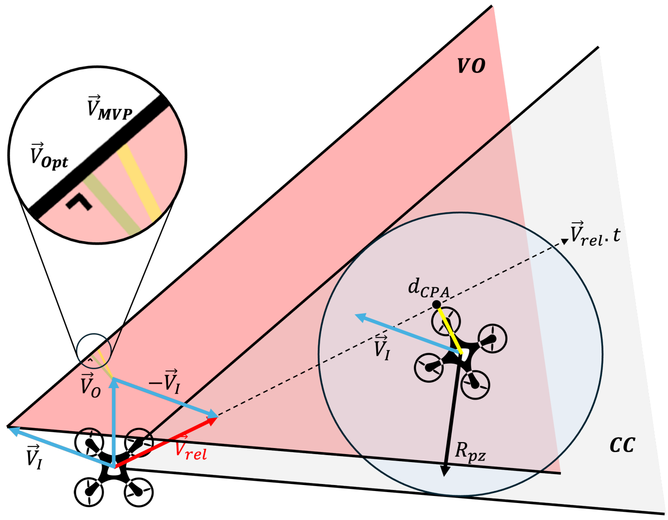

Figure 1: Illustration of the Velocity Obstacle (VO) and Collision Cone (CC) for collision avoidance, showing the relative velocity vector (V_{rel}) and its components. The diagram contrasts the optimal velocity (V_{opt}) and the MVP strategy within the permissible velocity space, highlighting how these strategies work to prevent conflicts by adjusting the velocity outside the VO region.

the construction of VO in a pairwise conflict situation, with the green line showing the change in velocity. Note that there are infinitely many resolution velocity in a given conflict. The resolution velocity can be placed anywhere along the velocity obstacle triangle or outside of it.

One drawback of VO is the oscillation and reciprocating problem [6]. Among different VO variations, SVO or VO - priority-based is selected since it implements the rules of the air, an existing convention for conflict resolution in manned aircraft [8]. The algorithm allows certain aircraft to have priority, thus removing the necessity to perform a maneuver in the case of conflict. In a hyper-dense UAS environment, with no navigational uncertainty, VO - priority-based is proven to perform better than the original VO in terms of number of losses of separation.

The next conflict resolution is MVP, using the closest point of approach (CPA) vector to produce the new velocity of the ownship. With this approach, the resolution velocity is simpler to produce compared to VO. In its original form, MVP allows conflict resolution by changing exclusively heading, speed, or both [9]. Changing both speed and heading results in shortest-way-out version of MVP, the version we consider in this paper. Even though it stems from a different calculation, the concept of MVP can be illustrated in the velocity obstacle triangle as seen in Figure 1. From the figure, it can be seen that the solution lies on the side of the VO triangle, proving that the resolution velocity from MVP results in a conflict free condition.

A slight difference between MVP and VO is that MVP is not perpendicular to the triangle side. This happens since the resolution velocity is calculated from the CPA vector. With this, MVP produces a slightly higher magnitude for the resolution velocity. Even though there's only a tiny difference,

[10] shows that MVP performs better in an extremely dense condition.

III. Propagation of Uncertainty

Propagation of uncertainty refers to the process of determining how uncertainties in input variables affect the uncertainty in the output of a function. In this context, the input variables represent measurements such as position, speed, and heading, which are subject to measurement errors or uncertainties. When these inputs are processed through a function—such as a conflict resolution algorithm—the output variables, like the resolution velocity, also inherit a degree of uncertainty.

In the simplest, linear case, the relationship between input and output uncertainties can be mapped using a set of straightforward rules. For instance, if a random variable with a standard deviation of σ is transformed by a function that scales the variable by a factor of two, the standard deviation of the output would be $\sigma/2$. This linear relationship makes it relatively easy to predict how uncertainties in the input will affect the output.

However, in non-linear functions, such as those found in state-based conflict resolution algorithms, the propagation of uncertainty becomes much more complex. A simple linear approximation is typically insufficient to describe how uncertainties evolve through the function. In such cases, Monte Carlo simulations are often employed to model and estimate the combined uncertainties, offering a more accurate representation of the behavior of the system under real-world conditions.

In the context of state-based conflict resolution, the accuracy of the resolution maneuver relies on precise input variables such as position, ground speed, and heading. However, these variables are inherently subject to measurement errors due to navigation and communication uncertainties. This introduces stochastic elements into the calculation of resolution velocities, potentially leading to suboptimal or unsafe maneuvers. Since all three conflict resolution algorithms discussed involve highly non-linear functions, Monte Carlo simulations are necessary to assess the propagation and performance of these algorithms under uncertainty.

Understanding how the uncertainty propagates is essential for ensuring the safety of aircraft operation in U-Space. The input variables for the conflict detection and resolution, with their uncertainty, directly affect the safety of the resolution manoeuvre. By analyzing the effect, we can determine the most suitable algorithm in a given condition. In this paper, we will focus on the positional uncertainty as described in the next section.

