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PARAMETER SELECTION FOR BIOGEOGRAPHY-BASED OPTIMIZATION IN UNMANNED AERIAL VEHICLE PATH PLANNING

Kai Yit Kok[1], Parvathy Rajendran[1], RuslanRainis[2], JasmeeJaafar[3] and Zulkepli Majid[4]
[1]School of Aerospace Engineering, Universiti Sains Malaysia, Nibong Tebal, Pulau Pinang, Malaysia
[2]Geography Section, School of Humanities, Universiti Sains Malaysia, Pulau Pinang, Malaysia
[3]Faculty of Architecture, Planning and Surveying, Universiti Teknologi Mara, Shah Alam,Selangor, Malaysia
[4]Faculty of Geoinformation and Real Estate, Universiti Teknologi Malaysia, Johor Bahru, Malaysia
E-Mail: aeparvathy@usm.my

ABSTRACT

Biogeography-based optimization (BBO) has recently become popular in unmanned aerial vehicle (UAV) path planning. Similar to other evolutionary algorithms, the performance of BBO is affected when the parameter setting is not finely tuned. Therefore, the BBO parameters are optimized in this research particularly for application in UAV path planning. Each combination setting of parameters is simulated 100 times to obtain the average performance. The optimum population size and mutation rate of BBO settings for UAV path planning are also proposed.

Keywords: biogeography-based optimization, evolutionary algorithm, UAV, path planning.

1. INTRODUCTION

Unmanned aerial vehicles (UAVs) have attracted considerable research attention mainly because of their low cost and no-man-on-board feature. Therefore, UAVs have become ideal for dangerous missions, particularly in military operations. These vehicles can also be used for surveillance, video monitoring, surveying, and reconnaissance [1]. As a result, fully autonomous flight has become the target for UAV development. Path planning optimization is an important factor in which various evolutionary algorithms have been implemented and studied to improve the autonomous flight of UAVs [2, 3].

Path planning creates a pre-arranged flight path for UAVs before or during their flight. Path planning is classified into global and local path planning [4]. Global path planning is an offline planning system that often uses terrain map information without receiving data from sensors when generating a flight path. By contrast, local path planning is an online planning system that may or may not use terrain map information and receive data from sensors when generating a flight path within the sensor coverage.

Introduced by Simon [5] in 2008, biogeography-based optimization (BBO) mimics the distribution of living organisms across islands through time and space [6-8]. Island with better environments are filled with more living organisms. These organisms migrate to other places when their present location has insufficient space. This concept has been widely practiced in various applications, including aircraft path planning. Similar to other evolutionary algorithms (EAs), BBO requires the input of several parameters, such as population size and mutation rate.

Population sizing has always been an issue in the application of EAs. People optimize the influence of population either by proposing different initialization methods or making population size to be dynamic to achieve maximum EA performance [9-11]. However, these methods increase the computational cost of applying EAs and require considerable time to be tuned for different applications.

Moreover, the optimum mutation rate for BBO for aircraft path planning has never been investigated. This study aims to optimize the population size and mutation rate for BBO when applied in UAV path planning. The values of population size and mutation rate are varied to identify their optimum values. A hundred simulations are performed for each combination of these two parameters to obtain the average performance of BBO for aircraft path planning.

2. METHODOLOGY

Figure-1 shows a 100×100 grid terrain map of our case study area. To increase the search speed, the altitude for each waypoint is set as a certain height from the ground at the waypoint coordinate. The virtual y-axis will be used when creating or varying a waypoint location to facilitate and increase the path planning efficiency. A large number of waypoints is set to make the problem more complicated and to identify easily the influence of the value of parameters.

The maximum generation number is set to 1000. The studied mutation rate ranges between 0% and 100% with an interval of 10%. The value of population size is iterated from 10 to 100 with an interval of 10. The initial and final locations of the flight path are set as {10, 90} and {90, 10}, respectively, to utilize the entire search space. Figure-2 shows the terrain map of the case study area.

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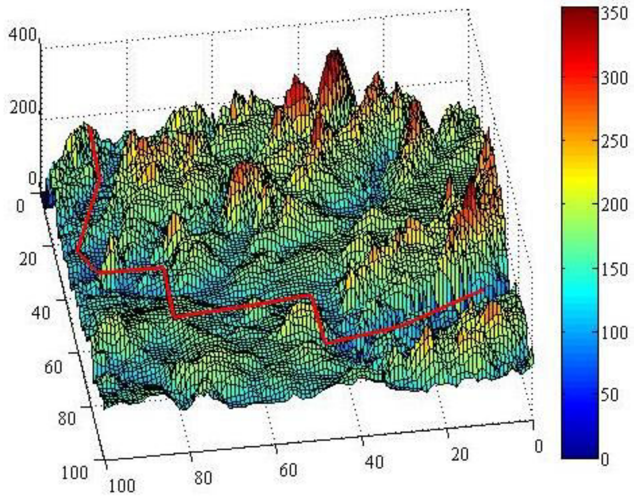

Figure-1. UAV 3DPath planning.

