Mid and Short Term Conflict Resolution in Autonomous Aircraft Operations

Georgios Chaloulos, Giannis P. Roussos, John Lygeros and Kostas J. Kyriakopoulos

***Abstract*— We investigate the conflict resolution problem in a self-separation airspace. Using the recent advances in the fields of robotics and control, we use navigation functions to resolve conflicts arising in the Short Term, which guarantee conflict avoidance, while in Mid Term, a model predictive controller makes sure that the designed system respects the operational constraints of the situation and maximizes some performance for the system. Both algorithms operate in a decentralized scheme, following the autonomous aircraft concept investigated under the European project iFly. Priority issues are discussed and ways to take them into consideration in our setting are shown. The algorithm performance is demonstrated on simulations in planar configurations.**

I. Introduction

Within the last years, major advances have been made in the field of control, both in centralized as well as decentralized techniques. One could expect this fact to drive similar innovations in the field of Conflict Resolution for commercial aircraft. The practise says otherwise; mostly traditional, human-operated control is used for the redirection of air traffic to resolve any arising conflicts, up to 30 minutes in the future. This is highly likely to become a major bottleneck in the projected air traffic density increase in the near future. A potential solution to this problem can be the use of computational tools, in order to simplify the tasks of human operators [1].

In the literature, several techniques and algorithms for the Conflict Resolution problem have been proposed. A very good survey can be found in [2]. One can divide Conflict Resolution in Air Traffic Control based on the time horizon considered in three categories; Long Term (horizon of hours - Flow Management problems [3], [4]), Mid Term (horizons of tens of minutes [5], [6]) and Short Term CR (horizons of minutes). Algorithms proposed so far are usually suitable for one of these categories [7]. While one would think that solving the problem over a very long horizon would be ideal, the large uncertainties involved in air traffic (weather forecast errors, pilot actions, modeling errors, etc.) can either result in a very conservative solution, or even an infeasible problem as the horizon grows. On the contrary, solutions for very small horizons tend to be "myopic", ignoring the global goal for the aircraft navigating in each sector.

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Recently, the air traffic community has shown great interest in unifying the European traffic sector, using centrally precalculated "business trajectories" that aircraft should follow. This is envisioned to help accommodate the projected traffic increase [8]. Our approach, on the other hand, is aiming further in the future (beyond 2035), in an autonomous navigation concept of operations, in which no ground support will be available and aircraft will navigate using autonomous navigation rules in some self separated part of the airspace. This concept is proposed by the European project iFly [9].

Our main goal in this paper is to take a first step towards combining Mid Term CR techniques with the use of Short Term CR in a decentralized fashion. The aim is to reduce conservatism when solving the Mid Term problem, while providing conflict avoidance guarantees of Short Term CR algorithms.

For the Short Term problem, methods involving artificial potential fields are used, which are very common in the motion control of mobile robots. Aircraft are considered as agents, navigating through an artificial potential field using navigation functions, a method which drives each agent away from conflicts and towards its goal. While being always able to generate a conflict-free solution for every problem configuration, navigation functions do not take into account aircraft constraints, such as bounded thrust and velocity, time constraints etc., generating possibly infeasible solutions for the aircraft.

To overcome this disadvantage of the navigation functions, the Mid Term CR algorithm will be responsible for finding a suitable configuration for the navigation functions, such that the aircraft constraints are not violated. We deploy the use of Model Predictive Control (MPC), a method widely known for its ability to handle constraints. The problem formulation follows the one in [10], [11] with the difference being that it is applied here in a decentralized fashion, while maintaining the properties of the centralized problem in terms of feasibility.

The rest of the article is organized as follows. Section II describes the Navigation Functions method used for the Short Term conflict resolution. Section III presents the Model Predictive Control strategy followed in the Mid Term. Section IV discusses how the problem can be applied in a decentralized fashion in such a way that the centralized problem properties are retained. Simulation results are presented in Section V. Finally, conclusions and directions for possible future work are presented in Section VI.

II. Navigation Function Control

A. Introduction

Artificial potential fields [12] have been widely used for collision avoidance in robotic applications. The notion of this class of methods is to create a potential field and then guide each agent towards its minimum, by following the fields negated gradient. A possible drawback of such an approach is the existence of local minima in the field, away from the destination. These minima can attract the agents and prevent them from reaching their final destinations. Navigation Functions [13] are a class of artificial potential fields that have exactly one, global, minimum and no local ones. Thus, the negated gradient of a Navigation Function can guide each agent toward its destination and away from any obstacles (read other agents) present in the workspace. As Koditschek and Rimon have demonstrated [14] strict global navigation is not possible as every obstacle introduces at least one saddle point in the potential field, nevertheless the sets of initial conditions that drive the system to these saddle points are of measure zero.