IV. Experiment Setup

The experimental setup for this study focuses on assessing the performance of different conflict resolution algorithms under varying conditions of navigation uncertainty. The simulations were conducted using the BlueSky open-source ATM simulator, complemented with an ADS-L plugin to replicate the real-world communication environment in which unmanned aerial systems (UAS) are expected to operate. Although ADS-L has both GNSS-based positional errors and communication losses, only the former is considered in this research to clearly analyze the positional impact on the conflict resolution algorithms. The positional uncertainty is modeled using a Gaussian Distribution and follows the convention in the ADS-L technical specifications [12]. From the technical specifications, the horizontal position accuracy is included in the broadcast message and the value varies from below 3 m, 10 m, 30 m, 0.05 NM, and all the way to higher than 0.5 NM. We select 30 m as a test case since values higher than that are too permissive for UAS operation - this corresponds to 'value' 5 for the horizontal position accuracy as per EASA [12].

A. Independent variables

Three independent variables are considered in this study. The first is the resolution method, with three levels: Modified Voltage Potential (MVP), Velocity Obstacle (VO) priority-based, and VO optimal change. The second variable is the initial heading, which is varied between 0 and 359 degrees in steps of 1 degree. The third independent variable is intruder speed with four levels: 5, 15, 25, and 35 kts. The ownship speed is kept constant at 20 kts.

Based on these variables, a full factorial experiment matrix is constructed, where each combination is run 500 times to ensure sufficient statistical power.

B. Dependent measures

The Intrusion Prevention Rate (IPR) (Eq. (1)) corresponds to the proportion of conflicts that were successfully resolved, and it is used as an indicator of algorithm effectiveness. The mean distance at CPA measures how close the aircraft come to each other during a conflict, providing insight into the severity of any remaining separation loss events.

$$\text{IPR} = \frac{n_{\text{cfl}} - n_{\text{LoS}}}{n_{\text{cfl}}} \tag{1}$$

Additionally, we assess how positional accuracy propagates into the resolution velocity and final position distribution. As outlined in Section III, positional errors introduce variability into the computation of resolution velocities, potentially causing deviations from the most effective flight paths. Finally, the mean and standard deviation of the final position are analysed to evaluate how these deviations evolve under varying angles.

C. Simulation settings

Conflict detection is configured with a look-ahead time of 15 seconds. This value is chosen since the results in [13] show that there is no significant improvement in the IPR and loss of separation severity beyond this value. For UAS, there is no standard separation size yet, therefore 50 meters is chosen as a horizontal separation margin as commonly used in literature [8], [11]. The simulations are conducted with an upper runtime boundary of 60 seconds, ensuring that each conflict scenario was resolved within a realistic time frame. This setup allows for thorough testing of each algorithm's ability to handle the

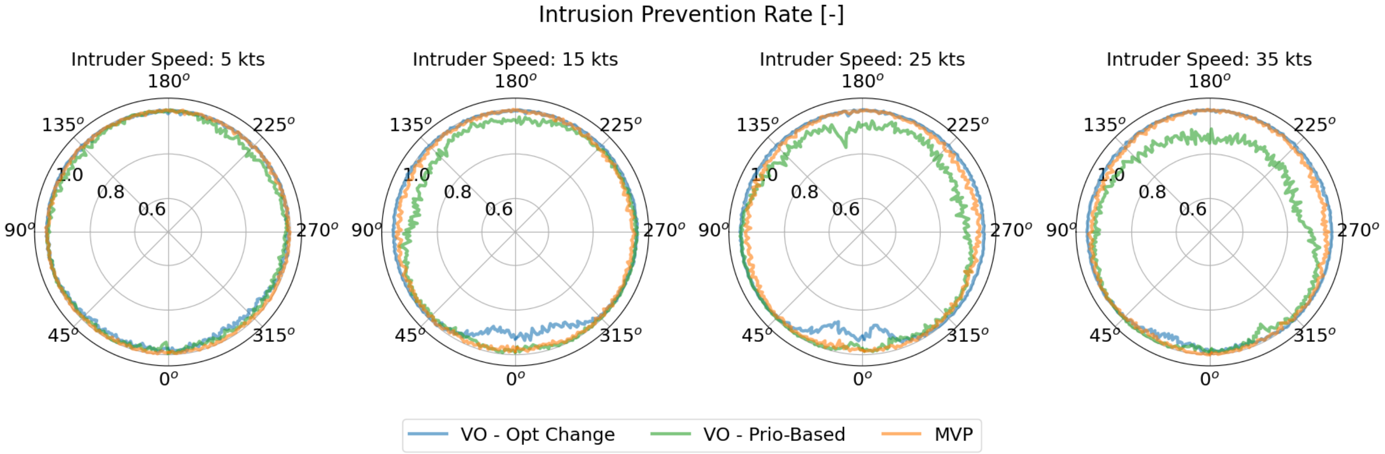

Figure 2: Comparison of intrusion prevention rate for different conflict resolution methods at different angles and speeds. Overall, MVP has the highest intrusion prevention rate. Note that VO - Optimal Change performs slightly worse than MVP, specifically at shallow angles.

dynamic and uncertain environment that UAS would face in a decentralized airspace.

