PATH PLANNING OF AN AUTONOMOUS MOBILE MULTI-SENSOR PLATFORM IN A 3D ENVIRONMENT USING NEWTONIAN IMPERIALIST COMPETITIVE OPTIMIZATION METHOD

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ABSTRACT:

This paper addresses an innovative evolutionary computation approach to 3D path planning of autonomous UAVs in real environment. To solve this Np-hard problem, Newtonian imperialist competitive algorithm (NICA) was developed and extended for path planning problem. This paper is related to optimal trajectory-designing before UAV missions. NICA planner provides 3D optimal paths for UAV planning in real topography of north Tehran environment. To simulate UAV path planning, a real DTM is used to algorithm. For real-world applications, final generated paths should be smooth and also physical flyable that made the path planning problems complex and more constrained. The planner progressively presents a smooth 3D path from first position to mission target location. The objective function contains distinctive measures of the problem. Our main goal is minimization of the total mission time. For evaluating of NICA efficiency, it is compared with other three well-known methods, i.e. ICA, GA, and PSO. Then path planning of UAV will done. Finally simulations proved the high capabilities of proposed methodology.

1. INTRODUCTION

UAVs can be used in geomatics applications, such as photogrammetry, monitoring and search-and-rescue tasks (Schøler et al, 2012). The use of UAVs, which can fly autonomously in 3D environments, is becoming a solution for kind of problems. Reliable navigation of an autonomous UAV in Complex missions has technical challenges and UAV planning is a essential task. Civilian applications of UAVs, such as search and rescue and aerial surveillance require precise maneuvers and optimal navigation and efficient path planning algorithms. Complex space for trajectory planning in mentioned conditions makes the problem NP-hard to be solved. Autonomous UAV would be conscious of other UAVs flying in environment surrounded by obstructions. Researchers have resolved this problem by path planning approaches.

In mobile robotics, many researchers tried to make UAVs more autonomous including automated takeoff and landing, target recognition and path planning. Path planning is illustrated as 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 necessary in search, surveillance, and tracking missions. A path planning algorithm is a series of steps to compute path plan by enough cognizance of environment and some constraints. The planned UAV trajectory should avoid the obstructions and satisfy the UAV's mission requirements. Any constraint is based on a model of the UAV and environment.

In last decade, many optimization methods based on meta-heuristics approaches have been proposed. The novel Imperialist Competitive Algorithm (ICA), which has been recently designed (Gargari, 2007), has shown improved performances in many optimization problems. The ICA

inspired by socio-political entity of imperialistic competition of human societies in the real world. 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 feasible solution space. In this paper, a modified version of ICA is used. In our work, the interactions of empires in ICA are enhanced based on the Newton's law of universal gravitation. Performance analysis employing a set of well-known benchmark functions proofs the effectiveness and power of the NICA.

Most related works, focused on 2D unconstrained problems (Office of the Secretary of Defense, 2005; Dogan, 2003; Dong et al., 2010; Kim et al., 2008).Yang et al. (2010) used a rapidly-exploring random tree (RRT) to solve problem in an cluttered environment. Chasparis et al. (2005) used linear programming for solving the path planning of UAV coordinations in an adversarial environment. Li et al. (2009) suggested an improved A* algorithm to solve the UAV-PP problem. Zhang et al. (2006) used a algorithm based on Voronoi and B-spline. Genetic algorithm (GA) (Ruan et al. 2008), ant colony optimization (ACO) (Wang et al. 2008), and particle swarm optimization (PSO) (Foo et al. 2009) were applied for solving UAV-PP problem.

The work wrote as follows. In Section 2 Imperialist Competitive Algorithm is introduced and then Newtonian Imperialistic Competitive Algorithm is proposed in section 3. This section is for results of NICA and its compressions. Section 4 defines the UAV-PP problem and section 5 holds the main results of UAV simulation in 3D environment. Conclusion is in last section.