The problem under consideration involves N aircraft-like vehicles flying level, while avoiding conflicts with each other. Each aircraft $i = 1, \ldots, N$ is modeled as a planar non-holonomic circular unicycle. The position and orientation of vehicle i are $\mathbf{q}_i = [x_i, y_i]^T$ and θ_i respectively. The motion of each vehicle is described by the following kinematic equations:

$$\dot{\mathbf{q}}_i = \begin{bmatrix} u_i \cos\theta_i \\ u_i \sin\theta_i \end{bmatrix} \tag{1a}$$

$$\dot{\theta}_i = \omega_i \tag{1b}$$

where u_i is the longitudinal (linear) and ω_i the angular velocity of vehicle i. The state of each vehicle is then $\mathbf{n}_i = [\mathbf{q}_i^T, \theta_i]^T$ while its input is $\mathbf{v}_i = [u_i, \omega_i]^T$.

B. CD&R using Dipolar Navigation Functions

Navigation Functions as introduced by Koditschek and Rimon [13] are not suitable for the control of nonholonomic, aircraft-like agents, as they do not take into account the relevant constraints. This can lead to undesired behavior when used in nonholonomic systems, such as having the agents rotate in place. *Dipolar Navigation Functions* [15] offer a significant advantage in this aspect: the integral lines of the resulting vector field are all tangent to the target orientation at the destination, eliminating thus the need for in-place rotation. As a result, each agent is driven to its target with the desired orientation. This is achieved by considering the plane with normal vector that is parallel to the desired orientation at the goal configuration, as an additional artificial obstacle H.

The potential of such a Navigation Function in a 2D workspace with two obstacles O_1, O_2 is shown in Figure 1. The destination is $\begin{bmatrix} x_d & y_d \end{bmatrix} = \begin{bmatrix} 7 & 0 \end{bmatrix}$, with orientation parallel to the x axis. The corresponding nonholonomic obstacle H is the line $x = 7$, as shown in the Figure. The NF-based control scheme used in this paper is described in detail in [16]. The Navigation Function employed has been used in [17] and provides almost global convergence to the agents' destinations, along with guaranteed collision avoidance.

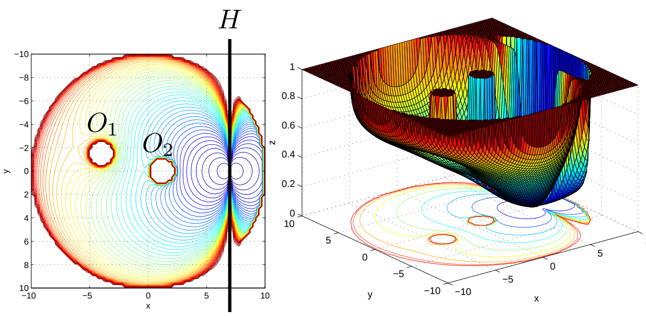

Fig. 1. 2-D Dipolar Navigation Function

III. Model Predictive Control Formulation

As discussed before, the Navigation Function based control scheme in [16] cannot guarantee constraint satisfaction of the resulting control policy. To overcome this drawback ,we employ the technique of Model Predictive Control (MPC) [18], a control methodology developed specifically to deal with state and input constraints. In such a setting, every 3 minutes a mid-term conflict resolution algorithm decides on the optimal parameters for the Navigation Functions for the following 21 minutes (7 periods of 3 minutes).

Unfortunately, due to the problem structure, finding the exact optimum control policy at each time step it is computationally intractable. Thus, we have to use a method that allows us to approximate this optimum policy. We choose for this purpose to use randomized optimization techniques. Randomized optimization algorithms are a very promising method in this context, since they can inherently deal with the complexity of the problem, with reasonable computational workload. There are several methods falling into this category, such as genetic algorithms, simulated annealing, etc. While all seem to work with more or less the same efficiency, only few have theoretical convergence to the optimum in finite time. This is the reason we chose the method described in [19]. This method is a variation of Simulated Annealing that works both for deterministic and expected value criteria.

The concept behind this randomized optimization algorithm is that, while randomly searching and trying to find the minimizer of the cost function, from time to time, accept a worse solution (instead of accepting only better solutions). This helps the algorithm overcome local minima and continue exploring the search space. Details on the method we use for this can be found in [19], as well as specific description of its application in the conflict resolution problem in [11], [10].

