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Effectiveness of autonomous decision-making for Unmanned Combat Aerial Vehicles in dogfight engagements

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I. Introduction

The main objective of this work is to perform a study of the utility of Unmanned Combat Aerial Vehicles (UCAVs) in dog-fighting (DF) engagements with DF defined as an aerial battle between two fighter aircraft taking place at close range. The key problem is to assess effectiveness of UCAVs in DF combat when using autonomous decision-making based on a representative guidance law and a game-theoretic algorithm. The UCAV DF problem is considered here as a two-player (two fighters), zero-sum, sequential-interaction game with limited information, i.e. each fighter only knows the last three positions of its opponent every time a decision needs to be made. A software simulator has been developed to represent a one-versus-one, clear-sky, close-range aerial battle involving 3-D trajectories with high angle-of-attack (AoA) maneuvers for fighters with similar/dissimilar performance capabilities, considered under four initial conditions: offensive, defensive, neutral and opposing engagements. Different "levels of intelligence" of the enemy are implemented to validate the performance of the UCAV autonomous decision-making against diverse opponents. The simulation-based parametric study elucidates the influence of fighters' performance capabilities and the fighters' skill on the outcome of the engagement.

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A. Existing approaches

In the context of manned aircraft, the fundamental source of information about DF maneuvers and tactics is [1]. Helicopter air combat was modeled in the foundational study [2] which introduced a library of seven basic maneuvers to represent the DF engagement as a seven-choice zero-sum game with perfect information that can be approximately solved by applying max-min search. In [3] and [4] DF trajectories were analyzed by applying fuzzy rules based on relative position of the aircraft to guide the attacker.

In the context of UCAVs, [5] proposed an "approximate dynamic programming approach" to optimize DF maneuvers. Their approach requires appropriate offline training but, once trained, the algorithm is capable of producing sensible DF maneuvers without explicit coding of air-combat tactics. A similar approach was adopted in [6] where the authors concluded that an optimal approach to DF may combine knowledge-based decision methods with approximate dynamic programming. In [7], it was shown that it is possible to guide a UCAV in close-range combat using the virtual pursuit point, effectively replacing a list of standard maneuvers (as in [2]) with a single guidance law, thus allowing real-time simulation for simplified UCAV flight dynamics. Unlike in [7], the work in [8] did not use a guidance law but employed the basic maneuver library of [2], albeit extending the number of elemental maneuvers from seven to eleven to account for increased maneuvering capabilities of UCAVs when compared to manned aircraft.

In the UCAV literature, basic Game Theory [9] has been applied to model DF engagements for UCAVs, usually relying on the max-min search. However, the game associated with DF engagements is not simple so that the corresponding game tree is large and thus it is computationally expensive to evaluate all possible states [10]. As pioneered in

[2], and followed in [8] among others, it is often necessary to obtain quickly an approximate solution of the DF game rather than bear the prohibitive cost of finding the exact solution.

B. Proposed approach

Our modeling of UCAV DF engagements is inspired by the guidance-law approach of [7] and the game-theoretic setting of [2]. This results in a novel representation of UCAVs as autonomous DF game players making real-time decisions without prior knowledge of air combat tactics. A continuous guidance law (different from [7]) is used and is then discretized into 14 different options, thus generating 14 possible moves in a two-player, zero-sum, sequential-interaction game with limited information, thus distinguishing our approach from that of [2]. This DF game is solved using the max-min search algorithm restricted to look ahead to a fixed depth in the game tree in order to allow real-time decision-making.

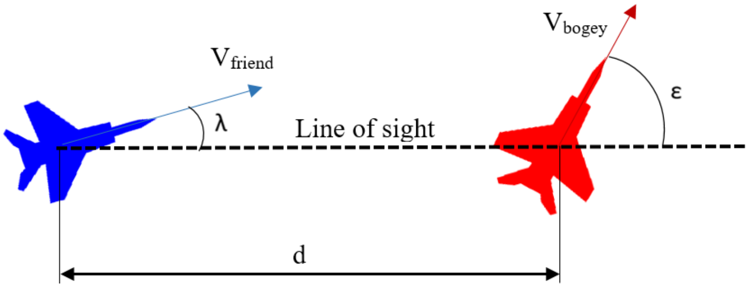

Fig. 1 Schematic representation of the parameters of the score function

UCAV autonomous decisions are ranked according to a novel score function which takes into account the optimal firing positions and evaluates the risk of collision with the target or target's debris. The fundamental score function to evaluate DF engagements was originally presented in [11] and it is a de facto standard in the air combat simulation literature [2], [12]:

$$Sc^* = \left(1 - \frac{|\epsilon + \lambda|}{\pi}\right)\left(e^{-\frac{d-d_{opt}}{K\pi}}\right) \tag{1}$$

