Cultural Algorithms for Air Traffic Conflict Resolution Problem

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Abstract—The air traffic conflict resolution represents a real time problem. Thus, it must be interesting to apply methods which their computing time is negligible. In this study, we use cultural algorithms to solve an artificial conflict involving five aircrafts. These algorithms present the advantage to evolve 10 times faster than genetic algorithms. We assume that the trajectories of all aircrafts evolve in the horizonal plane. Conflicts are resolved using an adapted horizontal maneuvers model to cultural algorithms. This study will be concerned with the realistic inexact conflict case, in which aircraft’s conflict points do not coincide either in time or in space.

I. INTRODUCTION

The conflict resolution problem can be described as follows: inside a sector, we want to give aircraft conflict free trajectories as close as possible to optimal trajectories. An aircraft is said to be conflict free when it is distant from the other aircraft of a separation norm at each point of its trajectory. This problem is quite simple as long as the number of the aircraft involved is small. However, the n-aircraft conflict resolution problem is highly combinatorial and cannot be optimally solved using classical mathematical optimisation techniques [1].

In this paper, we use Cultural Algorithms to solve an inexact conflict involving five aircrafts. These algorithms have been successfully applied to global optimization of constrained functions [2], [3], scheduling and real problems [4].

This paper is organised as follows: section 2 describes briefly different conflict resolution techniques which have been used. The problem formulation and the horizontal avoidance maneuver model are presented in section 3. In section 4, Cultural Algorithm system is described. Finally, in section 5 the result obtained for 5 aircrafts using Cultural Algorithms is presented.

II. CONFLICT RESOLUTION TECHNIQUES

Several techniques were developed to solve conflict detection and resolution problems. In this paper we focus on conflict resolution. The studies of conflict resolution may be categorized into three different cases according to the methods by which a solution is obtained. First, optimized conflict resolution produces a resolution maneuver which minimizes a given cost, a function of deviation from the original trajectory, flight time, fuel consumption, or energy [5], [6], [7],[8].

A second class of conflict resolution problems may be referred to as rule-based conflict resolution, in which a maneuver is resolved according to pre-described rules [9]. The rules may be simple to understand and easily applicable, but they do not properly account for unexpected events. For example, a conflict situation may fall into several predefined cases due to uncertainties in the aircraft’s position and heading. In these cases, the ambiguity in which rule to choose may lead to an unsafe resolution. The method may also require many rules to completely cover all possible conflicts.

A third class of conflict resolution techniques uses force field methods and assumes aircraft flies in the force field generated by a potential function, the forces induced by the potential function form a resolution maneuver[10], [11].

III. PROBLEM FORMULATION AND THE AVOIDANCE MANEUVER MODEL

A. Problem Formulation

Using only information about each aircraft’s position and heading, one can define a conflict to be the less than the standard separation which we suppose to be 5 nautical miles (1Nm=1852m) in the horizontal plane. We consider that each aircraft has a nominal trajectory, during a time window, which is a straight path of constant heading. In this study, we focus on the inexact conflict case, in which conflict points of aircrafts do not coincide in time and space. Note that for each aircraft ai involving in conflict both points Ai and Ei corresponding to the conflict space access point and to the conflict space exit point respectively are known (figure 1).

Fig. 1. Inexact Conflict description of 5 aircrafts

Ai represents the Conflict Space Access Position (CSAP), and Ei the Conflict Space Exit Position (CSEP) of aircraft ai. The conflict resolution problem can be considered as a
criteria optimisation problem constrained by the separation rules. In this paper, the global criterion is to minimize the trajectory deviation, produced by the avoidance maneuver, from the original flight path.

**B. Horizontal Avoidance Maneuver Model**

In this model the trajectories of all aircrafts are assumed to evolve in the horizontal plane and each aircraft's position at an instant $t$ is described by the coordinates $(x(t), y(t))$. In this case the avoidance maneuver, which we consider in this study, is a heading change.

When a conflict is detected, each aircraft involved in the conflict prepares to initiate a conflict resolution maneuver. The maneuver must to start before that each aircraft reaches its CSAP.

The resolution maneuver for each aircraft is set to be an isosceles triangular path $(P_1P_2P_3)$ composed of two straight segments of constant heading and of constant velocity (figure 2). For each aircraft $a_i$, the destination point $P_3$ is computed as the point at which the aircraft must rejoin its original trajectory after completing the conflict resolution maneuver.