V. Results and Analysis

A. *Intrusion Prevention Rate*

Figure 2 illustrates a comparison of intrusion prevention rates for the three conflict resolution methods for all combinations of initial heading and intruder speed. Since VO - priority-based is a modified version of VO - optimal change, the two conflict resolution methods will be compared to each other. Next, VO - optimal change will be contrasted to MVP.

For an intruder speed of 5 kts, the intrusion prevention rates (IPR) for both VO - optimal change and VO - priority-based are nearly identical across all headings. However, at higher intruder speeds (15 to 35 kts), the two algorithms begin to diverge in performance, with the priority-based VO underperforming at larger conflict angles (90 to 135 degrees). Interestingly, at shallow conflict angles (-45 to 45 degrees), the optimal-change VO algorithm performs worse than the priority-based VO. For instance, at an intruder speed of 15 kts and a heading of 90 to 135 degrees, the mean IPR for priority-based VO is 0.92, whereas for optimal change VO, it is 1.00. Conversely, at the same speed but within the 0 to 45 degrees range, the mean IPR for optimal change VO drops to 0.94, compared to 0.98 for the priority-based VO. Another interesting observation is the asymmetrical VO - priority-based. This happens due to the priority rules assigned depending on the state of the ownship and intruding aircraft.

The analysis showed that among the three algorithms, MVP consistently outperforms the others in terms of IPR, achieving the highest average IPR of 0.985 ± 0.009. VO - optimal change follows closely with an IPR of 0.983 ± 0.024, while VO - priority-based ranks third with 0.960 ± 0.036. Notably, MVP not only has the highest average IPR but also demonstrates greater consistency, as indicated by its lower standard deviation compared to the other methods.

B. *Mean Distance at CPA*

The IPR results show that the average IPR for the three algorithms are more than 96%. With 500 repetitions per scenario this means that there are fewer than 50 observed losses of separation per scenario. To increase the power of the distance at CPA results, this metric is therefore averaged for each range of 45 degrees heading.

Figure 3 shows a comparison between methods for their mean distance at CPA. For four different intruder speed categories, from 5 to 35 kts with 10 kts increments, the three conflict resolution methods are plotted. For each resolution method in each plot, there are eight values corresponding to the mean distance at CPA for 0-45 degrees, 45-90 degrees, and so on up to 315-360 degrees initial heading.

Overall, MVP achieves the greatest average distance at the closest point of approach (CPA), with a value of 44.11 ± 2.69 meters. VO - optimal change follows closely at 43.89 ± 4.27 meters, while VO - priority-based ranks lowest with 43.18 ± 3.41 meters.

C. *Position Uncertainty and Resolution Velocity*

To understand the source of difference in IPR, we look at how the position uncertainty is related to the resolution velocity. Figure 4 shows how the position uncertainty is mapped into the resolution velocity for VO (in blue) and MVP (in orange) for the ownship aircraft for an initial heading difference of 5 degrees and intruder speed of 15 kts. This figure is generated by running a Monte Carlo simulation to propagate the position uncertainty to the resolution velocity space. The Monte Carlo simulation is used in place of an analytical propagation analysis, as the the methods includes trigonometric functions and logic, for which it is difficult to compute the resolution velocity distribution using the Gaussian position distribution. The horizontal axis represents the y-body component, corresponding to the velocity in the lateral (sideways) direction, while the vertical axis represents the x-