Here, Sc^* represents the score that depends on the relative orientation of the combat fighters through λ and ε which are the angles between the velocity vector and the line of sight (see Fig. 1), whilst d and d_{opt} represent the distance between the fighters and the optimal distance for cannon attack, respectively. Finally, K is a constant controlling the influence of each term. Based on expert knowledge [1] and information about capabilities of a typical cannon [13], the values d_{opt} = 700 m and K = 600 m have been adopted in this work.

The score function (1) only penalizes the payoff when the distance between combat fighters is greater than the optimal distance for a cannon attack but without penalizing the risk of collision with the target or target's debris; hence the modified score function has been used:

$$Sc = \left(1 - \frac{|\epsilon+\lambda|}{\pi}\right)\left(e^{-\frac{|d-d_{opt}|}{K\pi}}\right). \qquad (2)$$

The score function (2) yields the maximum score (+1) when BLUE is pointing directly at the tail of RED (with RED pointing directly away from BLUE) whilst the distance between the aircraft is optimal; the minimum score (–1) occurs for the opposite case. Since this work is based on zero-sum game representation, the score of BLUE is the opposite of the score of RED and hence RED will try to minimize the score of BLUE (see III-A).

II. DF modeling and simulation

In this work, a point mass model of the aircraft similar to [14] and [15] was employed and the assumed aircraft parameter values are based on the F-16 fighter in nominal flight conditions [16] but in some of the simulations reported in Section III these values were varied in order to simulate dissimilar engagements.

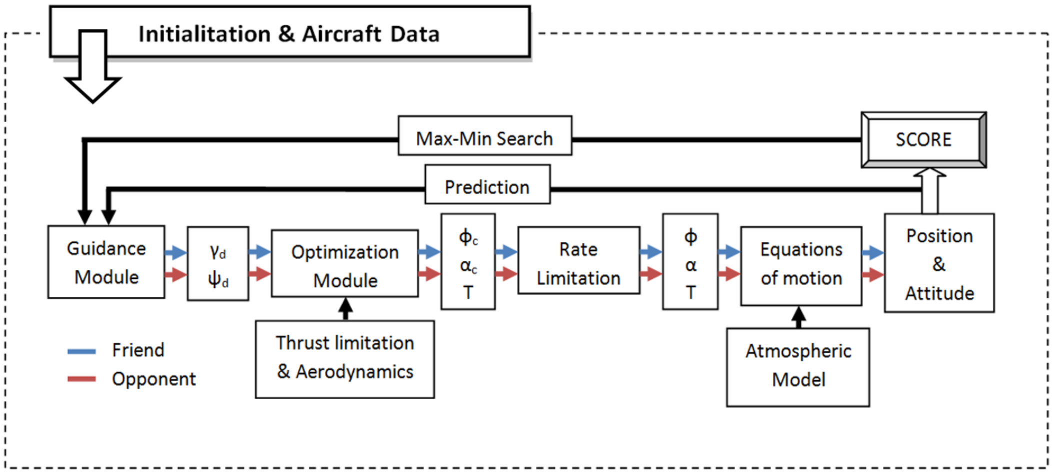

Fig. 2 Block diagram of the model: "d" indicates "desired" whilst "c" indicates "commanded".

A. Initial conditions

As in [17], four different initial conditions of the DF engagement are defined (see Fig. 3) based on the initial relative position and orientation of the fighters.