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2. IMPERIALIST COMPETITIVE ALGORITHM

The global optimization problem is suitable in every field of geomatics. Up until now, many evolutionary algorithms (EA) have been recommended for finding the answers of global optimization problem. Recently, ICA method is offered based on a socio-politically strategy.

ICA breaks initial population into various sub-populations, and then searches for the optimal answer using two operations of *assimilation* and *competition*. The assimilation operation moves each *colony* in a group toward the best solution (called *imperialist*) in the same group (Gargari, 2007)

This algorithm starts with random initial solutions. Each unique agent of an empire is called a *country*, and the colonies and imperialist collectively form *empires*. Imperialistic competitions between these empires will be the entity of the ICA. During this competition, weak empires breakdown and forceful ones take ownership of their colonies. Imperialistic competitions direct the search procedure in the direction of the optimum solutions.

3. NEWTONIAN IMPERIALIST COMPETITIVE ALGORITHM

We want to improve the assimilation operator and movement of countries in ICA. Test done using a set of famous functions. Efficiency of our proposed algorithm proved. Two common Properties of the swarm-based methods are exploration and exploitation. The exploration is ability to search the space, where the exploitation is the ability to hunt the optimum (Gargari, 2007). The exploration is a significant theme in swarm-based heuristic algorithms.

In first iterations, to escape trapping in local optimum, the algorithm must use the exploration to explore the space and find new points. Over time, exploration will be reduced and exploitation fades in, therefore the algorithm adjusts itself in the semi-optimal points. To have a proper search, an important way is a suitable balance between exploration and exploitation. All the swarm-based algorithms use exploration and exploitation, but they use various methods and operators. In other words, all heuristic algorithms have a unique concept.

ICA is unable to execute global search properly in the big problem spaces. During the search process, ICA may trap into local optimum. This causes the bad convergence.

In this paper, a new method is proposed which balances the exploration and exploitation of NICA using colonies powers information.

In the absorption policy step of ICA algorithm, the colonies move in the direction of imperialists with random angles. The colonies motion has a monotonic behavior because of the constant parameter; indeed, the swarm movement could not be changed with search process. Therefore, if the algorithm traps in the local optimum, it cannot leave the trap and move towards the global optimum. To balance between the explorative and exploitative search, gravity between countries is defined and the movement of colonies to the imperialists is adjusted during the search procedure.

Newton's gravitational force is based on acting from distance. This means gravity acts between separated particles on time. In the Newton law, each mass attracts other particles with a force. In ICA, population move to the imperialist by a random deviation. In order to enhance this operator, we offer a Newtonian absorption policy among all solutions. The idea is that neighboring countries have a tendency to improve their

political relations. When countries have consensus, weaker countries are more impressionable, based on their proportion with other nations. The countries have less political power, conjunct with their neighbor determinant countries. Political decisions for weaker countries are based on international Political agreements of their Allied nations.

In order to model international relationships for ICA, a pervasive absorption charge is proposed among all countries. The consequent force applied on each colony by its imperialist and all other local colonies of that imperialist would be calculated by considering the power of countries.

In the NICA, all the countries attract to others based on their powers, by the gravitational force, and this force causes a global movement of all nations towards the countries with more power. Hence, countries work together using international communication, modeled by gravitational force. The powerful countries (good solutions) move slower than weaker ones. This promises the exploitation of the algorithm. The absorption charge is defined as follow (eq.1).

$$E_{ij} = \zeta \frac{C_{aj} \times C_{pi}}{D^2}, \qquad (1)$$

We have a swarm with N countries. The position of the ith country (X_i) is defined by equation (2).

$$X_i = (country_i, ..., country_N, imperialist_d) \qquad (2)$$

Where *country$_i$* is the position of ith country and *imperialist$_d$* is the position of dth imperialist, respectively. At a specific time 't', we define the absorption acting on country 'i' from country 'j' as equation (3).

