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Deconfliction in High-Density Unmanned Aerial Vehicle Systems

Timothy B. Nysetvold* and John L. Salmon†
Brigham Young University, Provo, Utah 84602

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Small unmanned aerial vehicles play increasingly important roles in many industries and organizations in the United States and around the globe. As usage becomes more widespread, airspace will become increasingly crowded. These high-density unmanned aerial vehicle (UAV) situations will pose many unique challenges, including in conflict resolution. Using agent-based models, conflict resolution and the well-clear and action-distance concepts for small multirotor UAVs in dense environments were explored. Specifically, the safety and efficiency of several collision-avoidance mechanisms under different possible densities, accelerations, and action distances were investigated. The results suggest that selecting appropriate action distances and collision-avoidance mechanisms will be vital to maintaining safety and efficiency. Interestingly, excessive action distances quickly degrade performance: using a simple method under high-density conditions ($1\ \mathrm{UAV/km^2}$), well-clear distances above approximately 750 m have extremely low efficiency (~1% as many deliveries accomplished in 5000 simulation hours compared to lower distances). More advanced algorithms also suffer from low efficiency at higher (~1 km) response distances. Different definitions for near-midair collisions and their effects on system safety and well-clear distance are discussed.

I. Introduction

A. Motivation

IN RECENT years, unmanned aerial vehicles (UAVs) of all shapes and sizes have been developed. Many have already become important parts of commercial aviation [1,2], and UAV use will continue to expand as regulatory certainty increases. Because multirotor UAVs are particularly useful for commercial applications within cities and towns, a dramatic increase in the density of these UAVs over populated areas is expected. UAV density in these areas is likely to grow higher than has been experienced in airspaces before. The proliferation of these small UAVs (SUAVs) will present novel air traffic control challenges. To overcome these challenges, SUAV air traffic control systems will require modification from current traffic control systems for manned aircraft, including a higher degree of automation. Manned air traffic control has long been moving toward automation [3,4]; the Federal Aviation Administration's (FAA) current NextGen initiative represents a substantial step in this direction. Many lessons have been learned from these initiatives, and many may be applicable to UAVs. However, there may be important differences between how manned aircraft behave in low-density environments and how unmanned aircraft behave in high-density environments. In this paper, we will analyze ways, in which high-density collision-avoidance systems differ from lower-density systems. Specifically, this paper examines automated collision-avoidance systems for small (0–55 lb) multirotor UAVs, commonly known as *drones*. Classified by the FAA as SUAVs [5], these aircraft may, in the future, fly in environments where densities approach $1\ \mathrm{UAV/km^2}$. These high densities and novel systems are desirable for economic reasons, but are substantially different than typical manned aircraft airspaces. These differences warrant exploration.

B. Background

Despite the differences between low-density manned aircraft traffic and high-density SUAV traffic, the fundamentals of air traffic safety remain the same. All aircraft, including SUAVs, must avoid colliding with other aircraft. Frequently, air traffic controllers assist by providing strategic guidance on routing and flight level. When air traffic control is unsuccessful and an aircraft determines that its course passes dangerously close to or collides with an intruder, it takes additional action to move safely out of the way.

When aircraft first identify a situation that could become dangerous, they undertake self-separation maneuvers. These maneuvers involve small course corrections to stay far away from obstacles and intruders. The goal of these maneuvers is to keep the aircraft "well clear": far enough from other objects that there is no danger of collision, and limited interference to aircraft with the right of way. If the situation becomes dangerous or the aircraft begins to interfere inappropriately with another, the aircraft is no longer well clear. Typically, this means that the aircraft must perform an action known as a *collision-avoidance maneuver*. Collision-avoidance maneuvers are more drastic than self-separation maneuvers, and are designed to quickly avert dangerous situations. If the collision-avoidance mechanism fails, then the aircraft may collide with the intruder or obstacle. This hierarchy of safety is shown in Fig. 1 and described in more detail in [6].

Because high-density spaces are likely to result in more losses of well clear than lower-density spaces, collision-avoidance mechanisms will be especially important to high-density space safety.

C. Review of Collision-Avoidance Mechanisms

Because of its importance to safe aircraft travel, collision avoidance is a well-established research area. A brief review of some methods of particular interest will be provided.

Airborne Collision Avoidance System (ACAS) II is an important set of standards and recommended practices for international collision avoidance. At this time, only one implementation of these standards [Traffic Alert and Collision Avoidance System II (TCAS II)] has been developed. Originally implemented in the late 1980s, it has been updated several times to include new features and more advanced technologies. The most recent version, 7.1, has been approved for manned aircraft in the United States since 2015; it is now required in European airspace [7]. In the TCAS II system, aircraft are required to carry a transponder, which interrogates and responds to similar nearby transponders. Using the information thus gathered, TCAS II provides "resolution advisories," which involve instructions to climb, descend, or maintain the current vertical speed to avoid near-midair collisions (NMACs). TCAS II 7.1 also includes substantial multiple-aircraft encounter logic, and is designed to work at densities of up to 0.3 aircraft/n mile ($0.115/\mathrm{km^2}$) [8]. For manned aircraft, TCAS II is a valuable and well-understood collision-avoidance mechanism; a further review of it is provided in [9].

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*Research Assistant, Department of Mechanical Engineering. Student Member AIAA.

†Assistant Professor, Department of Mechanical Engineering, 360D EB. Member AIAA.

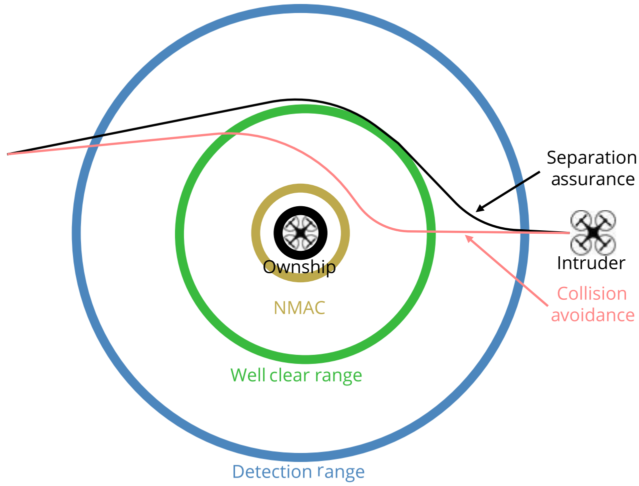

Fig. 1 Illustration of how collision-avoidance paths differ from separation-assurance paths.

However, TCAS II has limitations; for instance, it is not designed for unmanned aircraft, or for aircraft in densities higher than $1/\mathrm{km}^2$.