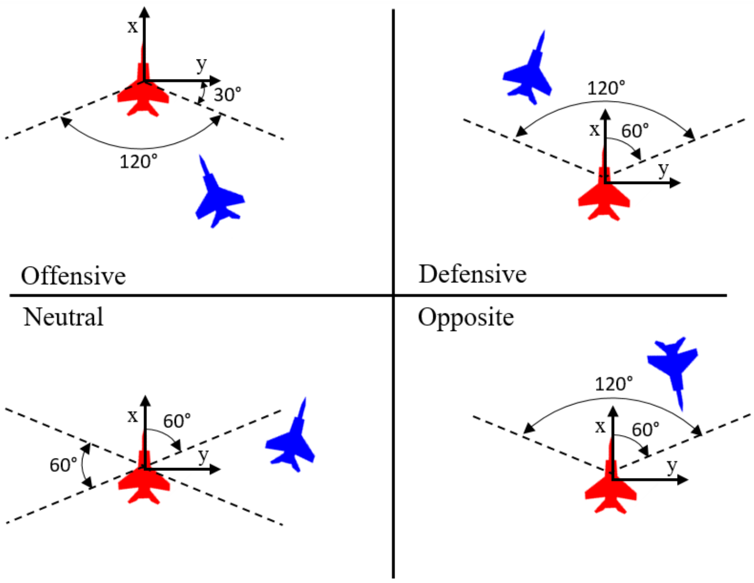

Fig. 3 Initial conditions for the DF engagement. In the "neutral" case, BLUE can start on the right or on the left of RED.

The initial position of BLUE is randomly chosen with the horizontal distance to RED between 350m and 1050m in the offensive, defensive and neutral cases and 2100m in the opposing case. The initial altitude of BLUE is also randomly chosen and can vary by 700m around the RED altitude. The limits for initial angular positions and maximum-minimum initial horizontal distances between the fighters are based on the DF literature [13], [17], [18].

B. Guidance law

The guidance law introduced here generates lead, pure and lag pursuit together with climb and dive maneuvers for both fighters rather than using a look-up table of the basic fighter maneuvers (BFMs). That guidance-based maneuver generation also captures the important fact that different pursuit strategies have different effects on the relative position of the aircraft: lag pursuit tends to reduce the rate of closure between fighters; lead pursuit tends to increase the rate of closure whilst pure pursuit is a neutral maneuver. On the other hand, climb and dive maneuvers can be applied to increase the distance between the fighters and to convert kinetic energy into potential energy (or conversely) which is a classical strategy in DF engagements. Based on that, a continuous guidance law (see Table 1) was generated and optimized and then discretized in order to apply the max-min search.

Table 1 Recommended maneuvers

Distance between fighters	Rate of closure / Speed of the fighter	Recommended maneuver
< 180 m	> 0.1	Climb maneuver
< 180 m	< 0.1	Lag pursuit
180 – 350 m	N/A	Lag pursuit
350 – 1000 m	N/A	Pure pursuit
1000 – 1500 m	N/A	Lead pursuit
> 1500 m	> 0.1	Lead pursuit
> 1500 m	< 0.1	Dive maneuver

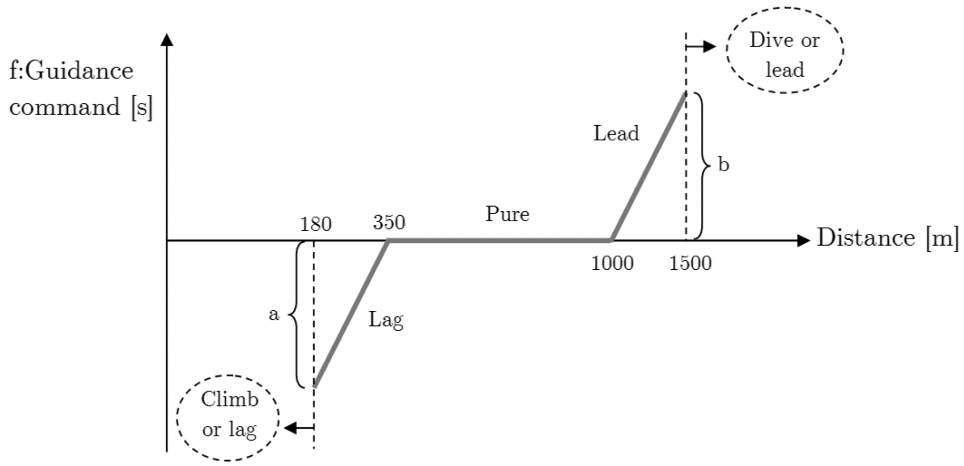

Fig. 4 Shape of the continuous guidance law

The boundaries between the different DF situations have been derived from expert knowledge and cannon lethality [11], [13], [17], [18]. The recommended maneuver is a continuous function of the distance between fighters as shown in Fig. 4; parameters *a* and *b* have been determined empirically by simulation.

