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Optimal Flight Trajectory Planning using Improved Evolutionary Method for UCAV Navigation in 3D Constrained Environments

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This article addresses a new approach to 3D path planning of UCAVs. To solve this NP-hard problem, imperialist competitive algorithm (ICA) was extended for path planning problem. This research is related to finding optimal trajectories before UCAV missions. Developed planner provides 3D optimal paths for UCAV flight with real DTM of Tehran environment. In UCAV mission, final computed paths should be smooth that made the path planning problems constrained. This planner can offer flyable 3D paths based on mission requirements. It's a comprehensive study for efficiency evaluation of EA planners, and then novel approach will be proposed and compared to ICA, GA, ABC and PSO algorithms. Then path planning task of UCAV is performed. Simulations show advantage of proposed methodology.

Keywords: *Unmanned combat aerial vehicle (UCAV); Flight Simulation; 3D Trajectory Planning; Imperialist Competitive Algorithm*

Introduction

There are many evolutionary planners for Unmanned Aerial Vehicles (UAVs) for optimal Navigation in UAV community. UCAV is from the family of unmanned aircrafts developed for performing reconnaissance missions. Long-range drones have an autopilot system for following predesigned way-points and continue motion based on planned mission, when they are out of the control of station's communication range. Operational drones need human control, but operator tasks are based on UCAV level of autonomy.

Many activities could be done to UCAV systems to reach to autonomous navigation. These steps maybe include mapping environment, onboard DTM generation, trajectory planning, and control systems. Path planning is a complex problem in the autonomous navigation. Its objective is to find an optimal constrained flight path in proper time to UAV be able to accomplish mission tasks. Choosing efficient algorithms for solving path planning problem is an influential step. Optimal path planning relies on optimization technics so it's usually solved offline.

Use of UCAVs, which can fly autonomously in aerospace environments, is necessary. Reliable safe navigation of UCAV in Complex missions has technical challenges and UCAV planning is an essential task. Aerospace applications of UCAVs require exact maneuvers and optimal decisions and robust path planning algorithms. Complex space around UCAV flight trajectory makes the problem NP-hard.

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Making UCAVs more autonomous for performing automated take-off and landing, target recognition and path planning, is a vital task in future aeronautics. Path planning is designing a chain of events such that an object can move in order to reposition from a beginning situation to a goal position. Path planning is vitally in search, surveillance, and tracking missions. Planning algorithm is a series of steps to compute plan by enough cognizance of environment and some constraints. The planned UCAV trajectory should avoid the obstructions and satisfy the UCAV's mission requirements. Any constraint is related to UCAV model and environment.

On the other hand, many evolutionary approaches based on natural concepts have been proposed. The novel Imperialist Competitive Algorithm (ICA) has shown improved performances in many optimization problems [1]. The original ICA is inspired by socio-political entity of imperialistic competition of human societies. The remarkable point is that assimilation operation of ICA in high-dimensional constrained problems often converges to a local optimum. This is the result of non-convexity of solution spaces. In this work, an improved ICA is presented, for this aim; the interactions of population are enhanced based on the power information of countries. Performance analysis with set of benchmark functions is evidence of the effectiveness of the ICAC.

Based on pervious works, path planning problem was presented to new hybrid techniques based on neural network [2], fuzzy logic [3], ACO [4], PSO [5, 6], GA [7] and the artificial potential field [8]. When we have large mission ranges in UCAV flight, trajectory planning will be a large scale constrained optimization process. General methods on 3D path planning could be applied to solve this NP-hard problem including graph search like A* [9] and D* and rapidly exploring Random Trees (RRT) [10] and other is potential fields, evolutionary techniques include PSO, GA, ACO and multi-objective evolutionary algorithms [11] . Every method has its own robustness in certain aspects that is related to the problem complexity.

By using Evolutionary based approaches for enhancing UCAV operational autonomy, we can combine flight dynamics, physical constraints, and mission objectives in the form of mathematical model. The concept of autonomous UAV flights, and levels of autonomy, is shown in **Fig.1**.

The structure of the paper is as follows. In Section 2 Imperialist Competitive Algorithm (ICA) is introduced and Improved ICA is proposed in section 3. This section is for results of ICAC and its compressions. Section 4 defines the UCAV-PP problem and section 5 holds the main results of UCAV simulation in 3D environment. Conclusion is the last section.