The aircraft community recognizes these limitations. To overcome them, a new version of ACAS, ACAS X, is under development at this time. One of its versions, ACAS Xu, is being developed to confront the challenges posed by unmanned aircraft. ACAS Xu adopts and expands the requirements of ACAS II, including logic designed to allow multiple sensor inputs, and additional logic for multiple aircraft encounters. The resolution advisories issued by implementations of ACAS X and Xu are expected to be more detailed and highly tailored than those issued by TCAS II. A detailed introduction to ACAS Xu is provided in [10]. Although it confronts many important issues, ACAS Xu remains focused on comparatively large, high-altitude UAVs. ACAS Xu is a step toward high-density SUAV air traffic control and collision avoidance, but it does not yet confront all of the difficulties that high-density low-altitude SUAV systems will face.

Many collision-avoidance methods and implementations beyond ACAS II and ACAS X have also been proposed and discussed. A valuable review of many conflict avoidance mechanisms can be found in [11]. Unfortunately, many of the more advanced algorithms discussed are not computationally friendly, and so their applicability to this research is limited. Chain, proposed in [12], is a good example of this: although it will produce a high-quality path, it requires solving a complex differential equation. (A more detailed mathematical treatment of the method is available in [13].) Chain has substantial advantages over less complicated mechanisms, including its ability to provide a complex path that will fully resolve whatever conflicts are observed when it is run. However, because the simulator must perform the collision-avoidance mechanism at least every time the aircraft observes a new, unexpected intruder within its avoidance range, using chain would require solving thousands of differential equations per minute of simulated motion.

Although many of the more complex algorithms proposed are beyond our computational resources to simulate, not all proposals are. Potential fields (PFs) are frequently used in large-scale robotics problems [14], and can be made computationally friendly. A detailed critique of their use is available in [15]. Most objective field approaches rely on evaluating the gradient of a forcing function at different points as the agent moves around its environment. The agent then moves down the gradient (like a ball rolling downhill) and eventually reaches the point of lowest gradient. An excellent implementation of a PF-based aircraft collision-avoidance method is discussed in [16].

D. Current Challenges

Despite the substantial effort invested in collision-avoidance mechanisms, challenges remain before any high-density UAV control system may be adopted. Well-clear thresholds, NMAC thresholds, UAV flight characteristics, and density effects may all play substantial roles in system emergent behaviors, such as safety and efficiency. The effects of these variables may also depend on the collision-avoidance mechanism selected.

Well clear is the threshold at which collision-avoidance maneuvers must begin to avoid an NMAC or other dangerous situation [17]. Thus, collision avoidance requires a defined well-clear threshold: without one, there are no starting criteria for the maneuver. For manned aircraft, guidelines are available for what constitutes well clear (acceptable separation) in different airspaces or flight regimes. For instance, in class A airspace, up to several miles of separation are required for aircraft to be considered well clear of others [18]. The FAA has recently adopted a well-clear definition for SUAVs vs manned aircraft [19], which is smaller than the separation standard for manned aircraft vs manned aircraft. However, no well-clear definition has yet been accepted for SUAVs vs SUAVs. An even smaller well-clear parameter than the one used for manned aircraft vs SUAVs may be sufficient.

Along with a definition for well-clear distances or times, SUAVs may also need a specific definition for NMACs. For manned aircraft, the FAA considers a situation where two aircraft pass within 150 m (500 ft) of each other (projected onto a horizontal plane) and within 30 m (100 ft) vertically of each other an NMAC [20]. The existing framework for SUAVs vs manned aircraft continues to use this definition [21]. However, given the differences between SUAVs and traditional aircraft, this definition may not be reasonable for SUAVs. In the national airspace now, aircraft passing with 150 m of each other rarely collide when they experience an NMAC [22]. Small (less than 1 m^2) quadcopters are likely to be even less dangerous at these ranges. This different danger profile should be reflected somehow if NMACs are to be comparable between SUAVs and manned aircraft. At least two methods of reflecting this reduced danger are possible: first, research, such as [22], could be performed on UAV systems to determine their likelihood of experiencing a collision under an NMAC situation. On the other hand, it would also be possible to define NMACs differently for SUAVs, such that the likelihood of collision given an NMAC is approximately the same as that of manned aircraft. Both methods would accomplish the same purpose. Because the lower likelihood of collision given NMAC is frequently not considered in the literature, the definition of an NMAC is important at this time. Well-clear standards and other air safety measures are created to minimize the risk of collisions, which are linearly related to NMACs. If the NMAC definition for UAVs is unreasonable, excessive mitigation may lead to worsened overall system performance.

The nonuniform nature of UAVs creates additional challenges. Safe well-clear and NMAC distances are dependent on a UAV's flight characteristics, which vary widely across types of UAVs. Accelerations, top speeds, and latencies vary among existing SUAVs. This variation can be expected to expand as the field matures.

Further problems are presented by the high densities of aircraft that will be experienced by low-flying SUAVs in high-traffic areas. As discussed earlier, several currently used collision-avoidance mechanisms have logic allowing them to respond to multiple conflict aircraft simultaneously. However, the scale of multiple conflictions that will occur in this airspace is larger than previous airspaces have experienced. It is not clear that all methods of dealing with multiple conflictions will be equally successful in the densities of traffic that may occur in SUAV-dominated spaces. A previous work by the authors suggests that encounters increase quadratically with density [23], suggesting that increases in density could quickly impact the collision algorithm behavior. Additional study is warranted on the effects that such high levels of multiple conflictions have on avoidance mechanisms, both simple and complex.

E. Assumptions

To make exploration of high-density spaces more tractable, a number of simplifications have been made.

Currently, a wide variety of UAV types and sizes exist. However, not all of these UAVs are expected to be present in high-density airspaces, such as the airspace above a city. Within these airspaces, small multirotor UAVs are expected to predominate due to their many commercial applications. Accordingly, the simulation models UAVs as small, multirotor aircraft. Not all aircraft in high-density spaces will fulfill these criteria; caution should be used in extending these results to systems with substantial fixed-wing aircraft presence.

The simulation takes place at a single altitude; aircraft cannot ascend or descend. This is a common assumption to many analyses of collision-avoidance maneuvers [11]. Restricting the simulation to two dimensions simplifies the computation and analysis involved in an avoidance method. It is also a conservative assumption; any collision-avoidance mechanism that can perform adequately in two dimensions is likely to be able to perform adequately in three. Furthermore, flight-level regulation or practical constraints may cause SUAVs to experience situations, in which ascending and descending are not allowed or possible. In these cases, a two-dimensional plane would be the best approximation of the airspace. Where three dimensions are available, adding several layers of two-dimensional systems may also be an effective way to increase density without affecting system safety [24]. In any case, two-dimensional investigations are useful and will be sufficient for these preliminary investigations.