Since the unicycle dynamics used by the Navigation Functions can only be considered as an abstraction for real aircraft dynamics, we employ a more realistic Flight Management

System (FMS), converting the Navigation Functions commands to the appropriate variables in the aircraft dynamics. The dynamics of the aircraft follow the ones in [20]. The reader is referred to [21] for an analytic description of the model. The linear velocity commanded by the Navigation Functions is used as the nominal airspeed that the FMS has to track, applying the thrust required, while the angular velocity is used for the bank angle control of the aircraft. This model hierarchy is depicted in Figure 2.

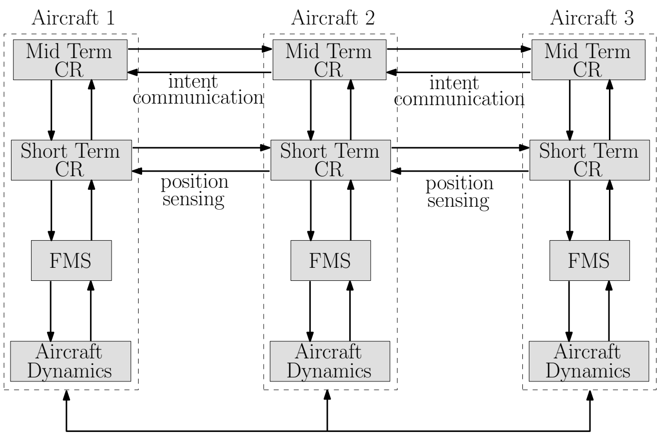

Fig. 2. Hierarchical control model

IV. Decentralized Strategy

As no ground support is present in the concept of autonomous aircraft [9], the aircraft should be able to identify and resolve all situations that might evolve into a conflict. For this to be possible, we assume that the intent of all aircraft is communicated between them at the Mid Term, see Figure 2.

One immediate way to decentralize the scheme proposed is to have each aircraft try to find an optimal route, such that it does not enter into the protected zone of all other aircraft, while respecting constraints that might be present in the situation. In this case, all aircraft will start with an initial centralized solution. Then on the next time step, each aircraft will have to assume that the already existing solution for all other aircraft is fixed and will not be changed in the near future. This though is very conservative and very frequently leads to infeasibility (in more than 80% of the cases the algorithm was not able to find a solution); as more information will be available, better solutions can be found at later times and as a result other aircraft may also decide to change their previously calculated solutions. In the approach described above though this is not taken into account.

Another approach is to assume that aircraft solve their trajectories sequentially in a round-robin fashion, i.e. after all aircraft have found a solution, they solve the problem in the next round - after some minutes - in the same order. This can be seen as an implicit priority rule, giving aircraft in the beginning of each resolution round right of way and more freedom to choose its trajectories. In this case the first aircraft will find a solution that minimizes only its cost function. Then, the first aircraft will broadcast the solution and this solution will be considered as a constraint by the second aircraft. This will proceed until one round of solutions is found and the next round starts again from the first aircraft.

One can reasonably argue that following such a decentralized policy may lead to aircraft with high priority (i.e. the first few aircraft to decide at each round) having a very big advantage over the remaining aircraft, who might have to do much larger maneuvers to avoid conflicting situations. There are mainly two ways to avoid such a situation; either the sequence that aircraft decide on each round could be random or a “fairness” factor can be entered in the cost function of the first aircraft such that they do not choose maneuvers that may result in such situations. We elaborate more on those two ways of dealing with this in Section V.

V. Simulation Setup and Results

A. Simulation Setting

In our simulation setting, we consider several aircraft in level flight, converging to the same point, denoted by (0,0) in Figure 3, that have to be deconflicted.

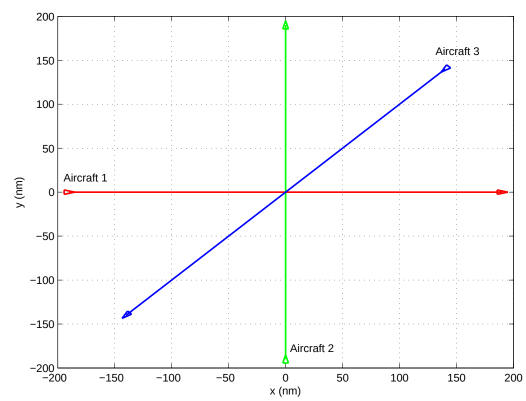

Fig. 3. Configuration for 3 aircraft encounter.

For all our simulations, we will assume that the aircraft are of type Airbus A321, flying at 33000ft, a typical cruising altitude for commercial flights. [20] suggests that the airspeed at this altitude can only vary in the region $[366, 540]$ knots, with a nominal value of 454 knots. We will enforce these constraints on our controller.