Imperialist competitive algorithm

Up to now, many evolutionary algorithms (EA) have been suggested for finding answers of global optimization problems. GA is a well-known bioinspired optimizing technique that evolves a population of nominee solutions, using particular operators inspired by natural selection. PSO and ABC are other computing methods which are based on the social behavior of birds and bees. Recently, ICA method is offered based on a socio-politically strategy.

ICA starts with initial populations. ICA also has some initial empires. Any individual is called a country. In every situation, we have sub groups, colonies and imperialists that form empires. Imperialistic competitions among empires are the core process of the ICA. During competition, weaker empires will be removed and powerful empires can get more control over their colonies. Imperialistic competitions will be stopped when there exists one empire with the same cost of its colonies, which is the optimal solution of the problem. First, initialize countries which are possible, and select fittest ones to be imperialist, then the others are colonies of these imperialists. Empires with more power have bigger Sphere of influence. Total cost of an empire is defined by Eq. (1)

$$T.C._n = Cost(imperialist_n) + \xi mean\{Cost(colonies\ of\ empire_n)\} \quad (1)$$

where TC_n is the total cost of nth empire and ε is a number between (0,1). Normalized power is in equation (2).

$$N.T.C._n = +\max_i\{T.C._i\} - T.C._n \quad (2)$$

where NTC_n shows the normalized total cost related to nth empire. Number of colonies of an empire is directly related to power. Initial number of jth empire's colonies will be as by Eq. (3)

$$NC_j = Round\left(\left|\frac{C_j}{\sum_{i=1}^{N_{imp}} C_i}\right| .(N - N_{imp})\right) \quad (3)$$

Possession probability of each empire is computed by Eq. (4):

$$P_j = \left| \frac{NTC_j}{\sum_{i=1}^{N_{imp}} NTC_i} \right| \quad (4)$$

ICA breaks initial population into sub-populations, and then searches for the optimal answer by repeating two operations: *competition* and *assimilation*.

The feature that makes ICA different from the other EAs is that ICA allows all empires to have interaction with others. The competition operation simply transfers colonies between the weakest empire and another empire, then ICA is similar to Island Model GA. Overall, ICA is an integration of Island Model and PSO. The assimilation operation moves each *colony* in a group toward the best solution (called *imperialist*) in the same group [1].
Assimilation operator of ICA is modeled by moving all the colonies toward the imperialist. This movement is shown in **Fig.2** that a colony moves to the direction of the imperialist by a random deviation that is between 0 and β×d (Eq. (5))

$$\{x\}_{new} = \{x\}_{old} + \mathrm{U}(0, \beta \times \mathrm{d}) \times \{\mathrm{V}_1\} \quad (5)$$

In order to increase searching ability, see Eq. (6).

$$\theta = \mathrm{U}(-\gamma, +\gamma) \quad (6)$$

Where γ adjusts the deviation from the first direction. Previous researches on ICA mostly replaced the assimilation operation with powerful meta-heuristics, but we focused on enhancing the ICA interactions. Imperialistic competitions between these empires will be the entity of the ICA. During these competitions, weak empires breakdown and forceful ones take ownership of their colonies. Imperialistic competitions direct the search procedure in the direction of the optimum solutions (see **Fig. 3**). The flowchart of original imperialist competitive algorithm is shown in **Fig. 4**.

ICAC: Improved ICA

ICA is weak to perform global search perfectly in the big problem spaces. We should improve the assimilation process in ICA. Two important features of the swarm-based methods are exploration and exploitation. The exploration is related to search of space, where the exploitation is hunting the optimum [1]. The exploration is a significant theme in swarm-based heuristic algorithms. Over time, exploring will be reduced and exploitation ability fades in, hence the algorithm adjusts itself in the semi-optimal points. There should be a balance between exploration and exploitation, to keep ICA safe from trapping in local optima.
In our work, ICA will be enhanced, using colonies powers information (see **Fig. 5**). For this aim, kind of force between countries is defined and the movement of colonies to the imperialists is adjusted during the searching solution space. In ICA, population movement has a random of deviation. In order to enhance this operation, we defined a pervasive absorption charge among all solutions that can be explained as international relation.
We have a swarm with N countries. The position of the i_{th} country (X_i) is defined by Eq. (7).

$$X_i = (country_i, ..., country_N, imperialist_d) \quad (7)$$

Where $country_i$ is the position of ith country and $imperialist_d$ is the position of d_{th} imperialist, respectively. At a specific time't', we define the absorption acting on country 'i' from country 'j' as Eq. (8).