UAVs are also assumed to have access to high-accuracy low-latency information about their own position and velocity. Position information about other UAVs within a small distance of the ownship is also assumed to be accessible, high accuracy, and low latency. (Although some methods require velocity data as well, the collision-avoidance mechanisms examined here require only position.) In the real world, acquiring this information can be difficult and imperfect data may affect UAV performance substantially. However, sensor development is an active area of research. The upcoming required adoption of automatic dependent surveillance-broadcast, and the existence of other enhanced data communication systems [25], will make this information easier to acquire. In any case, SUAV integration into the national airspace is unlikely until available sensor data are of sufficient quality to allow for accurate maneuvering [26].

UAV kinematics are simplified by assuming that all the multirotor UAVs of interest are capable of accelerating at some constant rate, common to all UAVs and defined at the beginning of the simulation. For fixed-wing aircraft, flight kinematics would be substantially more complicated. Even for approximately symmetric rotorcraft, flight kinematics will not be totally symmetric. However, modeling these deviations would be mathematically complex and computationally expensive. Treating multicopter UAV accelerations as constant and omnidirectional is a useful, although imperfect, approximation.

This assumption is also conservative. Drag would have significant effects, and accelerations would slow and deceleration would become faster as the UAV's velocity increased. In the simulator, this behavior is disregarded in favor of simplicity. In most cases, we are interested in how fast a UAV can slow down, and so this simplification produces a worst-case estimate of crash probabilities.

In the real world, not all UAVs would have identical accelerations. The interactions between UAVs capable of different accelerations may have effects on collision avoidance, but previous research suggests they are not dominant [23]. In the interest of simplicity, these effects are neglected here.

Finally, UAVs typically undertake self-separation actions before losing well clear. However, the interactions between self-separation strategies and collision-avoidance mechanisms are complex. To better understand how collision-avoidance mechanisms affect system behavior, self-separation actions have been neglected.

II. Methods

A. Simulation Engine

Our simulations make use of an improved version of the agent-based model previously developed in [23].

In each round of simulation, some number n UAVs are placed at random locations within a 10×10 km plane. In the case that two UAVs were generated within NMAC distance of each other, both are assigned new locations. Each UAV is assigned a goal location (objective), randomly chosen within the space, to which it attempts to travel. When a UAV successfully reaches its objective, a new randomly chosen objective is generated for it, and it travels toward the new objective. In this way, each UAV persists throughout the entire simulation length, and density remains constant at all points in the simulation. Because simulation run time is long compared to the time taken to reach any randomly chosen objective, each UAV is expected to achieve several objectives over the course of the simulation, and the distance between a UAV and any one assigned objective will not play an important role in simulation results. This highly randomized method develops many complex approach patterns over time.

Each of the n UAVs generated is modeled as a moving point in two-dimensional space with acceleration, velocity, and position vectors. For each step of the simulation, each UAV does the following:

1) Check for intruders inside the assigned well-clear distance.

2) If there are intruders, determine the path according to the assigned collision-avoidance strategy.

3) Use the equations of motion to move along the chosen path.

Any time a UAV passes within the selected NMAC distance, it is assumed that they have experienced a collision. They are removed from the airspace. To keep the airspace at the desired UAV density, collided UAVs are replaced by new UAVs generated at a central location in the airspace. UAVs are generated at this location only after collisions take place, and only when doing so would not provoke an NMAC. If any UAV is within NMAC distance of the generation location when generation should take place, generation is delayed until an NMAC would no longer occur.

The simulation is performed using MATLAB; the source code is available on request to the corresponding author.

B. Procedures

To address the challenges identified in Sec. I.D, several experimental parameters were selected. These are 1) number of SUAVs (n) present in the space, 2) well-clear distance, 3) NMAC distance, 4) UAV acceleration, and 5) collision-avoidance method.

To understand the effect of these parameters on high-density systems, the simulator was run on a wide variety of test cases. For each combination of variables selected, at least 50 total hours of simulation time was used; with at least 50 UAVs in flight at all times, this makes a minimum of 2500 h of UAV flight time per case. Although more flight time will be necessary for a rigorous statistical treatment, this sample size is large enough to draw some preliminary conclusions.

For each parameter, several values were selected. In the case of the number of UAVs present, accelerations, and well-clear distances, selections were based on expected values for unmanned aircraft. A range of accelerations designed to reflect current commercially available UAV quadcopters (between 1 and 10 ms^2) were simulated. Because drag forces are neglected, it was necessary to impose a speed limit on the space. All UAVs were arbitrarily limited to a maximum speed of 30 m/s, which approaches the upper limit of commonly used SUAV speeds. The higher-acceleration simulated UAVs can arrive at those speeds within a few seconds of takeoff, which also matches current SUAV performance.

Well-clear distances were allowed to vary between 1.4 km and 0 m. For comparison, these distances fall between 0 and roughly 2 times the recently adopted well-clear distance for unmanned aircraft vs manned aircraft. It seems likely that future interest for well-clear distances will focus somewhere within this range.

The number of UAVs present in the airspace, and thus, the density, was chosen to create densities that might occur in a future city. The simulation space is 100 km^2, approximately the size of a small city. It could be desirable to use anywhere between zero to a few hundred UAVs at a time over a city of this size in the near future. Arbitrarily, values of 50, 100, and 200 UAVs were selected for investigation.

To examine whether the definition of an NMAC made a difference to system performance, two substantially different NMAC distances were selected. The first was the standard FAA NMAC distance of 150 m. To clearly identify whether this area merits further investigation, an NMAC distance of 15 m was also selected. If no differences in system behavior were identified after an order-of-magnitude change in NMAC distance, it would be clear that the parameter had no effect.

To maximize data collected in the simulation, UAVs were only removed from the space when they violated the 15 m NMAC. If UAVs approached each other at less than 150 m, but greater than 15 m, the incident was recorded, but aircraft were allowed to continue flying.

With respect to collision-avoidance methods, we analyzed three different algorithms: the naive deconfliction method (NDM), a modified NDM (MNDM), and a PF-based approach. The differences between these algorithms will suggest some conclusions about how certain conflict avoidance mechanism characteristics affect system behavior.