$$E_{ij}^d(t) = \zeta(t) \frac{C_{pi}(t) \times C_{aj}(t)}{D_{ij}(t) + \varepsilon} (country_j(t) - country_i(t)) \qquad (3)$$

where C_{aj} is the power of country j, C_{pi} is the power related to country i, $\xi(t)$ is absorption constant, ε is a small constant, and $D_{ij}(t)$ is 2D distance between two countries i and j, calculated according to equation (4)

$$D_{ij}(t) = \left\| X_i(t), X_j(t) \right\|_2 \qquad (4)$$

To give a stochastic characteristic to NICA algorithm, total force is randomly weighted sum of the forces of others (equation 5).

$$E_i^d(t) = \sum_{j=1, j \neq i}^N rand_j E_{ij}^d(t) \qquad (5)$$

Where $rand_j$ is between [0, 1]. Hence, the acceleration of the country i at time t, and in direction d^{th}, is:

$$a_i^d(t) = \frac{E_i^d(t)}{C_{ii}(t)} \qquad (6)$$

Where C_{ii} is the Power of ith country, the next velocity of country is considered as follows. Therefore, position and its velocity is calculated based on equations (7) and (8).

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \qquad (7)$$

$$country_i(t+1) = country_i(t) + v_i^d(t+1) \qquad (8)$$

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

When countries developed, colonization policy will be weaker. To attenuate political dependence over the time, a gravitational constant is initialized at first generation of algorithm and will be monotony reduced with time to control the search accuracy. see equation (9)

$$\zeta(t) = \zeta(t_0) \times (\frac{t_0}{t})^{\alpha}, \quad \alpha < 1 \qquad (9)$$

Gravitational and inertia powers are simply calculated by the fitness evaluation. A powerful country means a more efficient nation. This means that better countries have more international relationships and grow more slowly. The gravitational and inertia powers are equal; the powers are calculated by their fitness. We update the Newtonian and inertial powers by the equations (11) and (12).

$$C_{ai} = C_{pi} = C_{ii} = C_i, \quad i = 1, 2, ..., N \qquad (10)$$

$$c_i(t) = \frac{fit_i(t) - weak(t)}{strong(t) - weak(t)} \qquad (11)$$

$$C_i(t) = \frac{c_i(t)}{\sum_{j=1}^{N} c_j(t)} \qquad (12)$$

Where *fit$_i$(t)* shows the fitness of the country *i* at time *t*, and *weak(t)* and *strong(t)* are : (for a minimization problem)

$$strong(t) = \min fit_j(t), \quad j \in \{1, ..., N\} \qquad (13)$$

$$weak(t) = \max fit_j(t), \quad j \in \{1, ..., N\} \qquad (14)$$

To avoid local optimum, the algorithm must use the exploration at beginning. The principle of NICA is shown in Figure 1.
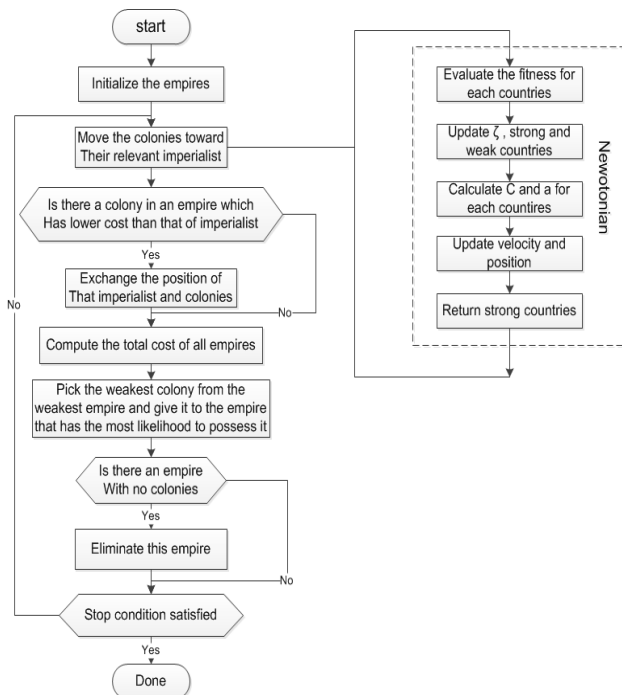

Figure 1. General principle of NICA

3.1 Analysis and consideration of empirical results

In this paper, the proposed algorithm, called Newtonian Imperialist Competitive Algorithm (NICA), applied to some famous functions to prove the NICA algorithm performance and compared with ICA and PSO and GA algorithms. The mathematical form and graphical drawings of benchmark functions are represented in Table1 and Figure 2, respectively.