$$E_{ij}^d(t) = \zeta(t_0) \frac{C_{pi}(t) \times C_{aj}(t) \times (country_j(t) - country_i(t))}{(D_{ij}(t) + \varepsilon)^3 \times (C_{pi}(t) + C_{aj}(t))} \times \left(\frac{t_0}{t - t_0}\right)^{\alpha} \quad (8)$$

Where C_{aj} is the power of country j, C_{pi} is the power related to country i, $\xi(t_0)$ is initial absorption constant, ε is a small constant, and $D_{ij}(t)$ is distance between two countries i and j, calculated according to Eq. (9).

$$D_{ij}(t) = \left\| X_i(t), X_j(t) \right\|_2 \quad (9)$$

Where $rand_j$ is in [0, 1]. Hence, the acceleration of the country i at time t, and in direction d_{th}, is given by Eq. (11).

$$a_i^d(t) = \frac{E_i^d(t)}{C_{ii}(t)} \quad (11)$$

Where C_{ii} is the Power of i_{th} country, the next velocity of country is considered as follows. Therefore, position and its velocity are calculated based on Eq. (12) and Eq. (13).

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \quad (12)$$

$$country_i(t+1) = country_i(t) + v_i^d(t+1) \quad (13)$$

Where $rand_i$ is in [0, 1]. This random number is for randomization of the search.

ICAC Comparative studies

For efficiency evaluation of the proposed algorithm, we applied it to some functions to check the ICAC performance. Then comparative study is done with ICA, PSO, and GA. The mathematical formula of benchmark functions is presented in **Table 1**.

Table 1: Benchmark functions

Mathematical representation	Range
$F_1(x,y)=(x^2+y^2)^{0.25}\times\sin\{30[(x+0.5)^2+y^2]^{0.1}\}+\lvert x\rvert+\lvert y\rvert$	[10,10]
$F_2(x,y)=J_0(x^2+y^2)+0.1\lvert 1-x\rvert+0.1\lvert 1-y\rvert$	[-10,10]
$F_3(X)=\Sigma_{i=1}^{n}(\lvert x_i\rvert-10\cos(\sqrt{\lvert 10x_i\rvert}))$	[-10,10]
$F_4(x,y)=x\sin(4x)+1.1y\sin(2y)$	[-10,10]

Parameters setting for implemented algorithms are illustrated in **Table 2**.

Table 2. parameter values of implemented algorithms

Mathematical representation	Range
$F_1(x,y)=(x^2+y^2)^{0.25}\times\sin\{30[(x+0.5)^2+y^2]^{0.1}\}+\lvert x\rvert+\lvert y\rvert$	[-10,10]
$F_2(x,y)=J_0(x^2+y^2)+0.1\lvert 1-x\rvert+0.1\lvert 1-y\rvert$	[-10,10]
$F_3(X)=\Sigma_{i=1}^{n}(\lvert x_i\rvert-10\cos(\sqrt{\lvert 10x_i\rvert}))$	[-10,10]
$F_4(x,y)=x\sin(4x)+1.1y\sin(2y)$	[-10,10]

For our simulation, ICAC algorithm is compared with ICA, PSO, ABC and GA algorithms. In **Fig. 6**, that is results for F_1, it's seen that convergence speed to the optima and the quality of solution has enhanced. We have similar computational results for rest of the functions (see **Table 3**)

		ICA	ICAC	PSO	GA	ABC
F_1	Average best-so-far	2.4×10^{-3}	2×10^{-3}	3.2×10^{-3}	0.252	1.8×10^{-3}
	Median best-so-fir	1.9×10^{-3}	1.2×10^{-3}	2.8×10^{-3}	0.231	1.5×10^{-3}
	Average mean fitness	3×10^{-3}	2.6×10^{-3}	3.9×10^{-3}	0.326	3.1×10^{-3}
F_2	Average best-so-far	-31.3×10^{-2}	-33.6×10^{-2}	-30.6×10^{-2}	-28.0×10^{-2}	-31.5×10^{-2}
	Median best-so-far	-31.6×10^{-2}	-32.8×10^{-2}	-31.2×10^{-2}	-29×10^{-2}	-30.2×10^{-2}
	Average mean fitness	-31×10^{-2}	-34.2×10^{-2}	-29.7×10^{-2}	-26.8×10^{-2}	-31.5×10^{-2}
F_3	Average best-so-far	-19.45	-19.51	-17.5	-16.10	-17.0
	Median best-so-far	-19.67	-19.73	-17.83	-16.23	-17.58
	Average mean fitness	-19.33	-19.42	-19.39	-15.86	-18.5
F_4	Average best-so-far	-18.19	-18.13	-13.70	-17.82	-16.70
	Median best-so-far	-18.29	-18.23	-13.82	-17.92	-16.95
	Average mean fitness	-18.13	-18.7	-13.63	-17.76	-16.50

Mathematical formulation of UCAV path planning problem

Unmanned air systems should be capable to perform surveillance missions with considering a variety of objectives [12].