1. Naive Deconfliction Method

The first algorithm implemented is a facile approach to collision avoidance, called the NDM. NDM is loosely based on the current TCAS II system, discussed in Sec. I.C. Instead of directing aircraft to ascend or descend to avoid the intruder(s) as TCAS II would, NDM directs the aircraft to deviate to the right or left to avoid the intruder. In some cases, this behavior will be less efficient than TCAS II, which is less limited than the NDM; nevertheless, it is useful as a first-order approximation.

Mathematically, this model is simple: the ownship, with position P_o, identifies any intruders within its action distance. The intruder closest to the ownship, with position $\boldsymbol{P}_i$, is selected. The direction from the ownship to the intruder is found using

$$\boldsymbol{v}_o = \frac{-(\boldsymbol{P}_o - \boldsymbol{P}_i)}{\|\boldsymbol{P}_o - \boldsymbol{P}_i\|} \tag{1}$$

The ownship then accelerates in the direction opposite v_o. Because the ownship's velocity is generally not along the same line as this acceleration, this typically results in a turn away from the intruder. In the special case that the acceleration vector is opposite to the ownship's velocity, which would indicate a head-on approach with another aircraft, the acceleration vector is rotated slightly to the right, as required by the Code of Federal Regulations 91.113. In this case, that slight right turn is created by multiplying the acceleration vector by a rotational matrix:

$$v_{o*} = v_o \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \tag{2}$$

Several θ values were found to yield adequate behavior; in this simulation, a θ of 1 deg was selected. Figure 2 shows the behavior produced when both UAVs implement this mechanism. Figure 3 shows the results when only one UAV implements NDM and the other performs no avoidance. Because the avoiding UAV turns sharply away from the intruder, a head-on approach creates a long avoidance path and lowers efficiency. Rudimentary exploration with the simulator reveals that the NDM mechanism has some drawbacks. First, it will sometimes leave UAVs in a situation, in which they still need to cross paths to get to their objective locations and have to reinitiate the NDM almost immediately. Nevertheless, several iterations of the NDM will generally resolve any single conflict. Second, NDM is unable to consider more than one intruder at a time, which poses a problem in high-density situations. Finally, NDM does not optimize the avoidance path to minimize its effects on the UAV's original flight path. Oftentimes, it will result in the UAV flying away from its objective for considerable distances, as in Fig. 3.

In worst-case scenarios, these issues, combined with slow UAV accelerations, can create extremely poor paths for multiple UAVs. Figure 4 exhibits the paths created in a four-UAV multiple-avoidance situation. It is clear that the paths are not safe. This particularly poor path is caused by a lack of multiple-confliction logic: two intruders at equal distances from the ownship cause the method to break down. Because each UAV alternates between being closer to one intruder

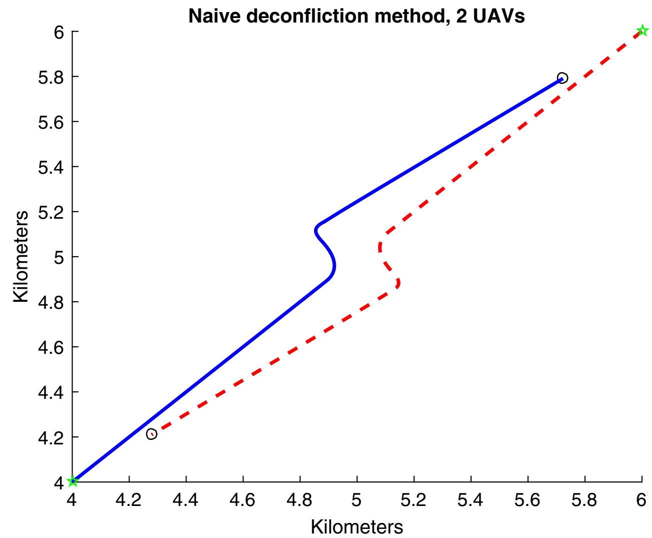

Fig. 2 Typical behavior of NDM for two UAVs.

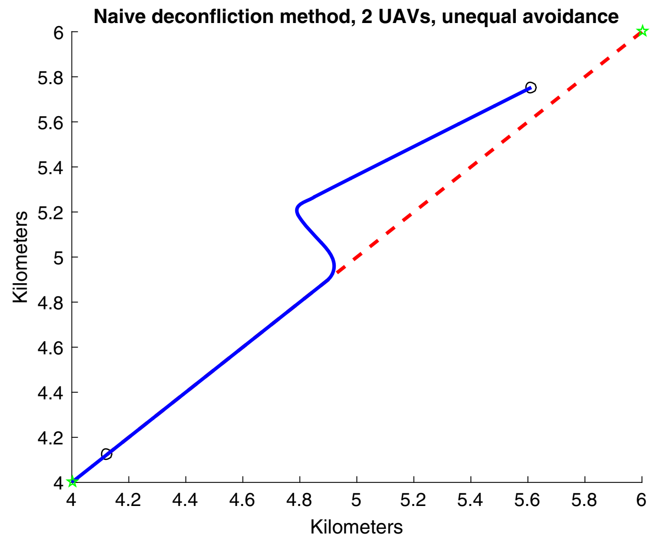

Fig. 3 Behavior typical for asymmetric NDM for two UAVs.

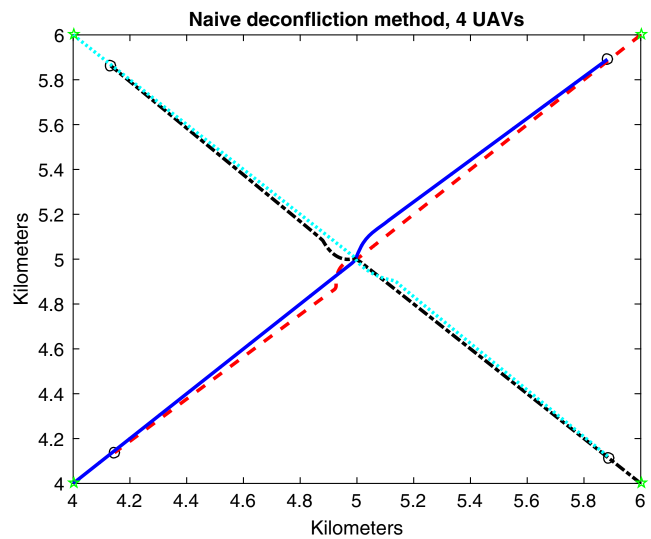

Fig. 4 Result from NDM for four UAVs in a head-on approach.

and the other, each UAV will oscillate along the same path that it was originally on. Thus, no collision avoidance can be accomplished, and the mechanism produces a crash.