Horizontal maneuver model can be described according to 3 parameters. The first parameter is resolution starting point $P_1(x(t_1), y(t_1))$ which varies from the initial position to CSAP; the second one is the final resolution point $P_2(x(t_2), y(t_2))$ which varies from CSAP to CSEP, and the heading angle $\alpha$.

The heading angle $\alpha$ is computed as:

$$\alpha = \arctan(\Delta y / \Delta x)$$  \hspace{1cm} (1)

Since the heading angle depends on $P1$'s and $P2$'s coordinates, the horizontal maneuver is then described only by $P1$'s and $P2$'s coordinates.

The distance square between two aircrafts $i$ and $j$ at an instant $t$ is:

$$D_{ij}(t) = (x_i(t) - x_j(t))^2 + (y_i(t) - y_j(t))^2$$ \hspace{1cm} (2)

The trajectory deviation from the original flight path for aircraft $ai$ is the triangle area $(P_1P_2P_3)$. It is computed as:

$$A = \frac{1}{2} \left[ (x_i(t_2) - x_i(t_1))^2 + (y_i(t_2) - y_i(t_1))^2 \right]$$ \hspace{1cm} (3)

IV. CULTURAL ALGORITHMS (CA)

**A. CA Principles**

Cultural algorithms (CAs) are a class of models derived from the cultural evolution process [12]. These algorithms support the basic mechanisms for cultural change [13]. Some social researchers have suggested that culture might be symbolically encoded and transmitted within and between populations [14], [13]. Using this idea, Reynolds developed a computational model in which cultural evolution is seen as an inheritance process that operates at two levels: the micro-evolutionary and the macro-evolutionary levels [12]. At the micro-evolutionary level, individuals are described in terms of “behavioral traits” (which could be socially acceptable or unacceptable). These behavioral traits are passed from generation to another one using several socially motivated operators.

At the macro-evolutionary level, individuals are able to generate “mappa” [14], or generalized descriptions of their experiences. Individual mappa can be merged and modified to form “group mappa” using a set of generic or problem specific operators. Both levels share a communication link. So, cultural algorithms can be described in terms of three basic components: the belief structure, the population structure and the communication channel.

A cultural algorithm models the evolution of the culture component of an evolutionary computational system over time. This culture component provides an explicit mechanism for acquisition, storage and integration of individual and group's problem solving experience and behavior that can be used as “beacons” to guide and enhance the evolutionary process. The basic pseudo code for Cultural Algorithms is given in figure 3 [15].

![Fig. 3. Pseudo code of Cultural Algorithms](image)

Some versions of cultural algorithms have been built, with different choices for the implementation of the micro and macro levels [16]. In this study, the population space is supported by an Evolutionary Programming system and the belief represents both situational knowledge, which provides the exact point where the best individual of each generation was found; and normative knowledge, which stores intervals for the decision variables of the problem that correspond to the regions where good results were found. The shell is called, CAEP, Cultural Algorithm with Evolutionary Programming.

**B. Implementation of CAEP to Conflict Resolution Problem**

1) Coding: The resolution maneuver model used in this paper, is described by two parameters: CRSP $P_1(x(t_1), y(t_1))$ and CRFP $P_2(x(t_2), y(t_2))$. So, each chromosome is built as a
A conflict resolution problem is given by a set of aircrafts entering in which conflict are going to occur in particular their initial position coordinates and their CSAP’s and CSEP's coordinates.

The initial population is generated randomly so that each parameter of candidate solution must be in some particular search space: Value of each P_i’s coordinate (X_{i1}, Y_{i1}) should be in a validate interval varying from the initial position to CSAP corresponding to aircraft a_i and value of each P_2’s coordinate (X_{i2}, Y_{i2}) is expected to be in a search interval varying from CSAP to CSEP corresponding to aircraft a_i.

3) Belief Space Initialization: The beliefs in CAEP can be described as an ordered pair \( \langle E, N \{p\} \rangle \), where E is a set of exemplars or best individuals, which constitute the situational knowledge contained in the belief space. The normative component, N, is the set of interval information for each of the p parameters. Each of the p problem parameter intervals is represented as a triplet \(<I_j, L_j, U_j>\), where I_j denotes the real closed interval of real numbers of parameter j, L_j represents the performance score of the lower bound for parameter j, and U_j represents the performance score for the upper bound for parameter j [15]. In this problem there are four parameters which corresponding to coordinates of P1 and P2.

4) Fitness Function: The information needed for the evaluation of the trajectories is stored in a fitness matrix M (figure 5). M_{ij} represents the lengthening trajectory A_i for aircraft a_i and M_{ij} measures conflict's gravity between two aircrafts a_i and a_j.