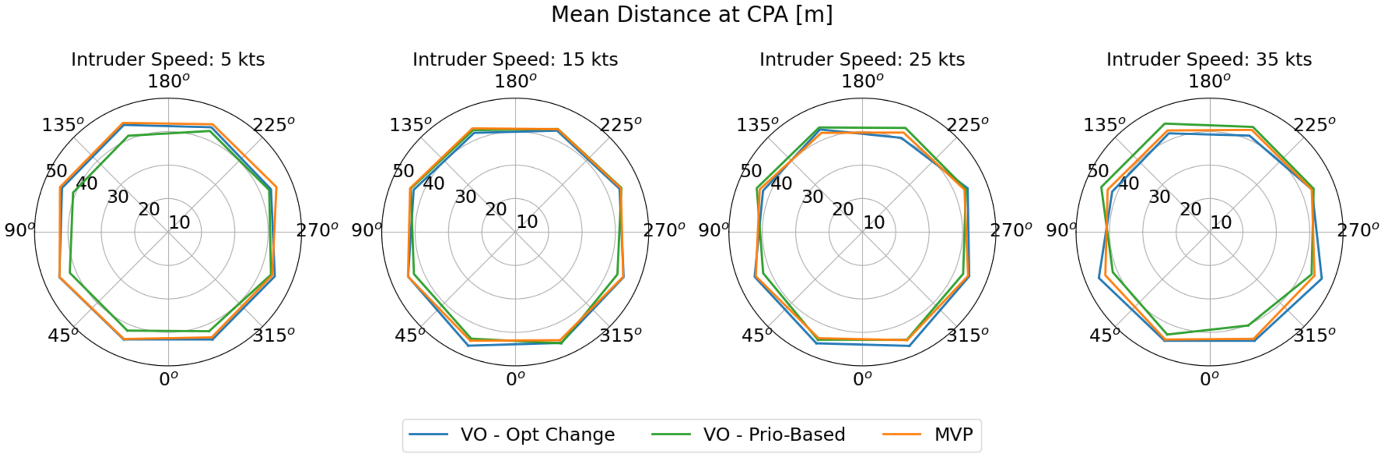

Figure 3: Comparison of mean distance at CPA for different conflict resolution methods at different angles and speeds. MVP and VO - Optimal Change have similar mean distance at CPA while VO - Priority-Based results in a closer distance.

body component, corresponding to the velocity in the forward direction.

For the MVP, the resolution velocity in the x-body component has a mean and standard deviation of 19.99 ± 0.55 knots, while for the VO, it is 19.25 ± 0.54 knots. In the y-body component, the values are -0.02 ± 2.14 knots for the MVP and 0.18 ± 1.78 knots for the VO.

Another possible source of dissimilarity between VO and MVP is the magnitude of the speed change from the true resolution velocity. Since the biggest IPR for both conflict resolution difference happens at shallow angle, Figure 5 shows the speed change from 0 up to 90 degrees. It is notable that the speed change for MVP is generally higher than VO for all initial intruder speed and heading difference. In line with the IPR values, the highest difference in speed change exists at 15 and 25 kts for shallow angles, with MVP requires higher magnitude. This disparity between the two potentially leads to the the distinct IPR at shallow angles.

So far, we have arrived at two probable sources of difference between the resolution algorithms. The first reason is that the position uncertainty is propagated differently into the resolution velocity space of MVP and VO as shown in Figure 4. The second one is that MVP has a higher speed change compared to VO, thus resulting in higher IPR. While the first one is inherent in the algorithm, the latter can be verified by increasing the speed change in VO algorithm.

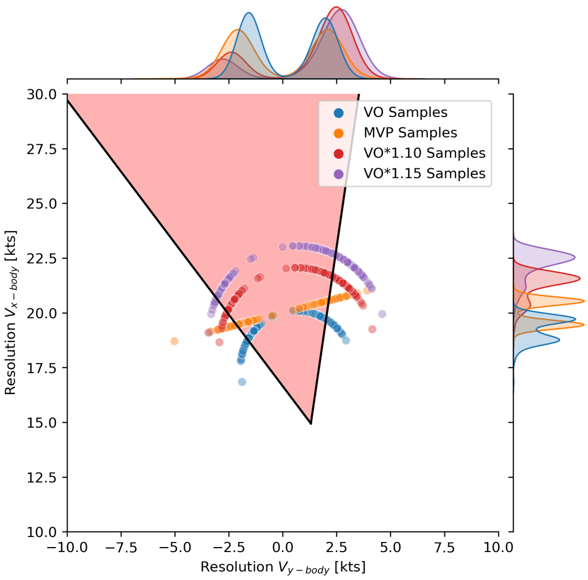

Figure 4: This plot compares the resolution velocity for x-body and y-body component of different conflict resolution algorithms. The shaded area indicates the velocity obstacle triangle, with density plots showing the distribution of each strategy's samples across the velocity axes.

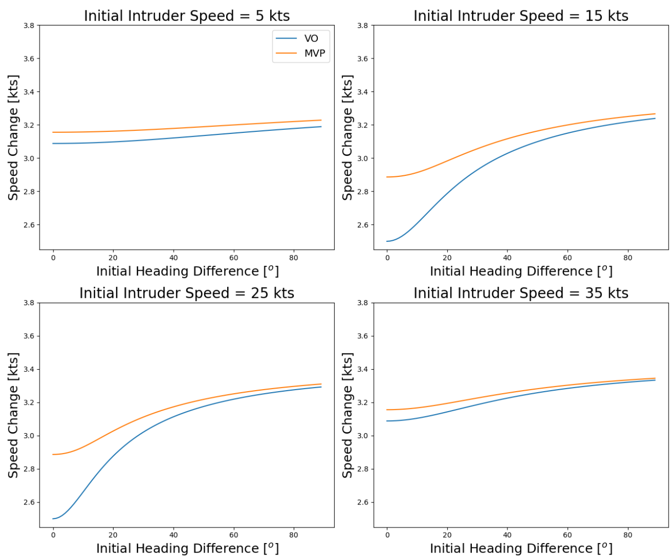

Figure 5: Comparison of speed changes for VO (blue) and MVP (orange) conflict resolution. MVP generally requires a higher speed change compared to VO.