The drawbacks of this algorithm demonstrate some of the problems that manned-aircraft collision-avoidance mechanisms not designed with multiple conflict resolution as a priority may have if extended to high-density UAV systems without additional investment in multiple conflict-resolution capability.

2. *Modified Naive Deconfliction Method*

To allow the NDM to respond to more than one UAV at a time, we created the MNDM. MNDM acts like NDM, except that, instead of flying radially away from the closest intruder, the aircraft observes all non-well-clear intruders. These intruder positions, $P_{i1} \ldots P_{in}$, are used to find the unit vectors required to fly radially away from them, as in Eq. (3). This vector is normalized, and the ownship accelerates along it away from the intruders.

$$\boldsymbol{v}_o = \sum_{k=1}^{n} \frac{-(\boldsymbol{P}_o - \boldsymbol{P}_{ik})}{\|\boldsymbol{P}_o - \boldsymbol{P}_{ik}\|} \tag{3}$$

An illustration of this behavior is provided in Fig. 5. The vectors from the two intruders within the well-clear distance to the ownship (V2 and V3) are added to form the ownship's new flight path (V1). Intruders outside the well-clear distance are ignored.

This modification is a facile approach to multiple conflict resolution. Collision-avoidance mechanisms with more advanced logic for multiple conflict resolution are likely to outperform this method. Nevertheless, this algorithm is useful for understanding if simple modifications and logic are sufficient to extend an algorithm to higher densities. The results of this approach, and of NDM, may be of use to future ACAS II or X implementations.

In one-on-one situations, the behavior produced by MNDM is identical to the original NDM. In multiple-intruder situations, however, the behavior changes significantly (as shown in Fig. 6). Note the much larger average separation created, with little loss of efficiency even with four UAVs in a head-on collision.

It is clear that requiring the method to respond to many UAVs improves both its safety and efficiency in some situations, such as the four-UAV head-on collision. Nevertheless, MNDM does not solve some of the fundamental problems in NDM, such as its failure to optimize avoidance paths, and its behavior is significantly worse at high well-clear distances. Unexpectedly, this approach seems worse than NDM in almost all real-world situations.

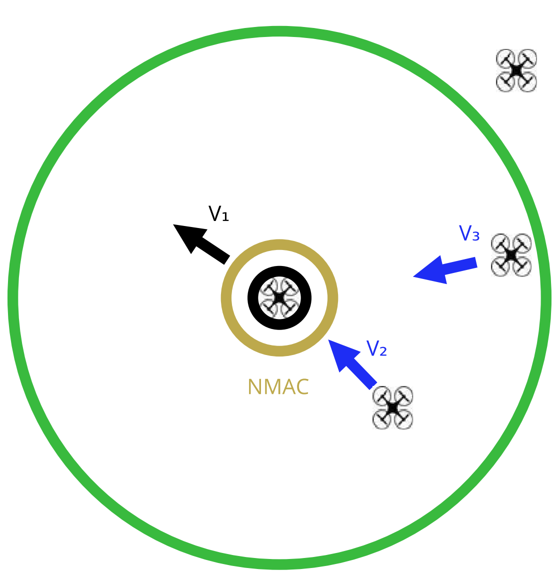

Fig. 5 Representation of MNDM.

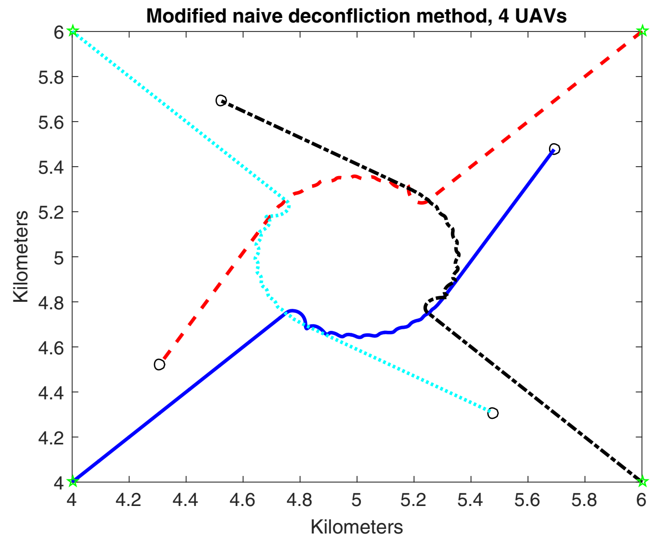

Fig. 6 Result from MNDM for four UAVs in a head-on collision.

3. *PF Method*

The final algorithm implemented is a PF method similar to the one described in [16]. Over time, it was found that repeatedly evaluating similar gradient calls was computationally expensive. To quicken the simulator, a generalized closed-form gradient solution was developed that created identical behavior to the original gradient-call method. In this closed-form solution, objectives are modeled by an attractive force, which has the gradient:

$$F_a = -(P_x - P_a) \tag{4}$$

in which P_x is the location of the ownship, and P_a is the location of the attractor. Each intruder is modeled by a repulsive force. This repulsive force has the gradient:

$$F_r = -(\boldsymbol{P}_x - \boldsymbol{P}_o)e^{(-(1/2)\|P_x - P_o\|^2)} + re^{(-(1/2)r^2)} \frac{x}{\|x\|} \tag{5}$$

in which $\boldsymbol{P}_o$ is the location of the ownship, $\boldsymbol{P}_x$ is the location of the repulsor (intruder), and r is the radial distance at which the force of repulsion is defined to be zero. Although r is in many ways similar to a well-clear distance (the distance at which a UAV must start performing a collision-avoidance maneuver), it is different in an important way. This PF method does not take any significant action when this boundary is crossed; the repulsive force is so small that the UAV only begins an almost imperceptible turn away from the intruder when it first enters the r distance shown in Fig. 7). This is different than a traditional collision-avoidance maneuver, and so r is not a typical well-clear distance. However, r is still an action distance, the threshold at which the mechanism begins to take action. Although it is different than a traditional well-clear distance, r is the best analog in PF to the well-clear thresholds used in NDM and MNDM, and will be used to compare between these algorithms. Contrast the illustration of the PF method in Fig. 8 to the MNDM of Fig. 6 with the same initial conditions.

The PF approach has some additional drawbacks. First, calculating the gradient of a PF is more computationally intense than NDM. Although most computing systems could perform it fast enough for real-time use, it does put higher limits on minimum computing power devoted to collision avoidance. More concerning is that, in some cases, PFs create local minima where UAVs may get "stuck." Because of the dynamic nature of the environment, these equilibria are frequently disrupted, but nevertheless could lead to decreases in efficiency in unusual situations.