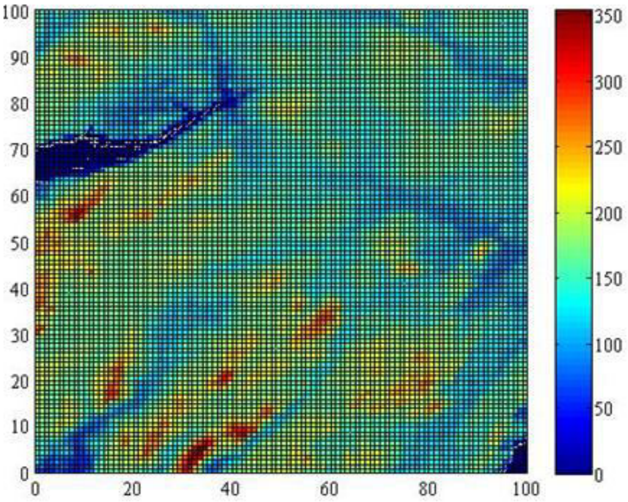

Figure-2. Map.

The length of flight path is used as the function of this study. The UAV will not hit the ground because we set the altitude of UAV high enough from the ground at each waypoint. The minimum turning radius is not restricted. The user may also include additional factors in cost evaluation when applying BBO in actual UAV applications with the same optimized settings that are applied in this study.

A BBO algorithm usually begins with the initiation of a population with random solutions. All solutions are then evaluated in terms of cost, and low cost solutions are treated as better habitat islands. Better habitats have more living organisms that are prone to migrate to other areas because of saturation. Therefore, these solutions will have a higher probability of replacing the particles of high cost solutions. The immigration (λ) and emigration rates (μ) are estimated as follows [12]:

$$\lambda_k = I(1 - {}^{k}/_{n}), \tag{1}$$

$$\mu_k = E({}^{k}/_{n})), \tag{2}$$

where I and E are the maximum immigration and emigration rates, k is the number of species, and n is the maximum amount of species in a habitat. The number of species in each solution is calculated on the basis of thecost ranking of the solution. We assume $I = E$ and combine equations 1 and 2as follows:

$$\lambda_k + \mu_k = 1. \tag{3}$$

After the migration process, a certain number of particles from the population will be involved in a random mutation and several lowest cost solutions will be preserved at the end of the generation. The same number of highest cost solutions will be replaced by the lowest cost solutions from the previous generation, and the algorithm will continue its migration in the new generation.

3. RESULTS AND DISCUSSIONS

Figures 3 and 4 show the average path and computational cost at 1000th generation in BBO with various combinations of population size and mutation rate. A high average path cost is observed when the mutation rate is 0%.This cost significantly decreases when the mutation rate is increased to 10%.Nevertheless, increasing the mutation rate will only decrease the BBO performance. Therefore, a 10% mutation rate has the lowest average path cost, as shown in Figure-3.

Increasing the population size can decrease the path cost further, as shown in Figure-3. Figure-4 shows that increasing the population size will increase the computational cost and will have an influence is larger than that of an increasing mutation rate. Figures 5 and 6 show the average path and computational costs of BBO with various population sizes from 100 to 1000 generations at a 10% mutation rate. A higher population size yields a smaller average path cost and a bigger computational cost and vice versa.

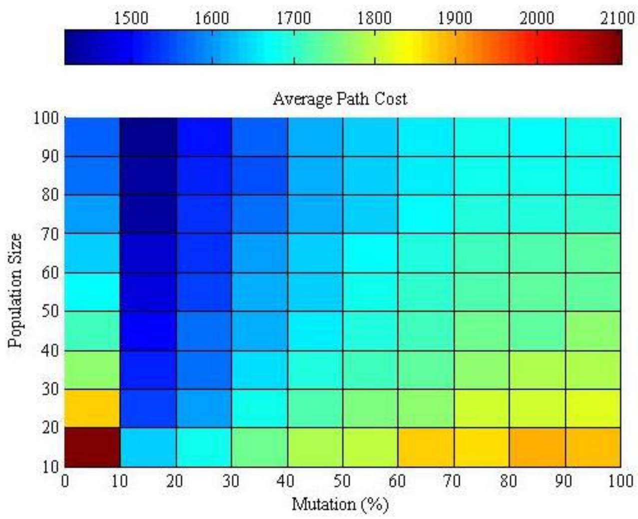

Figure-3. Average path cost at 1000th generation.