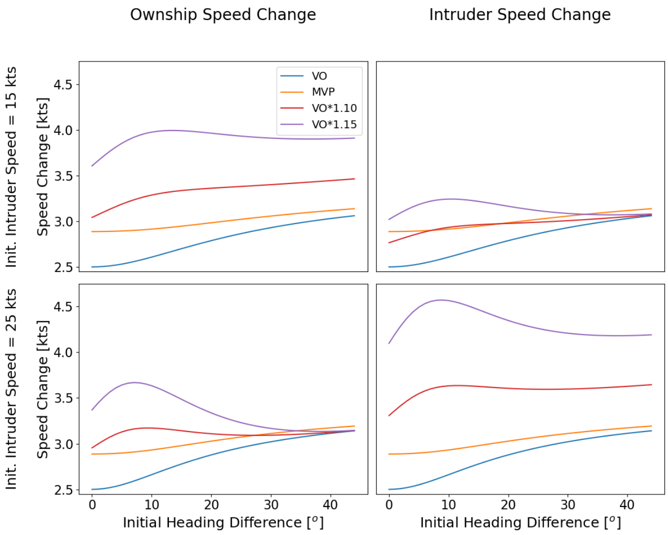

Figure 6: Speed change for Ownship (left) and Intruder (right) for different conflict resolution methods as a function of initial heading difference.

D. Scaled Velocity Obstacle

For the VO method, the resolution velocity is obtained by projecting the current ownship velocity to the velocity obstacle triangle. In this way, a bigger speed change can be obtained by multiplying the ownship velocity with a ”scaling factor” before the projection. This applies when the ownship speed is bigger than the intruder's at shallow angle. In contrast, when the ownship speed is lower, its speed is divided by the scaling factor. The results of this scaled velocity obstacle can be seen in Figure 4 and Figure 6.

Figure 4 shows a sample of the resolution velocity distribution for VO scaled by 1.10 (in red) and 1.15 (in purple). These two values are selected arbitrarily close to 1.00 so that they do not differ significantly from the original value. Another important remark is to have the highest resolution velocity from the two higher than the MVP. After the scaling, the distribution still follows the ‘arc’ shape as in the original VO samples.

Figure 6 shows the speed change for the VO scaled by 1.10 (in red) and 1.15 (in purple), for both the ownship and intruder. Since the biggest disparity appears at shallow angles for 15 and 25 kts, the region of interest is constrained to these conditions. Next, when compared to the MVP, it is notable that the speed changes of the scaled VO algorithms are higher. Thus, if higher speed change truly leads to higher IPR, these two algorithms should have a better safety performance compared to MVP and VO.

Using the same simulation configuration as outlined in Section IV, we obtained the IPR for the scaled VO in comparison to the initial VO and MVP, as illustrated in Figure 7. Despite the higher speed change of the two scaled VOs compared to the MVP and original VO, their IPR is significantly worse. Moreover, when the scaling factor is increased from 1.10 to 1.15, the IPR is reduced further.

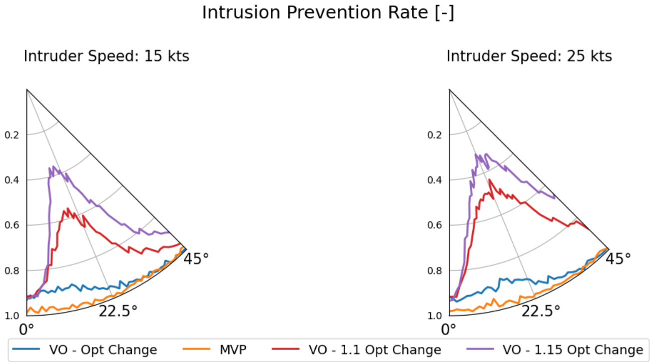

Figure 7: Intrusion Prevention Rate comparison for VO - Opt Change, MVP, $VO*1.1$, and $VO*1.15$ strategies at intruder speeds of 15 kts (left) and 25 kts (right). The plots illustrate how the two scaled VO show significantly worse safety performance compared to the rest.