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

Table 1.Benchmark functions

Algorithmic parameters for all algorithms are illustrated in Table 2.

ICA		NICA		PSO		GA	
Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
N_{pop}	100	$N_{pop,}$	100	#swarm	100	Population	100
N_{imp}	6	N_{imp}	6	$C_1 = C_2$	1	Crossover	0.7
β	2	ξ	0.2	ω_{min}	0.1	Mutation rate	0.2
ξ	0.2	ζ	10	ω_{max}	0.2		
γ	0.99						

Table 2. parameter values of implemented algorithms

We made simulations for evaluating the speed of convergence and the quality of NICA solution, in comparison to ICA, PSO and GA algorithms. All the benchmarks tested by 10 dimensions separately. The average of optimums for 20 runs obtained.
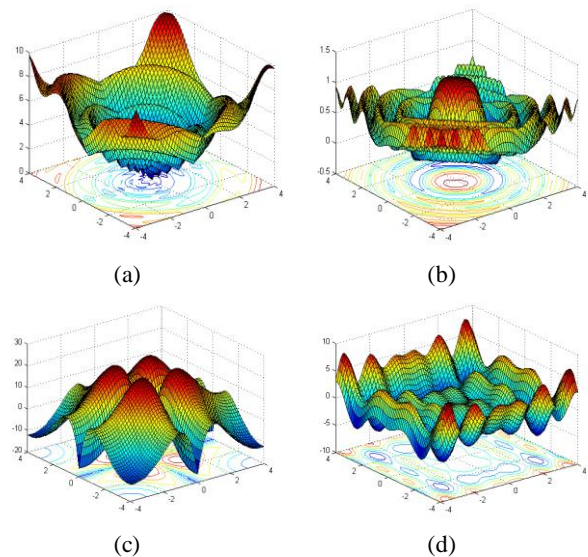

(a) (b)

(c) (d)

Figure 2. Visualization of benchmark functions
(a) F$_1$, (b) F$_2$, (c) F$_3$, and (d) F$_4$

In Figure 3, belongs to F$_1$, it is seen that the convergence speed to the optimal point and the quality of global optima solution has improved in compare with three other algorithms. In the plot of the F$_1$, at the first 5 iterations, NICA algorithm has better convergence speed than the GA, ICA and PSO and then NICA won the competition.
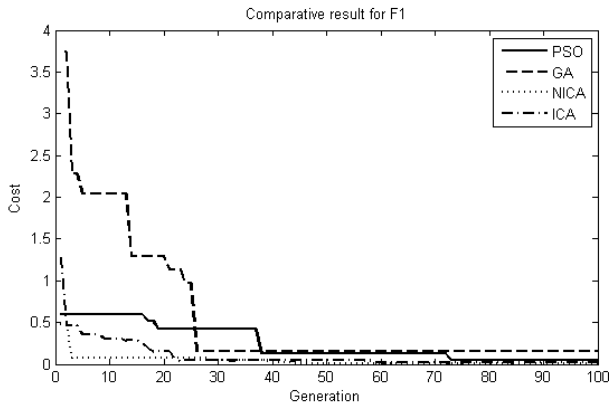
Figure 3. Comparison of performance of NICA, PSO and GA for minimization of F_1