The continuous law shown in Fig. 4 is discretized to produce 14 possible maneuvers for each fighter. Hence, a score matrix with 14x14=196 possible outcomes is generated and must be evaluated at each time step. BLUE will apply max-min search algorithm to choose certain maneuver each time step whereas RED choice will depend on its level of intelligence (see Section III).

C. Optimization

Once the guidance module generates the desired path and heading angles, this information is passed to the optimization module which computes an optimal combination of controls (angle of attack, roll angle and thrust) to follow the desired trajectories for each fighter. This optimization is based on minimizing the following cost function:

$$c = (\psi_d - \psi)^2 + (\gamma_d - \gamma)^2 \tag{3}$$

The specific energy of the aircraft, *e*, remains constant during DF combat:

$$e = \frac{1}{2}V^2 + gh = \text{constant } \rightarrow \dot{e} = V\dot{V} + g\dot{h} = 0 \tag{4}$$

which, combined with the equations of motion, yields:

$$T = \frac{D}{\cos\alpha} \tag{5}$$

thus reducing the dimension of the cost function:

$$c(\alpha, \phi, T) \rightarrow c(\alpha, \phi) \tag{6}$$

The cost function c, defined by (6), can be reformulated in terms of angular rates, see [4], resulting in the equivalent cost function c^*:

$$c^* = c_\psi + c_\gamma \tag{7}$$

where:

$$c_\psi = \left(\frac{\frac{1}{2}\rho V S\left[\left(C_{D_0} + kC_L^2(\alpha)\right)\sin\phi\ \tan\alpha + C_L(\alpha)\sin\phi\right]}{m\cos\gamma} - \dot{\psi}_d\right)^2 \tag{8}$$

$$c_\gamma = \left(\frac{\frac{1}{2}\rho V S}{m}\left(\left(C_{D_0} + kC_L^2(\alpha)\right)\cos\phi\tan\alpha + C_L(\alpha)\cos\phi\right) - \frac{g\cos\gamma}{V} - \dot{\gamma}_d\right)^2 \tag{9}$$

The resulting optimization problem must be solved under the thrust constraint:

$$T_{max} \geq \frac{\frac{1}{2}\rho V^2 S\left(C_{D0} + kC_L^2(\alpha)\right)}{\cos\alpha} \tag{10}$$

Additional constraints were introduced based on the F-16 fighter data, see Table 2.

Table 2 Angular and angular rate limitations included in the simulator (similar performance capabilities engagement)

Parameter	Minimum Value	Maximum Value
AoA Rate	-40[deg/s]	40[deg/s]
Roll Rate	-230[deg/s]	230[deg/s]
AoA	-15 [deg]	45[deg]
Roll	-180[deg]	180[deg]

The optimization module presented here is structurally similar to the one in [4], but in our case the simplifying assumptions of [4] are avoided, especially small angles of attack during the engagement, constant aerodynamic coefficients or lack of rate limitations. This optimization problem is nonlinear and was solved using MATLAB's function `fmincon` with the interior point algorithm. The `fmincon` results were validated by proper setting of tolerances, initial seeds and also analysis of the plots of the relevant outputs.

III. Results and analysis

Using the DF simulator (Section II), several hundred engagements have been generated by randomly varying the initial conditions as per Section II-A and Fig. 3.

A. Level of intelligence (LOI)

The maneuver chosen by BLUE is based on max-min algorithm and the LOI choice controls the quality of maneuvers chosen by RED. Assuming similar performance capabilities for BLUE and RED, if the LOI is high, then RED will select every time a decision needs to be made the maneuver that minimizes BLUE's reward. If the LOI is medium, then RED will select a maneuver which averages the payoff. Finally, if the LOI is low, then RED will choose the maneuver that maximizes BLUE's profit. All attacks inside the lethality cone (see Fig. 5) have high probabilities of damaging the opponent.