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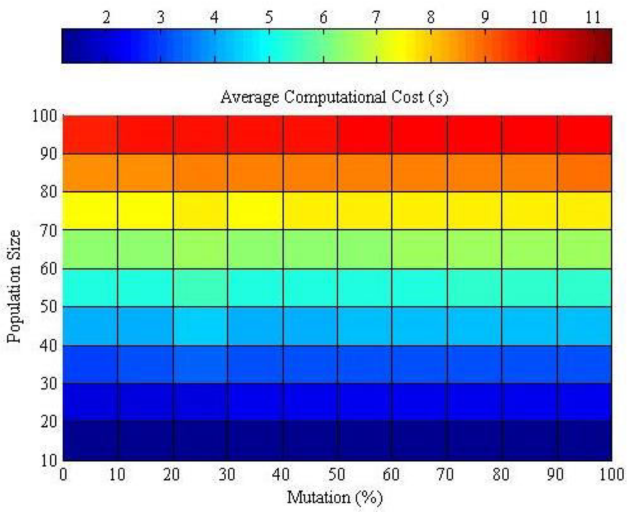

Figure-4. Average computational cost at 1000th generation.

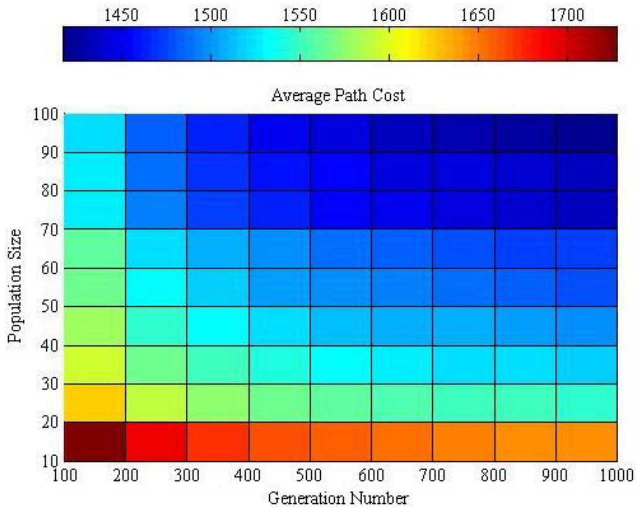

Figure-5. Average path cost at 10% mutation.

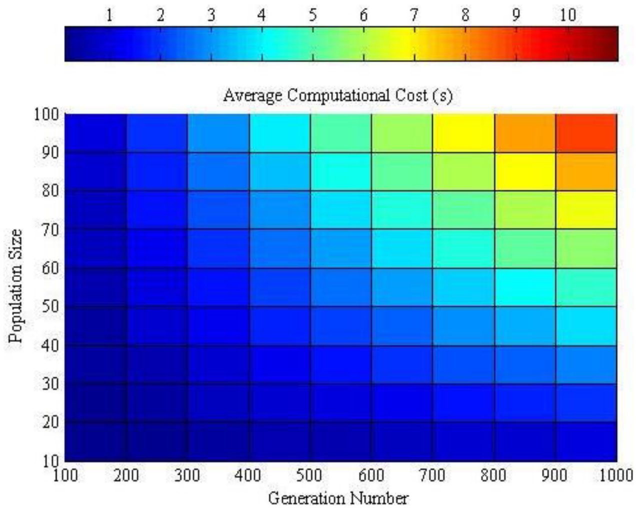

Figure-6. Average computational cost at 10% mutation.

To estimate the balanced point of population size, the influence of population size on both average path and computational costs with a benchmark population size of 100 is plotted in Figures 7 and 8, respectively. Figure- 7 shows that the influence of population size on average path cost tends to increase along with the generation number. Nevertheless, increasing the population size does not have the same effect of reducing the path cost.