There are several considerations for an efficient path planner including: optimality, completeness and complexity, which are related to vehicle motion dynamics. The extra dimensions of UCAV-PP problem increase computational complexity for the evolutionary planner, because the design space is extended. Also Planners should be able to solve constrained optimization problems.

Path presentation using Bezier curves

We have exact configuration of UCAV paths. In many of related works, Bezier curves have used for trajectory generations for computing smooth and feasible routs for UCAVs. Bezier curves are defined by some control points P_0 to P_n, where n is called Bezier order .The Bezier formula is as Eq. (14):

$$\begin{aligned}\mathbf{B}(t) &= \sum_{i=0}^{n}\binom{n}{i}(1-t)^{n-i}t^i\mathbf{P}_i \\ &= (1-t)^n\mathbf{P}_0+\binom{n}{1}(1-t)^{n-1}t\mathbf{P}_1+\cdots \\ &\quad \cdots+\binom{n}{n-1}(1-t)t^{n-1}\mathbf{P}_{n-1}+t^n\mathbf{P}_n, \quad t\in[0,1]\end{aligned} \tag{14}$$

Where $\binom{n}{i}$ is the binomial coefficient that is calculated based on Eq. (15).

$$\binom{n}{i}=\frac{n!}{i!(n-i)!} \tag{15}$$

Polynomial form of the implemented Bezier curve is as Eq. (16).

$$\begin{aligned}\mathbf{B}(t) &= \sum_{j=0}^{n}t^j\mathbf{C}_j \\ \mathbf{C}_j &= \frac{n!}{(n-j)!}\sum_{i=0}^{j}\frac{(-1)^{i+j}\mathbf{P}_i}{i!(j-i)!}=\prod_{m=0}^{j-1}(n-m)\sum_{i=0}^{j}\frac{(-1)^{i+j}\mathbf{P}_i}{i!(j-i)!}.\end{aligned} \tag{16}$$

Fitness function Definition

The evaluation function measures the cost of the path. In our system simulations, fitness function has three independent terms to minimize the distance (CF); producing smooth trajectory, avoiding hard turns, and keeps UCAV apart from DTM (T). We supposed a linear form of these three terms. The general formulations of the problem are in Eq. (18).

$$G_1=\sum_{i=1}^{dn-1}\sum_{j=1}^{3}\left[(X_{j,i+1}-X_{j,i})^2\right]^{1/2} \tag{17}$$

These objectives were considered in f: length path (G1), flight altitude (G2), and terrain collision avoidance (G3). See Eq. (18).

$$\min f=\sum_{i=1}^{3}a_iG_i \tag{18}$$

UCAV Flight Constraints

In this problem, we have constraints that must be satisfied according to the restrictions of the UCAV and environment. According to Eq. (19) Optimal path of the UCAV must satisfy following constraints: Turning radius (φ_S), Map limits, maximum flight height (H^L), safe flight (S_d) maximum climbing and diving slope (φ_ϵ), Flight prohibited zones (NFZs), Fuel limit (C_F).

$$x_3^{UAV}-x_3^{DTM}<S_d,\ \ \varphi_{i,i+1}<\varphi_S,\ \ x_3^{Path}<\mathrm{H}^L \tag{19}$$

Where $\varphi_{i,i+1}$ is the angle between the extension of the line connecting Bezier points i and i+1, φ_S is the safe

turning angle for controlling lateral and vertical accelerations. To avoid UCAV from terrain collision, S_d is a safe distance determined by operator, x_{3Path} is the path curve coordinate, and x_{3DTM} is the terrain point coordinate. A_L is for limiting the peak height of UCAV. This term, C_F, is computed based on the length of the UCAV path. C_F, in Eq. (20) is explained as the additional distance passed if the UCAV takes the alternate path compared to the original route.

$$C_F=10\left(\frac{L}{L_0}\right)=\sum_{i=1}^{n-1}\left|p(u_{i+1})-p(u_i)\right| \qquad (20)$$

Where L0 is computed by summing of all line segments composed of the primary trajectory. L, is sum of path n's line segments $p(u_i)$. p_n is defined as distance between segment i and on path n and the corresponding segment i on the best solution. The objective values and constraints will be combined at the evaluation of the algorithms to acquire the fitness of each solution.