E. Accumulated Uncertainty

Figure 8 presents the final position for a scenario involving an intruder speed of 15 knots and a conflict angle of 5 degrees, recorded 60 seconds after the simulation began. Along the y-body axis, the distribution of the final position shows that for the MVP algorithm, the UAS moved an average distance of 15.29 ± 24.07 meters, while for VO, it moved 119.53 ± 23.17 meters. In the x-body direction, the distances recorded were 613.19 ± 7.42 meters for MVP and 589.38 ± 23.92 meters for VO. This is a promising way to visualise the consequence of how position error has accumulated and propagated in the CR algorithm, resulting in a non-deterministic final position. It also highlights the higher variance in positional outcome for

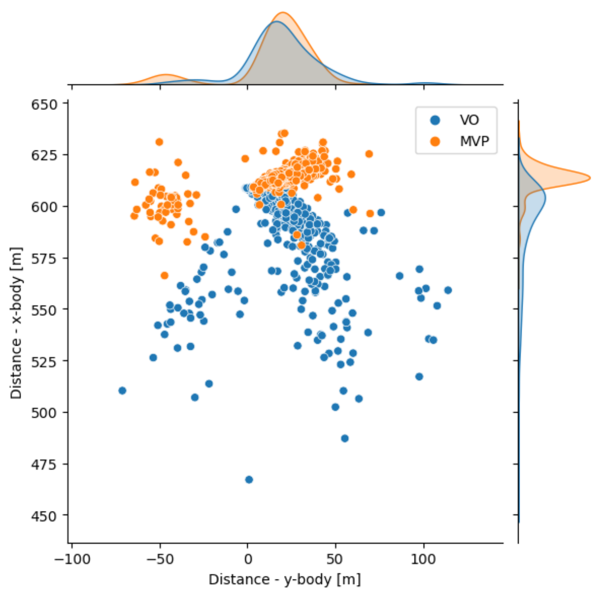

Figure 8: Comparison of the logged final ownship position for scenario with intruder speed of 15 kts and conflict angle of 5 degrees. The position for VO (in blue) shows a higher standard deviation in comparison to MVP (in orange). This potentially explains the difference in IPR.

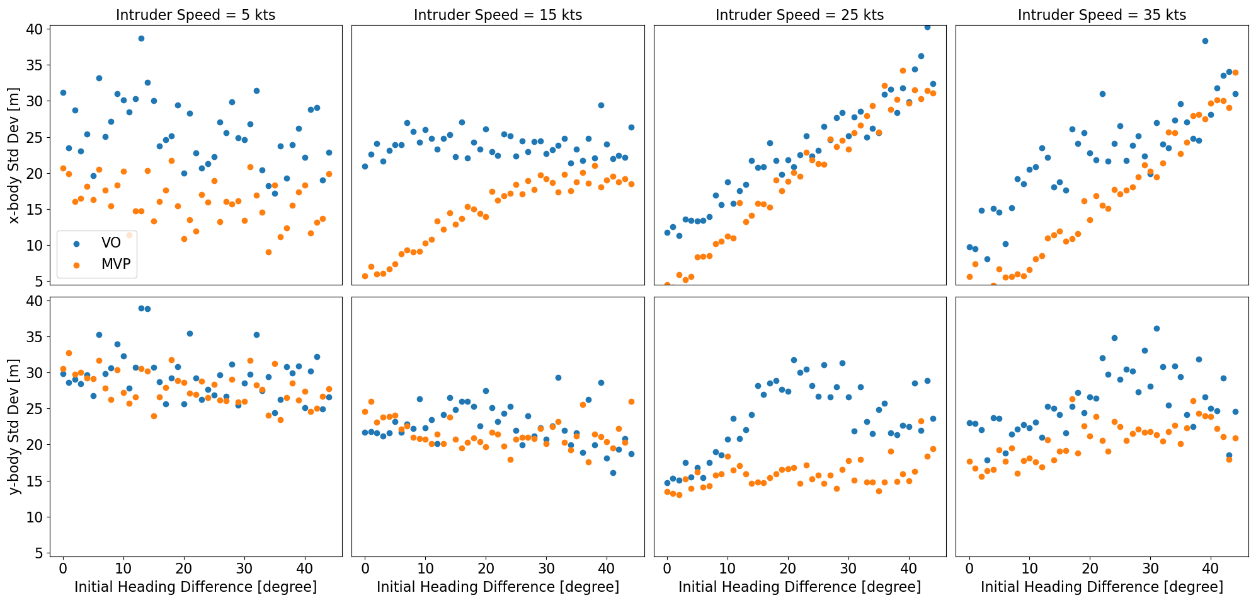

Figure 9: The figure shows the standard deviation of the x-body (top row) and y-body (bottom row) components of final position across different intruder speeds and initial heading differences. It compares the performance of the Velocity Obstacle (VO) and Modified Voltage Potential (MVP) algorithms, with MVP generally displaying lower x-body and y-body variability, indicating greater robustness to positional uncertainty input.