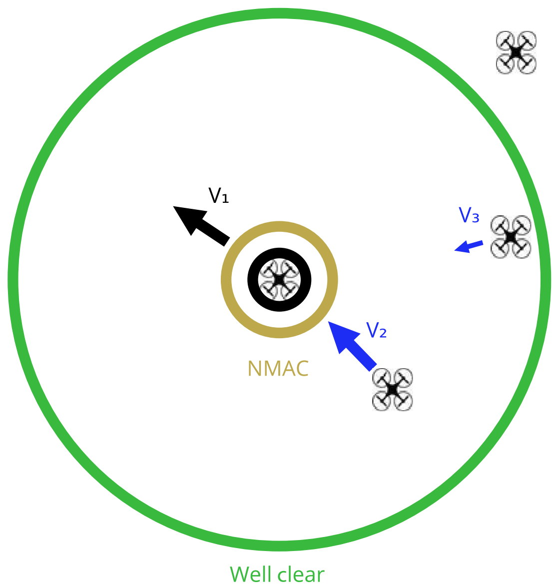

Fig. 7 Representation of PF collision-avoidance method.

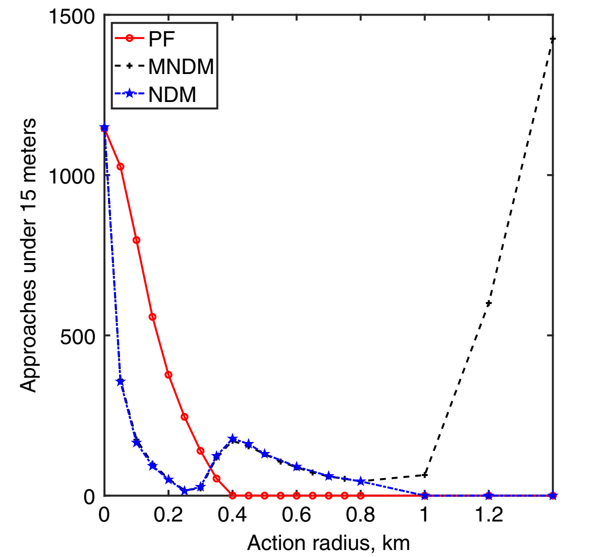

Fig. 9 Average number of sub-15 m approaches in 5 h as a function of well-clear distance (for NDM and MNDM) or *r* (for PF method).

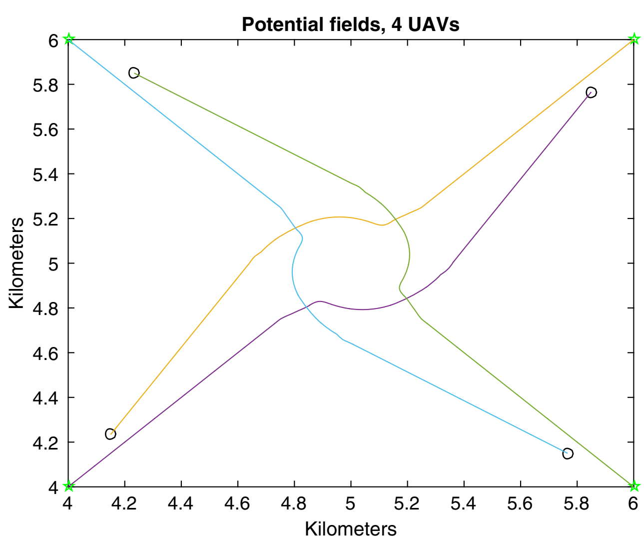

Fig. 8 Result from PF for four UAVs in a head-on collision.

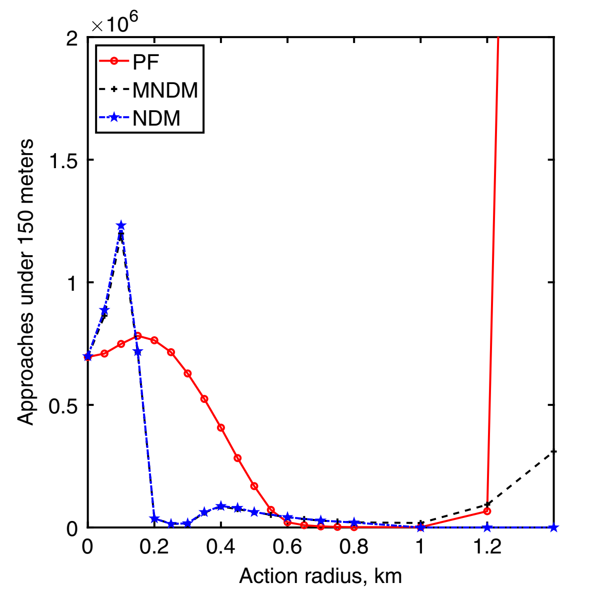

Fig. 10 Average number of sub-150 m approaches in 5 h.

III. Discussion of Results

A. Safety and Efficiency

The results show that, for well-clear distances, complex trends are present and bigger is not always better. Figure 9 shows that, at the 15 m NMAC distance, most improvement in NMAC rate was produced before 0.25 km of avoidance radius in NDM and MNDM. The PF-based method behaves differently, with significant gains out to 0.4 km of action distance.

In Fig. 10, similar trends are present despite the order-of magnitude difference in NMAC distance. It is interesting to note that, in both graphs, large-enough action distances cause increases in NMAC rates. This behavior is attributed to the rise in induced conflicts as action distances grow. Behaviors in all the selected collision-avoidance mechanisms lead to a disproportionate amount of traffic on the edge of their action distance. Thus, when action distances are close to the NMAC distance, the number of observed approaches increase. As UAVs become increasingly conflicted, collision-avoidance mechanisms become increasingly ineffective and NMACs increase.

Comparing the two figures, it is also clear that expanding the NMAC range has effects on action distances necessary to maintain NMAC rates. In Fig. 9, the PF method approaches 0 NMAC in the time allotted with an action distance of 0.4 km. In Fig. 10, with a larger NMAC distance, the same level of safety is achieved at approximately 0.7 km. In NDM and MNDM, more complex behavior is present.