Regarding the uncertainty, we will only consider the wind speed as source of uncertainty. Wind speed (in general) can be modeled as a sum of two components: a nominal, deterministic component (available through meteorological forecasts) and a stochastic component, representing deviations from the nominal. Since the forecasts are available prior to the flights, flight plans are calculated taking them into account, so for simplicity reasons, we set the forecasted wind speed equal to zero. The structure of the forecast inaccuracies is modeled according to [22]. As wind is a source of uncertainty in our system, the algorithm will produce a different set of trajectories for the aircraft for each different wind realization in the system. For demonstration purposes, we only plot one case for each variant of the proposed scheme.

B. *Fixed priorities*

First, we consider the case where the aircraft decide on each round in the same order, as in round-robin algorithms. The cost function used is the distance of each aircraft from the final destination at the end of the mid term conflict resolution algorithm, i.e. after 21 minutes. The trajectories that the aircraft need to fly in this case are plotted in Figure 4. For comparison purposes, we also include in Figure 5 the trajectories that a centralized conflict resolution algorithm would suggest.

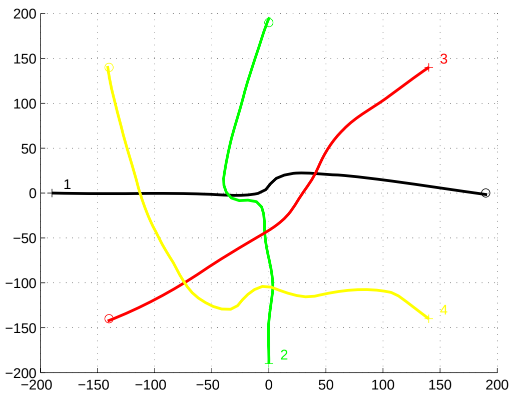

Fig. 4. Aircraft trajectories for round robin decentralized conflict resolution

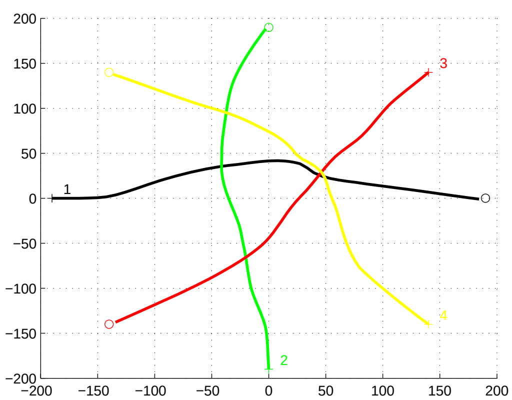

Fig. 5. Aircraft trajectories for a centralized conflict resolution

A very important fact is that decentralizing the proposed conflict resolution scheme does not affect the feasibility of the traffic situation, as all cases that could be solved by a centralized algorithm can also be solved in a decentralized fashion. The plots indicate that all aircraft reach their destinations, despite the presence of uncertainty and the "mismatch" between the model used by the Navigation Functions and MPC to resolve the conflicts with the real aircraft FMS.

Comparing now the two different solutions, one can observe the fact discussed in IV; in the decentralized scheme, some aircraft are clearly favored, being the first to plan their trajectories at each round. Despite the fact that three of them have a quite smooth trajectory to fly, the fourth one (the last to choose at each round) is forced to perform a very costly maneuver, having to avoid all the others.

C. *Random priorities*

Next, we randomly choose a different sequence of aircraft at each decision round, according to which they will calculate and broadcast their intended trajectories. It is important to note that in our setting this also retains the feasibility properties of the original centralized problem; as long as the centralized conflict resolution can find a solution for the situation, the decentralized will also produce one.