.

the VO algorithm.

Figure 9 compares the final position standard deviation in the x-body and y-body components for varying intruder speeds and initial heading differences. The x-body standard deviation shows a significant disparity between VO and MVP, particularly at shallow angles, which gradually decreases as the angle increases. Notably, the difference is much smaller at intruder speeds of 5 kts and 35 kts. This pattern is consistent with the IPR variation between VO and MVP, as shown in Figure 7.

VI. Discussion

When comparing between optimal change VO and priority-based VO, it is clear that the optimal change is generally better than the latter except for the shallow angles. In a two aircraft conflict situation, the overall performance for optimal change VO is higher because it requires both agents to perform manoeuvre. In this way, the conflict resolution is more robust to uncertainty.

In general, MVP outperform the other algorithms in both IPR and distance at CPA. The drop in IPR in shallow angles for optimal change VO is the most crucial downside of the algorithm. This is crucial for airspace structuring concepts like the Layers concept [16], which limits allowed heading ranges at different altitudes to reduce conflict probability.

In order to explain why this gap in performance exists, further analyses were performed. The uncertainty propagation analysis in terms of velocity shows that the mean and standard deviation of the resolution velocity are similar between the two methods, with MVP having higher speed change. However, the distribution of the resolution velocity differs significantly between MVP and VO Importantly, the resolution velocity for MVP is mapped differently from VO, as seen in . For MVP, the resolution velocity samples are distributed in a “line”. Both have two peaks which corresponds to the sides of the VO triangle. It is difficult to explain these shapes geometrically or algebraically due to the non-linearity of the resolution velocity calculation - naturally, the geometry of resolution is likely the cause.

Scaling the Velocity Obstacle’s speed change showed that the greater velocity change inherent to the MVP algorithm is not the principal cause. Although the difference in the magnitude of the resolution velocity between the two algorithms is less than 0.5 knots, this small difference accumulates over time, resulting in the standard deviation of the final distance at X-body position for VO being higher than MVP, especially at shallow angles. The difference decreases as the angles approach 45 degrees.

Therefore, this is deemed to be inherent to the method itself, and how uncertainty propagates through the resolution logic. MVP and VO starts from a small difference in the resolution velocity, as shown in Figure 1, but the final position distribution shown in Figure 8 shows the difference in the two methods. MVP demonstrates greater robustness to positional uncertainty, even when the VO-based method attempts to increase speed changes. This robustness is evident in the standard deviation of final logged ownship positions, which show lower variation in all initial heading and intruder speed situations. These findings highlight the importance of considering for how positional uncertainty propagates to resolution velocity space and accumulates over time when selecting a conflict resolution algorithm.

VII. Conclusion and Future Work

In this study, we have examined the effects of positional uncertainty on the performance of autonomous separation algorithms, specifically focusing on Modified Voltage Potential (MVP), Velocity Obstacle (VO) priority-based, and VO optimal change methods. Through a series of Monte Carlo simulations conducted in the BlueSky ATM simulator, we assessed the safety performance of these algorithms under varying initial intruder speeds and heading differences. The primary metrics used for evaluation were the Intrusion Prevention Rate (IPR) and the mean distance at the Closest Point of Approach (CPA), which provided a comprehensive understanding of how each algorithm manages conflicts under uncertainty.

The results indicate that MVP consistently outperforms VO-based methods, particularly in scenarios with shallow conflict angles. Additionally, the comparison between VO priority-based and optimal change highlights that both-agent maneuvering is more effective than priority rule in maintaining separation than the former, especially when uncertainty is present. MVP's superior handling of positional uncertainty, as demonstrated by its higher IPR and mean distance at CPA, can be attributed to its more effective propagation of uncertainty within the resolution velocity space. Attempts to improve the performance of VO through scaling revealed that simply increasing speed changes does not necessarily lead to better outcomes; in fact, it degrades the safety performance. From the recorded position of the UAS at the end of the simulation, the variation in the x-body position is significantly lower for MVP especially at shallow angles. This shows that MVP is more robust to the position uncertainty even after the resolution manoeuvres are performed and accumulate over time. This highlights the importance of how the uncertainty is propagated into the resolution velocity space.

Given these findings, MVP emerges as the most reliable and robust conflict resolution method under conditions of positional uncertainty. While VO and its variants may have specific applications where they perform adequately, MVP's ability to maintain safe separation across a broader range of scenarios makes it the preferred choice for autonomous UAS operations. This is particularly critical in the increasingly complex airspace where UAS are expected to operate, as ensuring safety under uncertainty is a necessity. Therefore, if tactical self-separation is adopted in the future, MVP can reliably support its implementation.