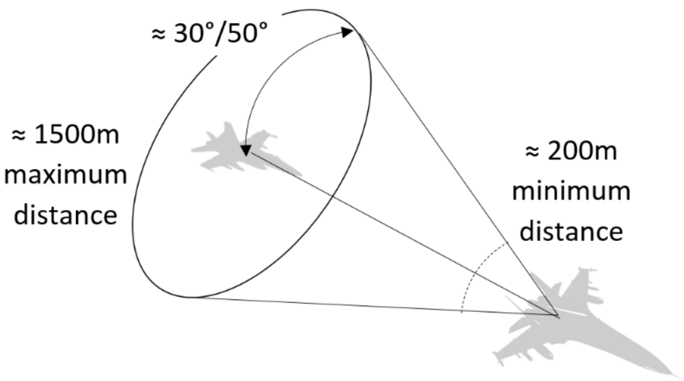

Fig. 5 Lethality cone

Based on the above characterization of the LOI choice, averaged engagement outcomes shown in Fig. 6 can be interpreted as follows. When RED's LOI is high or medium, the outcome is highly dependent on the kind of engagement selected. These results are consistent with the case in the DF literature [18] corresponding to similar performance capabilities of the fighters and the training of the pilots (represented here by the LOI of the opponent). It is remarkable that when RED's LOI is medium for neutral initial conditions, BLUE is able to obtain a positive average score (+0.38) even though the a priori average score of this scenario should be close to zero.

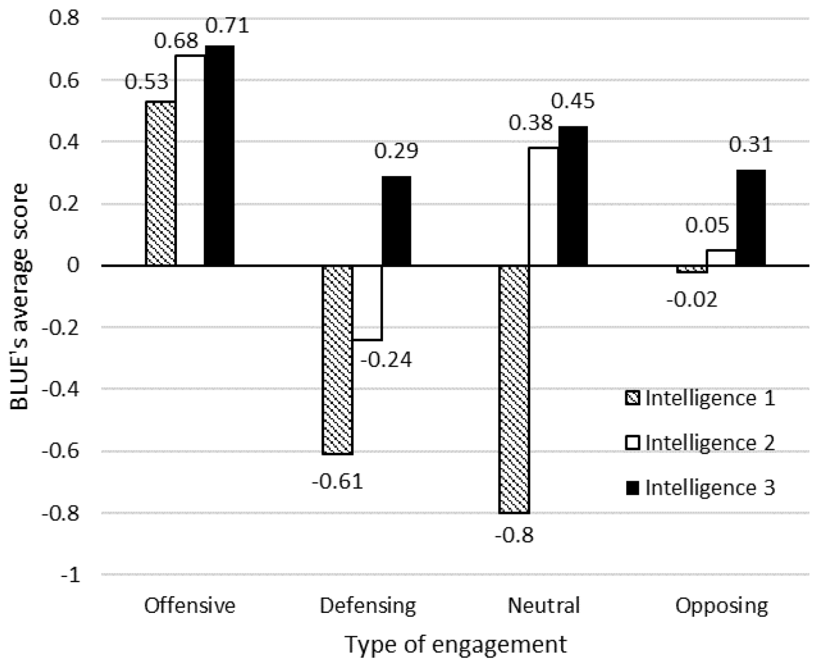

Fig. 6 Outcome of the engagement depending on the "level of intelligence" of the enemy (RED) under different initial conditions.

When RED's LOI is high, i.e. RED always acts optimally (worst case for BLUE), the performance of BLUE is ≈10% worse than the performance of RED under the same initial conditions. This result is consistent with the max-min search which minimizes one's maximum loss and if BLUE's selection was not based on the max-min search, then the average score of the engagement would be even worse. When RED's LOI is low, in all cases the outcome of the engagement is clearly favorable to BLUE; however, BLUE could have selected other maneuvers to obtain a higher average score because the max-min search is a conservative ("worst-case scenario") method [9], [19].

B. Similar and dissimilar engagements

Variation of the performance capabilities performed here focused on the following parameters: maximum thrust and maximum angular rates, see Table 3.

Table 3 Modified parameters to simulate similar/dissimilar performance capabilities engagements.

Parameter	Advantage-Value	Disadvantage-Value
AoA Max Rate	40 [deg/s]	32 [deg/s]
Roll Max Rate	230 [deg/s]	184 [deg/s]
Max Thrust	130,000 [N]	104,000 [N]
Max AoA	45 [deg]	36 [deg]

The advantage difference of 20% (or above) was used as a threshold to classify the engagement as "dissimilar" and RED's LOI was set to medium as a reference engagement with the results shown in Fig. 7.