To ensure that a chromosome describing a situation without any conflict is better than a situation with a conflict, the fitness function is given by figure5.

\[
M = \begin{bmatrix}
A_1 & C_{12} & C_{13} & \cdots & C_{1p} \\
C_{12} & A_2 & C_{23} & \cdots & C_{2p} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
C_{p2} & C_{p3} & C_{p4} & \cdots & A_{p1}
\end{bmatrix}
\]

Fig. 5. Fitness function

If the matrix M is diagonal (no conflict) the chromosome fitness is computed as:

\[
F = \frac{1}{2} \left( 1 - \frac{1}{N} \sum_{i=1}^{N} M_{ii} \right) \quad F < \frac{1}{2} \tag{4.a}
\]

Otherwise:

\[
F = \frac{1}{2} \left( 1 + \sum_{i<j}^{N} M_{ij} \right) \quad F \geq \frac{1}{2}
\]  

5) Reproduction Operator: Each parameter of candidate solution undergoes to mutation operator which is influenced, through influence function, by belief space knowledge.

6) Influence Function: Some different instantiations of CAEP were produced by Chung using different influence functions [15]. In this paper, we implement the CAEP (N_i+ S_u) version which uses normative knowledge to determine the step size, and situational knowledge to determine the direction as shown in the following, for all components i=1,…, n and j=1,…,p where n represents the population size and p is the total number of parameter:

\[
x_{i,j}^{n+1} = \begin{cases} 
    x_{i,j}^{n} + \text{Size}(I_j).N_{i,j}(0,1) & \text{if } x_{i,j}^{n} < E_j \\
    x_{i,j}^{n} & \text{if } x_{i,j}^{n} > E_j \\
    x_{i,j}^{n} + \text{Size}(I_j).N_{i,j}(0,1) & \text{otherwise}
\end{cases}
\]  

(5)

Size(I_j) represents the size of the normative knowledge interval for the parameter j and N_{i,j}(0,1) is a realization of a Gaussian normal devation for the jth parameter of the ith individual.

7) Selection: In CAEP system, the selection operator consists in a strategy of type [17].

V. EXPERIMENTAL RESULTS

To verify the usefulness of cultural algorithm system in conflict resolution problem, in this section the result obtained for an inexact conflict (figure6) example involving five aircrafts is presented. The CAEP was implemented to solve the conflict shown below. The parameters of CAEP system are Population size and Number of generations. CAEP was performed using the values of parameters as follows:

\[
\text{Pop.size: 100 and } N_{\text{gen}}: 80.
\]

For this example of conflict, the coordinates of CSAP and CSEP for each aircraft are known and are given in table 1.
Figure 7 gives the two dimensional representation of the result obtained. It represents the trajectory of each aircraft after conflict resolution using cultural algorithm.

Note that the generated trajectories consist of 4 points. Both of them (denoted by •) correspond to the initial and final positions of each aircraft. The intermediate positions (denoted by ◊) consist in positions identified by cultural algorithm system. They correspond to the positions that aircraft must to reach in order to avoid the conflicts zone.

This figure shows that only four aircrafts (A2, A3, A4 and A5) have changed their heading to avoid the conflict. Table 2 depicts the coordinates of P1 and P2 of each aircraft, which correspond to Conflict Resolution Starting Position (CRSP) and Conflict Resolution Final Position (CRFP) respectively.

TABLE I
COORDINATES OF CSAP AND CSEP FOR EACH AIRCRAFT

<table>
<thead>
<tr>
<th>Aircraft</th>
<th>CSAP Coordinates</th>
<th>CSEP Coordinates</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>85 59</td>
<td>38 59</td>
</tr>
<tr>
<td>A2</td>
<td>82 82</td>
<td>57 50</td>
</tr>
<tr>
<td>A3</td>
<td>68 69</td>
<td>63 50</td>
</tr>
<tr>
<td>A4</td>
<td>50 68</td>
<td>72 51</td>
</tr>
<tr>
<td>A5</td>
<td>42 54</td>
<td>82 69</td>
</tr>
</tbody>
</table>

VI. CONCLUSION

In this paper, the conflict resolution problem was solved using cultural algorithms. These algorithms have been successfully applied to global optimization of constrained functions, scheduling and real problems.

The result obtained shows that CAEP system is very efficient for the studied problem. It has the great advantage which resides in the convergence speed and in the accuracy of the obtained solution. In fact, these algorithms exploit knowledge acquired from individual experiences about problem to solve, to influence and to direct the evolution of population.

REFERENCES