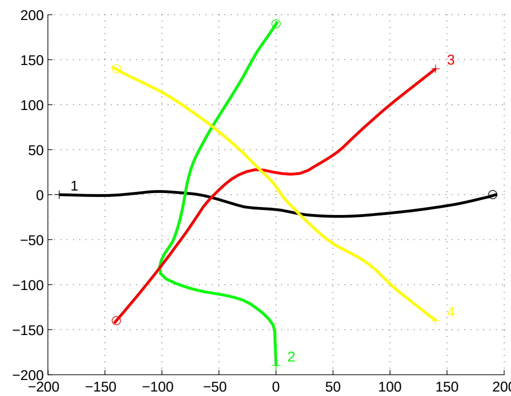

Fig. 6. Aircraft trajectories for random order decentralized conflict resolution

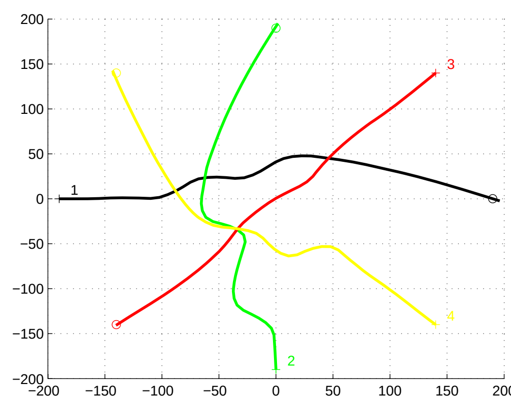

Fig. 7. Aircraft trajectories for random order decentralized conflict resolution

Figures 6 and 7 display the simulation results in this specific case for two different random sequences. In this case, an aircraft might start with a high priority, deciding early in the round, but then some other aircraft may gain priority, forcing it to cover a much bigger distance until the destination. Depending on the different random sequence that aircraft decide, this can lead to only a few aircraft being affected, or in some cases even all aircraft might have to follow a longer trajectory.

D. Cooperative cost

As both previous decentralized solutions did not yield very good solutions in terms of either individual (fixed order) or overall (random order) costs, we will consider the case where the Mid Term algorithm couples the decentralized systems also through the cost. The cost we will consider in this case is again only terminal, but we introduce a "fairness" factor α to take into account the effect that the solution of one aircraft has on the others. Then, the cost for each aircraft will take into account the costs incurring for the following aircraft in each decision round, multiplied by α. We only take into account the effect to the aircraft next in the decision round, as previous aircraft have already announced their solutions. It is easy to see that setting $\alpha = 0$, aircraft solve the problem as in the previous cases, while $\alpha = 1$ makes the first aircraft at each round to solve exactly the centralized problem.

Figures 8 and 9 show the trajectories the aircraft follow solving the problem both with a fixed as well as a random decision order at each decision round. One can observe in both cases that there is no aircraft clearly favored by such a scheme, regardless of the order that the decisions are made in each round. Trajectories though in a random order of decision scenario seem much smoother, very similar to a centralized solution.

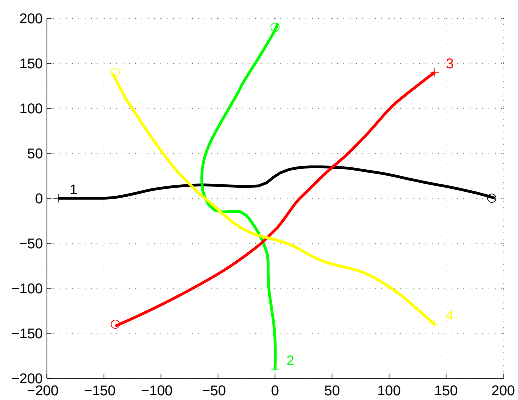

Fig. 8. Aircraft trajectories with $\alpha = 0.4$ for fixed order decentralized conflict resolution

VI. Conclusions and Future Works

A decentralized scheme for Mid and Short Term conflict resolution has been presented. The combination of model predictive control and navigation functions used provides conflict-free trajectories for the aircraft, while maximizing a performance function for the aircraft involved. The decentralized scheme proposed has the same feasibility properties as the corresponding centralized one and the simulation results demonstrate that this approach can serve as a potential solution for the conflict resolution problem in an autonomous aircraft scenario.

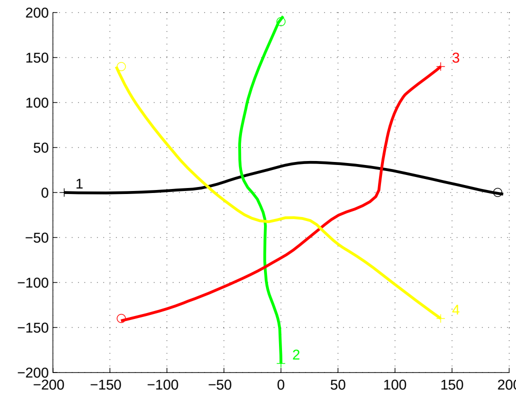

Fig. 9. Aircraft trajectories with $\alpha = 0.4$ for random order decentralized conflict resolution

Efforts for future work should primarily focus on validating the algorithms against some real traffic data. Other possible extension directions could include the consideration of cost functions reflecting human factors, e.g. produce maneuvers as simple as possible for the pilots to fly. Finally, an extension to 3D also has to be investigated, in order to solve the conflict resolution problem more efficiently.

VII. Acknowledgments

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