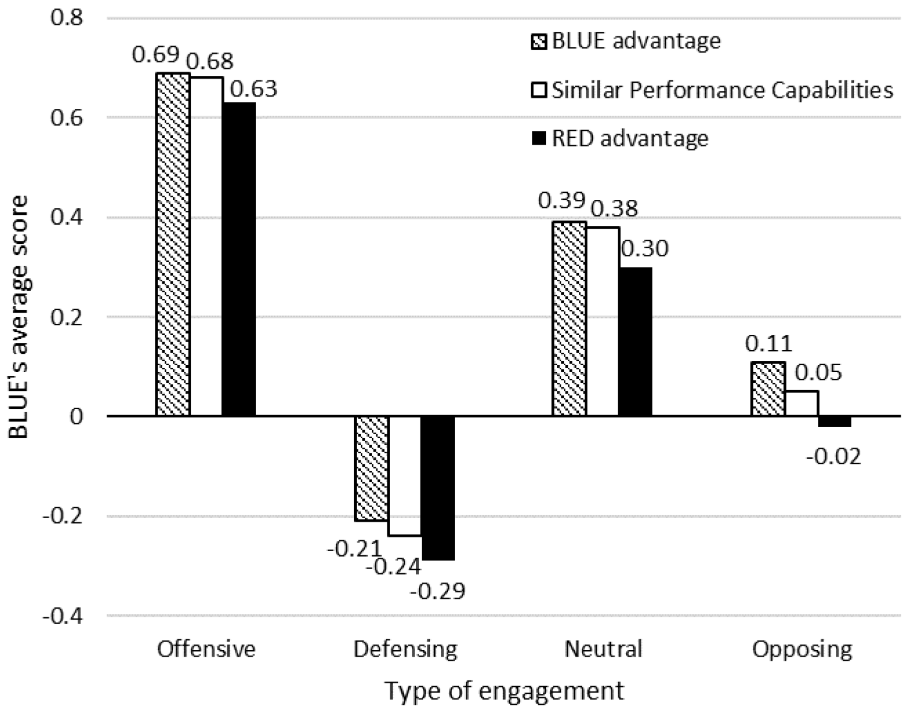

Fig. 7 Outcome of the engagement depending on fighters' performance capabilities under different initial conditions.

In all the cases, advantage in performance capabilities increases the average score but it is not straightforward to establish a direct link between the increase of the mean score and the performance capabilities, due to the nonlinear character of this relationship. The outcome of the engagement is strongly dependent on the initial conditions whereas the difference of capabilities has a secondary influence on the outcome. This indicates that the traditional DF strategies [18] are not optimal to make the most of the advantage in performance capabilities.

Comparison of Fig. 6 and Fig. 7 shows that the influence of the LOI on the average score is much greater than the influence of the performance capabilities of the combat fighters. There are two reasons why the LOI influence is decisive (and underscores the importance of pilot training). Firstly, the assumption that the specific energy of the fighters remains constant simplifies the control optimization problem but it generates a constraint which links the thrust, speed and angle of attack thus complicating the use of advantageous performance capabilities. Secondly, the fighters do not always operate at the limits of their capabilities and hence the reduction on the maximum thrust, angle of attack and angular rate limits is not directly proportional to the variation of the average score.

C. Analysis of the load factor

The load factor is a key parameter to determine the turn performance and hence the performance capabilities of the combat fighter. Fig. 8 shows the average values of the load factor recorded during engagement under different initial conditions. The bars represent the percentage of time the fighters are flying inside certain range of load factor while the dotted line is the cumulative value.