The good convergence rate of NICA could be deduced from Figure 4; NICA wants to find the global optimum faster than others and hence has a higher convergence rate.
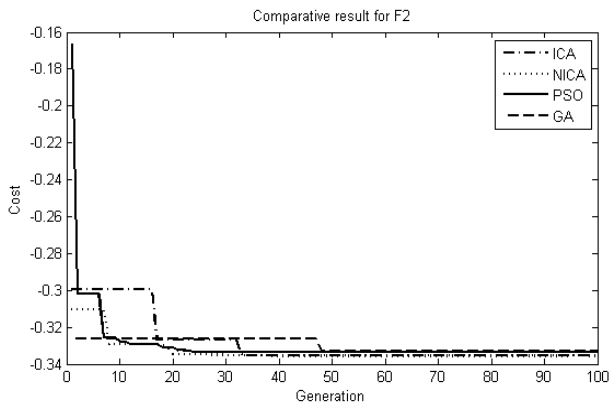

Figure 4. The cost of F2 function

NICA has a good performance for F2 function and can escape from the local peaks and reach to global optimum.

In Figure 5, NICA has remarkable results both in optima solution quality and in convergence speed rather than the ICA, PSO and GA algorithms.it is seen that the NICA exploration is less than exploitation power for this function.
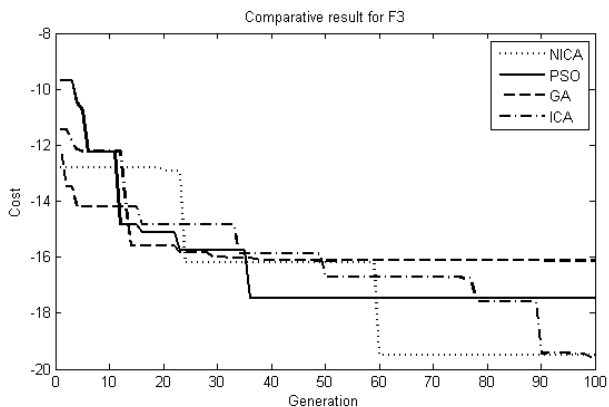

Figure 5. The cost of F3 function.

In Figure 6, F4 function, NICA has better performance in solution quality and in convergence speed rather than PSO and GA algorithms, but NICA curve is near to ICA. At this test in 22th iterations, PSO trapped in local optimum.
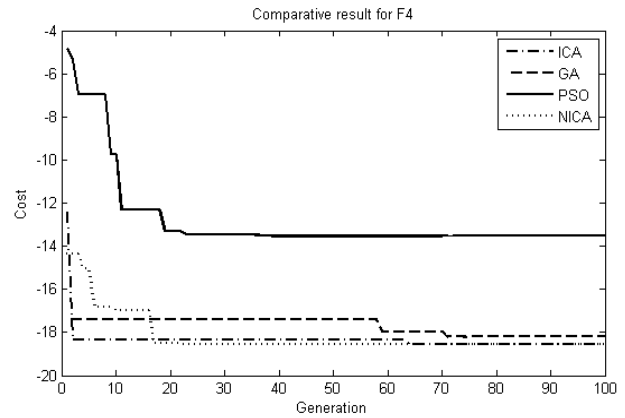

Figure 6. The cost of F4 function.

		ICA	NICA	PSO	GA
F_1	Average best-so-far	2.4×10^{-3}	2×10^{-3}	3.2×10^{-3}	0.252
	Median best-so-far	1.9×10^{-3}	1.2×10^{-3}	2.8×10^{-3}	0.231
	Average mean fitness	3×10^{-3}	2.6×10^{-3}	3.9×10^{-3}	0.326
F_2	Average best-so-far	-31.3×10^{-2}	-33.6×10^{-2}	-30.6×10^{-2}	-28.0×10^{-2}
	Median best-so-far	-31.6×10^{-2}	-32.8×10^{-2}	-31.2×10^{-2}	-29×10^{-2}
	Average mean fitness	-31×10^{-2}	-34.2×10^{-2}	-29.7×10^{-2}	-26.8×10^{-2}
F_3	Average best-so-far	-19.45	-19.51	-17.5	-16.10
	Median best-so-far	-19.67	-19.73	-17.83	-16.23
	Average mean fitness	-19.33	-19.42	-17.39	-15.86
F_4	Average best-so-far	-18.19	-18.13	-13.70	-17.82
	Median best-so-far	-18.29	-18.23	-13.82	-17.92
	Average mean fitness	-18.13	-18.7	-13.63	-17.76

Table 3. Minimization result of benchmark functions in Table 3. Maximum number of iterations = 100.