UCAV Flight Simulations and experiments

Simulations of proposed planner performed in the same computer and all the tests were under the same conditions. For performance analysis of the ICAC planner, it was tested with different parameters. Each experiment was in loop to 50 times for reaching to reliable result. We used Matlab environment on a PC with 2.33 GHz Intel Core 2 Duo and 4 GB of RAM memory. It is assumed that the mission space has 100km×100 km size, in a local reference system, UCAV Launching station is (-40 ,40) and the UCAV Landing point is Located on(40,-40,-2). Flight altitude of UCAV defined within the range (-40, 40), and (θ_s,S_d) was (55°,0.04). Comparative study was done with other powerful methods, i.e. ICA, GA, PSO and ABC.At our system tests, final UCAV optimal routs are on real DTM (see **Fig. 7**). Also **Fig. 8** shows the Summary of experimental results.

In Fig. 8, cost value of each path planning simulation is illustrated. The average results for 80 correct runs have compared. During iterations of near 12 steps, cost values decreased rapidly. It's obvious that based on the plots, ICAC planner can find optimal 3D trajectories very quickly. As shown in **Fig. 9**, proposed planner produces a smooth 3D path for sending uplink to UCAV autopilot.

Conclusions

In this article, a new approach is proposed for planning of 3D trajectories based on enhanced ICA. This work can enhance the UCAV's offline optimal planning, navigation, and guidance in realistic missions. The proposed method based on charged imperialist competitive algorithm represents the trajectories using Bezier curve which can ascertain the generated path is smooth and flyable. This study is part of system simulations on our pervious work. Our method provides valid 3D trajectories with low computational complexity; while control station can obtain sub-optimal routes based on mission requirements. The simulation results show that this novel algorithm not only can produce path with more robustness, but also has higher convergence speed than GA, PSO, ABC and ICA.

Figures and Drawings

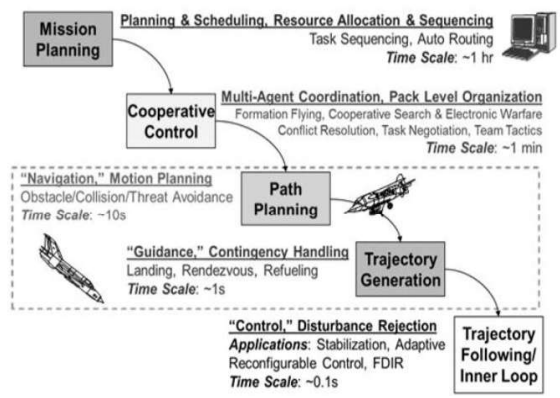

Fig 1: Autonomy Hierarchy based on [13]

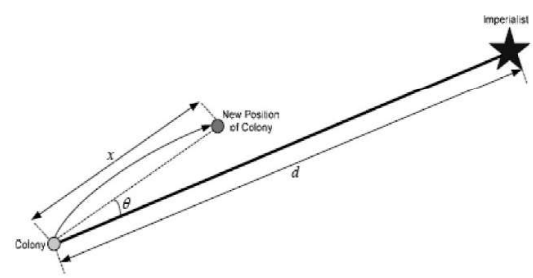

Fig 2: Moving colonies toward imperialist(*assimilation*)
$\theta \sim U(-\gamma, \gamma)$, $x \sim U(0 , \beta \times d)$