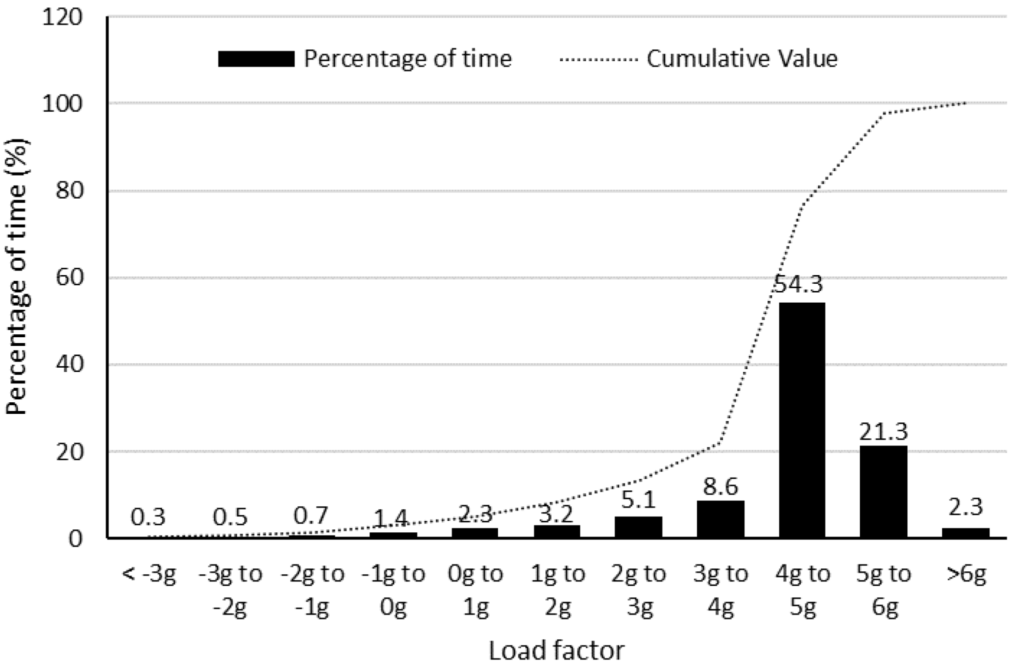

Fig. 8 Average percentage of time the fighters are flying inside certain range of load factor.

The results in Fig. 8 demonstrate that in DF engagements the maneuvers with high load factor occur often, e.g., 86.5% of the time of the engagement the fighters are supporting a load factor > 3g's. The cumulative percentage of maneuver performed at n < 1g is only 5.2% which means that reduced / zero / negative gravity situations are rare in DF engagements, consistently with the fact that aircraft are optimized to fly under positive load factor.

D. Trajectories

In this section, example trajectories for representative engagements are presented and analyzed. The figures were obtained for engagements of 25 [s] with a time-step size of 0.1 [s].

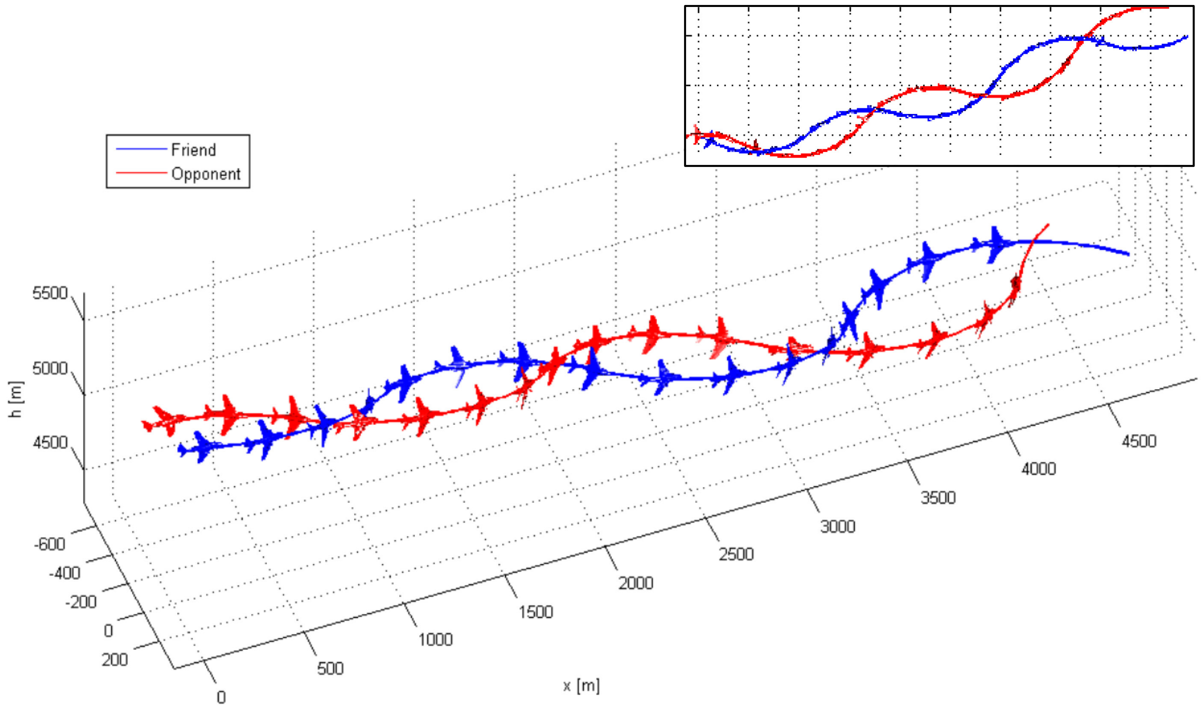

Fig. 9 Engagement for the neutral initial position, RED's LOI high and similar performance capabilities.