4. PATH PLANNING PROBLEM

UAVs offer advantages in civil applications. UAV can be used in dangerous conditions. One goal in UAV's missions is to use UAV in the optimized manner (Richards & How, 2002). Recently, 3D UAV-PP problems are useful in the field of disaster management. The addition of one extra dimension increases computational complexity for the trajectory planner, because the design space is extended. Planner should be able to solve constrained problems. Meanwhile, multi-objective path planners are necessary for management of complex missions.

4.1 Path presentation using Bezier curves

In related research, Bezier curve technique is used for paths (Foo et al., 2009). For computing smooth, dynamically feasible trajectories for UAVs, we used Bezier curves. Using Bezier curves entitled to flight trajectory allows for more exact configuration of UAV. A smooth path is important for UAV flight because UAVs cannot follow line segments. Bezier curve is on equation (15).

$$x_1(d) = \sum_{i=0}^{n} B_i^n d^i (1-d)^{n-i} x_{1,i}$$

$$x_2(d) = \sum_{i=0}^{n} B_i^n d^i (1-d)^{n-i} x_{2,i}$$

$$x_3(d) = \sum_{i=0}^{n} B_i^n d^i (1-d)^{n-i} x_{3,i} \qquad (15)$$

$$B_i^m = \frac{n!}{i!(n-1)!}$$

where d is in [0,1], n for control points,$(x_{1,i}, x_{2,i}, x_{3,i})$ is the coordinates of ith control point define the path points $(x_1(d), x_2(d), x_3(d))$.

4.2 Terrain model

In remote sensing missions, UAV should fly in mountain terrain. Unlike previous works that used artificial flight environments; we used real dataset for evaluation of UAV-PP algorithm. This natural area is located on the north of Tehran (Figure7).

4.3 Fitness function

The evaluation function measures the cost of the path. The fitness function has three different terms to minimize the distance; making a smooth trajectory without hard turns, and keeps UAV apart from DTM. We supposed a linear form of these three terms. The general formulations of the problem is in equation (16)

$$\min F = \sum_{i=1}^{dn-1} [(x_{1,i+1} - x_{1,i})^2 + (x_{2,i+1} - x_{2,i})^2 + (x_{3,i+1} - x_{3,i})^2]^{1/2}$$

$$x_3^{curve} - x_3^{surface} < S_d, \quad \theta_{i,i+1} < \theta_S, \quad x_3^{curve} < A^L \tag{16}$$

Where $\theta_{i,i+1}$ is the angle between the extension of the line connecting Bezier points i and $i+1$, θ_S is the safe turning angle for controlling lateral and vertical accelerations. To avoid UAV from terrain collision, S_d is a safe distance determined by operator, x_3^{curve} is the path curve coordinate, and $x_3^{surface}$ is the terrain point coordinate. A^L is for limiting the peak height of UAV.
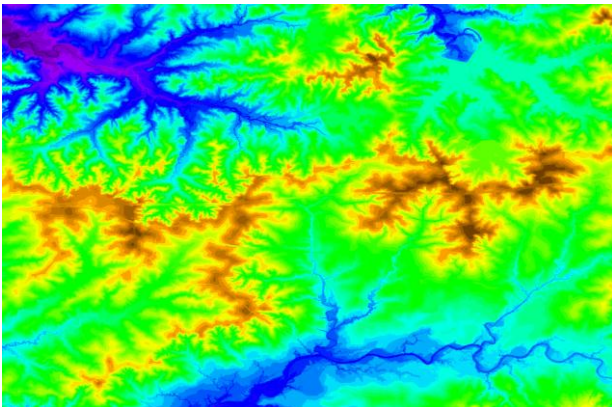