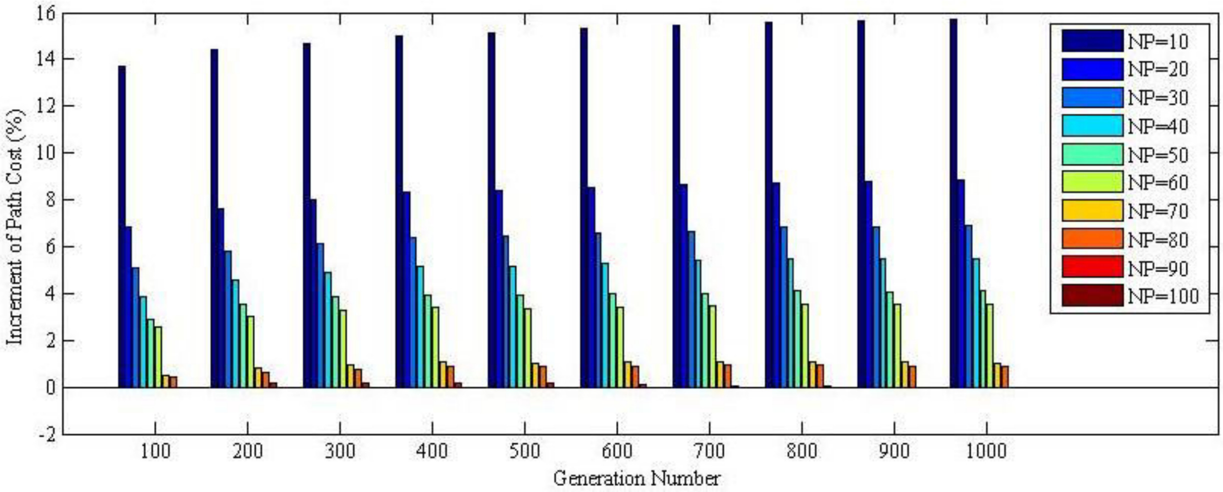

Figure-7. Increase in path cost using a population size of 100 as reference.

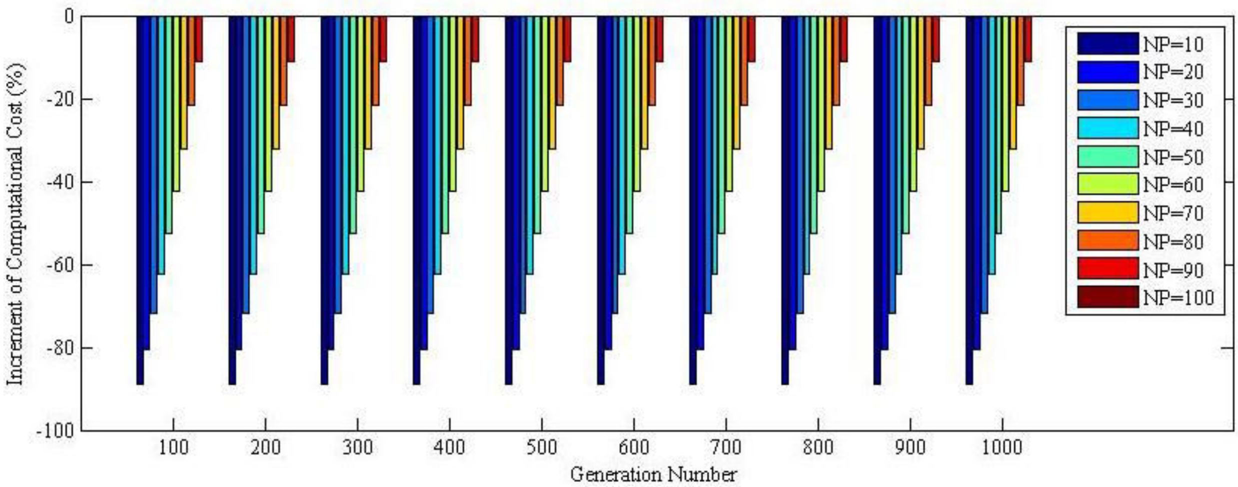

Figure-8. Increase in computational cost using a population size of 100 as reference.

The reduction rate of computational cost remains consistent among various population sizes. Nevertheless, the actual computational cost increases along with population size and generation number. Therefore, the optimum population size in BBO can estimated as 40 because the average path cost is 4% to 6% higher and the computational cost is 62% lower than the population size of 100.

4. CONCLUSIONS

On the basis of the analysis results, the optimum population size for BBO in UAV path planning can be estimated as 40 after considering both the average path and computational costs. BBO without a mutation rate will lead to a high average path cost, and increasing the mutation rate will lower the success rate for improving solutions. Therefore, an optimum of 10% mutation rate is obtained.

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