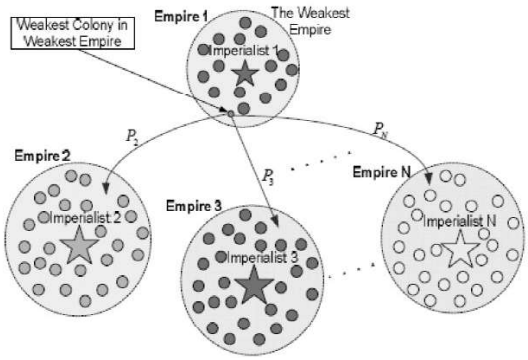

Fig 3: Imperialistic competition process

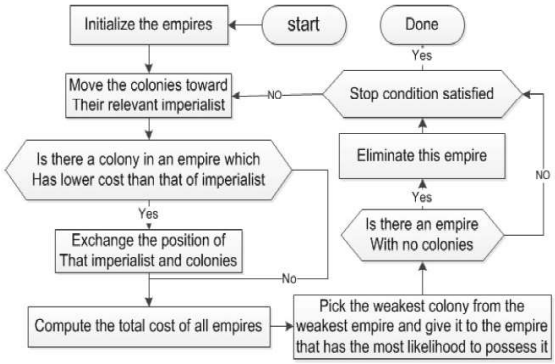

Fig 4: The original ICA

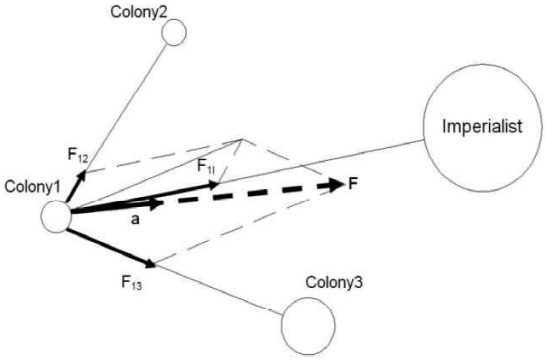

Fig 5: proposed assimilation process

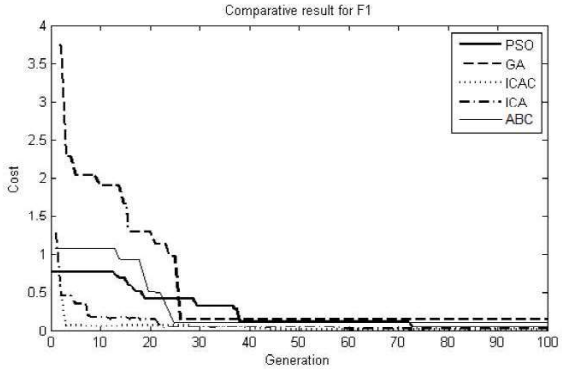

Fig 6 : Comparison of performance of ICAC, PSO , ABC and GA for minimization of F1

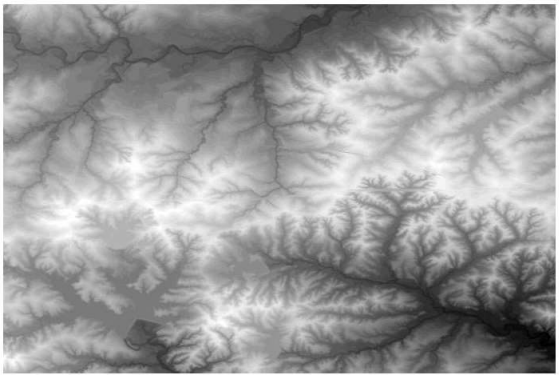

Fig 7: Digital Terrain Model (DTM) of North Tehran as a real dataset for UCAV flight environment.

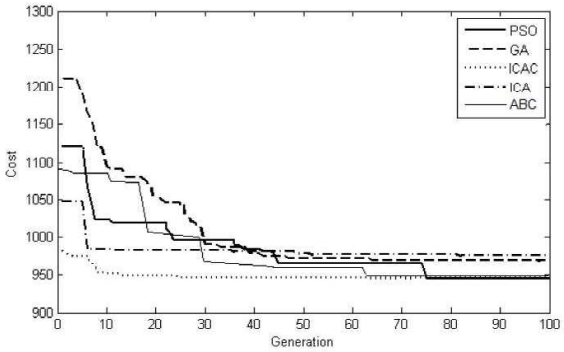

Fig 8: Plot of cost values of paths, related to PSO,GA,ICAC,ICA,ABC

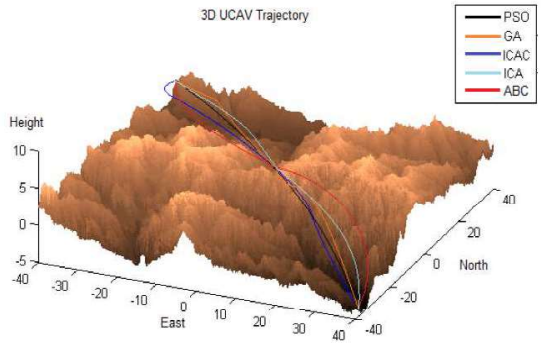

Fig 9: Illustration of the final generated optimal UCAV paths. ICAC planner produced the best solution. (left: NW-SE ,right: SE-NW)

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