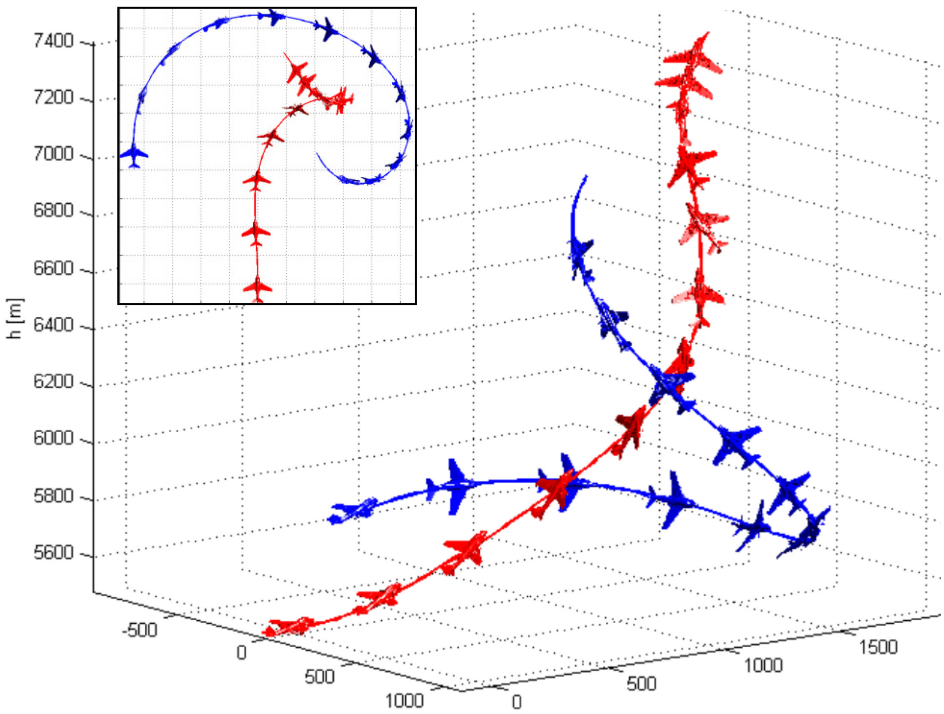

Fig. 10 Engagement for the defensive initial position, RED's LOI low and similar performance capabilities.

The simulator generates trajectories consistent with the familiar DF maneuvers [1], [3], [4], [13] and basic flight maneuvers (BFM) are automatically generates although no BFM were explicitly specified. Fig. 9 clearly shows a flat-scissor maneuver which is common when the performance capabilities of the aircraft are similar and the initial condition is neutral. Fig. 10 shows that the max-min search algorithm takes advantage of a low-LOI opponent: this engagement starts for the defensive condition for BLUE, RED tries to increase the distance with respect BLUE by climbing but, at the same time, BLUE combines turn and climb in such a way that at certain instants of time it is pointing at the rear of the opponent.

IV. Conclusions

The study presented here shows that UCAVs are suitable for DF engagements and they can autonomously perform aggressive DF maneuvers as those shown in Fig. 8. In the context of autonomous decision-making by the UCAV, the max-min search algorithm is a practical and effective method for solving DF games especially when opponent's "level of intelligence" (LOI) is set to high or medium. When the opponent's LOI is set to low, less conservative strategies could be more suitable to make the most of BLUE's advanatge. Also, instead of relying on stereotyped (pre-stored) maneuvers, the use of a continuous guidance law based on lead / pure / lag pursuit and climb / dive maneuvers is a natural and effective solution. Such continuous guidance law is optimized and must be discretized to apply the game-theoretic max-min search. The finer the resolution of that discretization is used, the better approximation is obtained but the computational load is proportional to the square of the number of samples, so it necessary to make a design trade-off between resolution and computational load.

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