Both NDM and MNDM show bumps in unsafe approaches with action distances between 0.35 and 1 km. Because these bumps are not present in the PF trends, it seems likely that it is not an artifact caused by traffic-generation patterns or a flaw in the simulator used, but rather represents some more complicated phenomenon. Although the cause of this bump is not immediately apparent, some suggestions may be made. The bump is more pronounced at the 15 m NMAC distance than at the 150 m NMAC, and so in part, it may be an effect of the chosen NMAC distance. The disappearance of this bump when the PF method is used suggests that more complicated factors are also involved. This bump may be related to the sharp decrease in efficiency experienced by NDM and MNDM at these action distances shown in Fig. 11. As the action distance expands, more maneuvers must be undertaken. As more maneuvers are undertaken and action distances expand, additional conflicts will be induced by previous collision-avoidance maneuvers. These additional induced conflicts

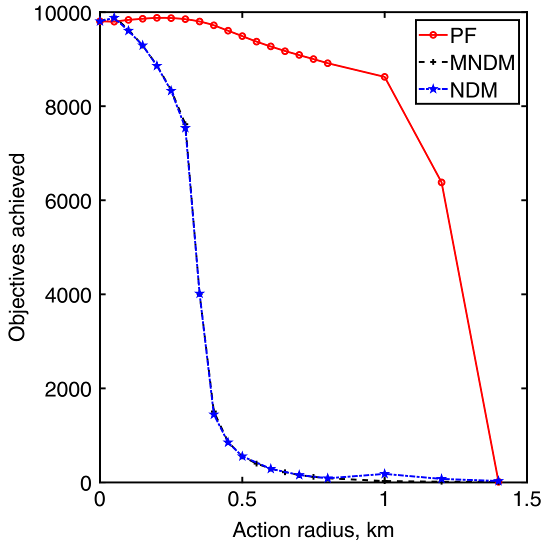

Fig. 11 Average number of objectives achieved in 5 h.

increase the amount of failures a given method will suffer. Additional unsuccessful multiple conflict maneuvers under NDM and MNDM may be responsible for part of this bump.

Regardless, the behavior of the data shows that not all values for action distance are equally desirable. When the action distance is too small, safety is compromised. When the action distance is too large, efficiency is compromised (and for some algorithms, safety as well).

The desirable action distance does not seem to be defined by the kinematics of the situation, although it is limited by it. Because the UAVs examined have constant deceleration, a UAV's stop distance can be calculated using the equation, $d_s = v_i^2/(2 * a_{av})$, and its stop time can be calculated using $t = v_i/a_{av}$. Given these ranges of accelerations and speeds, the maximum distance a UAV would need to come to a dead stop is 45 m. This would produce a minimum action distance of equal to $d_{\mathrm{ownship}} + d_{\mathrm{intruder}}$, which, in this simulation, would be at most 90 m.

Figure 9 shows, however, that an action distance of 90 m does not eliminate all crashes. Multiple conflict issues inherent to high-density spaces may cause this issue. Because UAVs need to avoid more than one UAV, the simplest maneuvers are frequently impossible and kinematics are no longer strongly predictive. Nevertheless, kinematics can provide a lower bound for a minimum possible action distance. There is also an upper limit on effective action distances. In fact, there is only a small band of feasible choices. In Fig. 9, crash rates for NDM and PF approach zero beyond a certain point, but efficiency quickly decays as increasing numbers of conflicts are induced (see Fig. 11). As shown in Fig. 10, different collision-avoidance mechanisms all demonstrate this behavior at sufficiently high action distances. In NDM, for example, a distance higher than 0.4 km dramatically decreases efficiency without correspondingly large safety benefits.

B. Collision-Avoidance Mechanisms: Lessons Learned

The results of the simulation, especially Figs. 9–11, suggest that simply preventing crashes is only a partial solution to the air traffic problems posed by UAVs. Maintaining system efficiency while keeping crashes low will be the real challenge. PF does a much better job of this than either of the other methods: most decay in efficiency is only found after the action distance exceeds 1 km, far larger than what was needed to bring crashes to a negligible level.

PF graduated responses and geometric complexity are probably the causes of its efficiency gains. A close approach produces a behavior similar to NDM, but a farther approach results in only a small turning action away from the intruder. In this way, only the minimum amount of action necessary to avoid the collision is taken by the ownship. The most time and effort possible are devoted to performing useful tasks rather than evasive maneuvers. As such, any modification to these methods that decreases their complexity and graduation will probably reduce their efficiency.

The PF algorithm does not take perceptible action when its r distance is reached, which sets it apart from many other collision-avoidance maneuvers. Nevertheless, a significant action is taken when the separation between the two aircraft is low. Because responses depend on the geometry of the situation as well, an intruder who is between the ownship and its objective will provoke a response of different intensity than an intruder at the same distance at an angle. Many other algorithms, such as chain and the dynamic window approach, have similarly graduated and geometrically determined responses. In many of these algorithms, the behavior varies continuously at all points inside some large range, regardless of well-clear boundaries.

At first glance, the fact that losing well clear does not lead to a step change in behavior is troubling. Traditionally, action should be taken immediately when well clear is lost to avoid a collision. In the PF algorithm, this is unnecessary. The strength of the PF (and other advanced algorithms) lies in adopting a corrective behavior when it is efficient, rather than only when it is necessary. If the aircraft's behavior and future path are already sufficient to prevent collisions and restore well clear in a quick and effective way, that behavior should not be changed. The loss of well clear may not need to imply a change in behavior if the behavior is already adequate. Because trespassing any defined well-clear boundary may not create a step response in UAV behavior, it may be useful to understand these mechanisms in terms of action distances (where the mechanism begins to change aircraft behavior), as well as well-clear thresholds.

C. Density

Figures 12 and 13 demonstrate the effects of density on system performance when using PF methods. Some of the effects are intuitively obvious; for instance, it is not surprising that both NMACs and objectives achieved increase with density at low action distances. Also unsurprisingly, high action distances lead to poor system efficiency due to high levels of induced conflict. Interestingly, it is clear that PF methods are not affected by density past certain points. The trends suggest that, at high-enough action distances, both efficiency and NMAC rates approach 0 regardless of density. More moderate action distances, however, still show important density effects.

D. NMAC Distance

Another important parameter for system efficiency and safety is the NMAC distance. Figures 9 and 10 show that there are significant

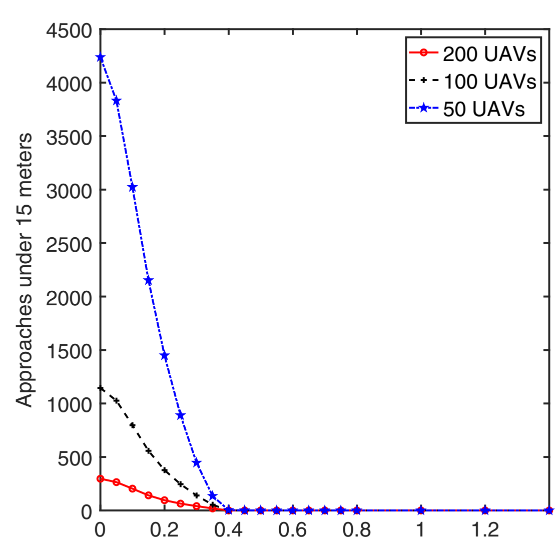

Fig. 12 Effect of UAV density on safety with the PF collision-avoidance system.