Figure 7. Digital Terrain Model of North Tehran

5. SIMULATION RESULT

In this section, to evaluate the effectiveness and performance of the NICA planner, it was tested by some computational experiments. We checked NICA with different parameters. Each set up is solved 10 times to find reliable result. The improved NICA planner simulated in Matlab environment. We performed simulations 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 80km×80km size, in an arbitrary coordinate system, UAV Launching location is (-40 ,40,1.95) and the UAV Landing Station is Located on (-40,40,-3). It is supposed that flight altitude of UAV is limited within the range (-10, 10).in parameter setting of UAV-PP, (θ_S, S_d) is set to (60°,0.05). To

evaluate the efficiency of NICA based planner, it is compared with other three powerful methods, i.e. ICA, GA, and PSO. Fig. 8 shows the Summary of path planning results using all four methods.
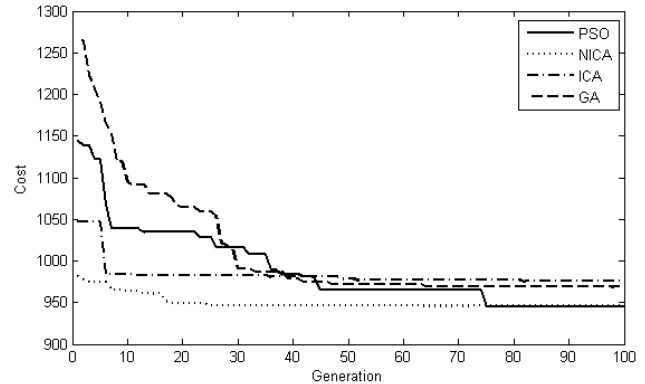

Figure 8. Plot of cost values of paths versus Generations through performance measures.

As shown in Fig. 8, the cost value of each path planning simulation is illustrated. The average results for the first 100 independent runs are compared on Figure 8. During the early iterations of 15 steps, the cost values decreased rapidly. These results indicate that NICA path planner confirms the high capabilities of proposed methodology.

At our implementation, final UAV optimal trajectory is based on a real model of the UAV and DTM. As shown in Figure 9, the NICA planner gradually produces a smooth 3D trajectory for UAV flight, from starting location to its target. Based on validations, the objective function of this path is at a minimal cost respect to the constraints.
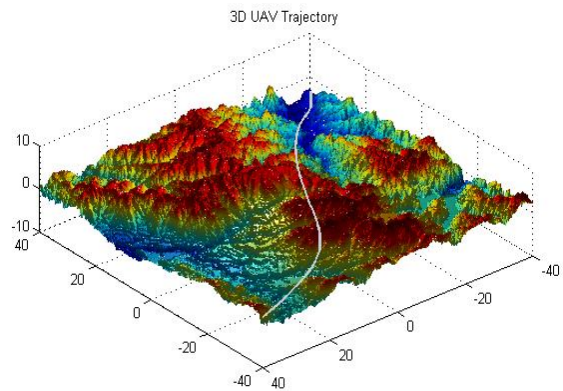

Figure 9. Illustration of the final generated optimal UAV trajectory based on NICA planner algorithm(left: NW-SE ,right: SE-NW)

6. CONCLUSIONS

Constrained UAV's path planning is a Np-hard optimization problem in 3D. This paper solved UAV-PP problem. This paper can enhance the UAV's navigation in real world missions toward more autonomy. The proposed method based on Newtonian imperialist competitive algorithm represents the trajectories using Bezier curve which can ascertain the generated path is smooth and flyable. The simulation result shows that the NICA algorithm can get optimal paths and has stronger robustness and better convergence performance than other tested optimization algorithms (GA, PSO, and classical ICA).

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