Future research should continue to investigate how various sources of uncertainty affect conflict resolution algorithms. These uncertainties include positional errors, speed and heading measurement inaccuracies for navigation, and communication-related issues such as message delays and losses. In addition, vulnerabilities specific to GNSS-based navigation, such as spoofing and jamming, should be examined to understand their impact on the self-separation procedure. As the integration of UAS into existing airspace systems advances, it is essential to assess how these algorithms perform under more realistic and varied conditions to ensure their safe and effective deployment. The methodologies used in this study also provide a valuable framework for evaluating other emerging conflict resolution strategies, ensuring they are rigorously tested before implementation in operational settings. Furthermore, future studies should aim to develop an analytical solution that describes how positional uncertainty propagates into resolution velocity. This would offer deeper insight into the mathematical relationship between input uncertainties and their effects on the resolution process, potentially improving the predictability and reliability of these algorithms under uncertainty.

References

[1] SESAR Joint Undertaking. "European drones outlook study: unlocking the value for Europe." In: (2017).

[2] EUROCONTROL. *U-Space Conops 4th Edition*. SESAR Joint Undertaking, 2023.

[3] Yazdi I. Jenie, Erik-Jan van Kampen, Joost Ellerbroek, and Jacco M. Hoekstra. "Taxonomy of Conflict Detection and Resolution Approaches for Unmanned Aerial Vehicle in an Integrated Airspace". In: *IEEE Transactions on Intelligent Transportation Systems* 18.3 (2017), pp. 558–567. DOI: 10.1109/TITS.2016.2580219.

[4] Paolo Fiorini and Zvi Shiller. "Motion planning in dynamic environments using velocity obstacles". In: *The international journal of robotics research* 17.7 (1998), pp. 760–772.

[5] Jamie Snape, Jur Van Den Berg, Stephen J Guy, and Dinesh Manocha. "The hybrid reciprocal velocity obstacle". In: *IEEE Transactions on Robotics* 27.4 (2011), pp. 696–706.

[6] Jur Van den Berg, Ming Lin, and Dinesh Manocha. "Reciprocal velocity obstacles for real-time multi-agent navigation". In: *2008 IEEE international conference on robotics and automation*. Ieee. 2008, pp. 1928–1935.

[7] Boris Kluge and Erwin Prassler. "Recursive probabilistic velocity obstacles for reflective navigation". In: *Field and Service Robotics: Recent Advances in Reserch and Applications*. Springer, 2006, pp. 71–79.

[8] Yazdi I Jenie, Erik-Jan van Kampen, Coen C de Visser, Joost Ellerbroek, and Jacco M Hoekstra. "Selective velocity obstacle method for deconflicting maneuvers applied to unmanned aerial vehicles". In: *Journal of Guidance, Control, and Dynamics* 38.6 (2015), pp. 1140–1146.

[9] Jacco M Hoekstra, Ronald NHW van Gent, and Rob CJ Ruigrok. "Designing for safety: the 'free flight'air traffic management concept". In: *Reliability Engineering & System Safety* 75.2 (2002), pp. 215–232.

[10] Jacco M Hoekstra and Joost Ellerbroek. "Aerial robotics: State-based conflict detection and resolution (detect and avoid) in high traffic densities and complexities". In: *Current Robotics Reports* 2.3 (2021), pp. 297–307.

[11] Marta Ribeiro, Joost Ellerbroek, and Jacco Hoekstra. "Review of conflict resolution methods for manned and unmanned aviation". In: *Aerospace* 7.6 (2020), p. 79.

[12] EASA. *ED Decision 2022/024/R: Technical Specification for ADS-L transmissions using SRD-860 frequency band (ADS-L 4 SRD-860)*. European Union Aviation Safety Agency, 2022.

[13] Muhammad Fazlur Rahman, Joost Ellerbroek, and JM Hoekstra. "Effect of CNS Systems Performance on Autonomous Separation in U-Space". In: *International Conference on Research in Air Transportation*. 2024, ICRAT–2024.

[14] Jacco M Hoekstra and Joost Ellerbroek. "Bluesky ATC simulator project: an open data and open source approach". In: *Proceedings of the 7th international conference on research in air transportation*. Vol. 131. FAA/Eurocontrol USA/Europe. 2016, p. 132.

[15] ICAO. *Annex 2 to the Convention on International Civil Aviation: Rules of the Air*. International Civil Aviation Organization, 2005.

[16] Emmanuel Sunil, Jacco Hoekstra, Joost Ellerbroek, Frank Bussink, Dennis Nieuwenhuisen, Andrija Vidosavljevic, and Stefan Kern. "Metropolis: Relating airspace structure and capacity for extreme traffic densities". In: *ATM seminar 2015, 11th USA/EUROPE Air Traffic Management R&D Seminar*. 2015.