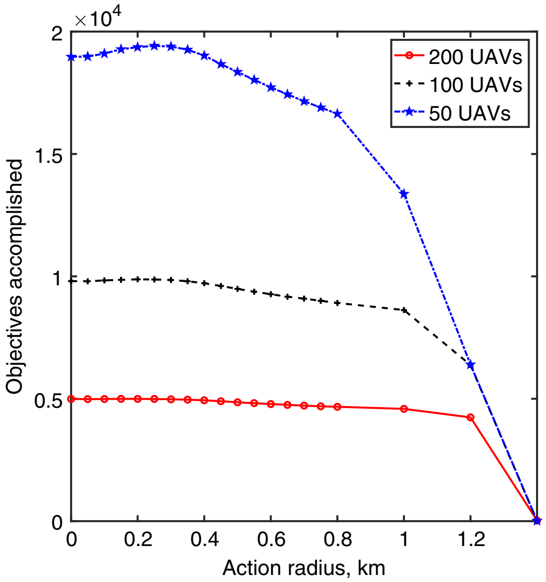

Fig. 13 Effect of UAV density on efficiency with the PF collision-avoidance system.

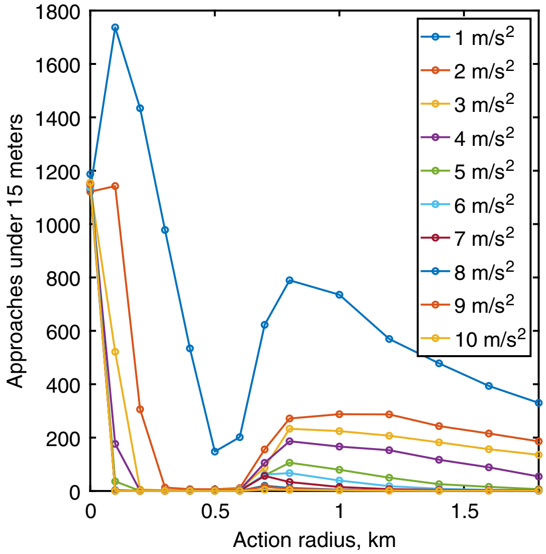

Fig. 15 Effect of UAV accelerations on safety in the MNDM.

differences between a 15 and 150 m NMAC. If a 15 m NMAC is selected, then 0.25 km for NDM or 0.4 km for PF would be the best choice for maximizing safety and efficiency. If a 150 m NMAC were chosen, it would be necessary to increase the action distance to maintain a similar number of NMACs. This increase in action distance would reduce efficiency.

Because the definition of an NMAC has a significant effect on system safety and efficiency, further research into how NMACs should be defined is warranted.

E. Accelerations

Higher accelerations for a given speed of UAV improve system safety regardless of the avoidance mechanism used. The magnitude of this effect, however, seems to decrease as accelerations increase. As Figs. 14 and 15 show, effects differ between collision-avoidance mechanisms. Nevertheless, it appears that the effects quickly become less significant, and costs will outweigh benefits at some point. UAV users or regulators can and should perform cost–benefit calculations based on these (or similar) simulations to determine at what point increasing acceleration ceases to be cost effective.

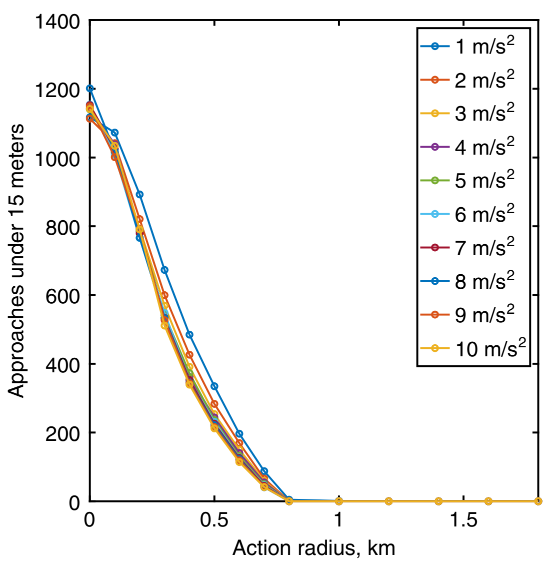

Fig. 14 Effect of UAV accelerations on safety in the PF method.

IV. Conclusions

Assuming favorable regulation, unmanned aerial vehicle (UAV) use will dramatically increase over the next decade. The demographic projections suggest that, over certain airspaces, high UAV densities (100 UAVs in 100 km^2, with higher traffic at peak times) will occur. In such situations, there are four important things that can be done to keep UAVs safe and effective.

First, increase accelerations relative to speed (by instituting a speed limit based on a UAV's acceleration). This gives UAVs a greater opportunity to use whatever collision-avoidance mechanism they employ. This effect is subject to the law of diminishing returns, and so speed limits should be chosen with care. Second, use an appropriate collision-avoidance method. The potential field algorithm performed significantly better in both safety and efficiency than naive deconfliction method (NDM) or MNDM because of its more graduated responses. More developed algorithms could improve behavior still further. Third, behavior can be improved by keeping collision-avoidance distances within the effective band. For each algorithm investigated, only a narrow band of collision-avoidance distances created acceptable safety and efficiency. For NDM, for instance, this band stretches only from 0.2 to 0.3 km. Experimentally tuning the chosen algorithm's action distance is an important part of the optimization problem. Regulators have recently adopted a comparatively small separation standard for small UAVs (SUAVs) vs manned aircraft. It seems reasonable that the separation standard for SUAVs vs SUAVs could be smaller still. The simulation results suggest that, for best performance in high-density areas, it should be.

Finally, safety and efficiency can both be increased by adopting a more appropriate NMAC distance for UAVs. To increase efficiency, this NMAC distance should be as low as safety will permit. An excessive NMAC range lowers both safety and efficiency by forcing collision-avoidance distances to increase. Sufficiently large-scale multiple conflicts caused by excessively large NMAC distances can eliminate the effective band, and cause significant decreases in both efficiency and safety for all of the methods examined.

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J. Kuchar
Associate Editor