Enhanced Particle Swarm Optimization for Path Planning of Unmanned Aerial Vehicles

Kai Yit Kok[1] and **Parvathy Rajendran**[2]

ABSTRACT

This paper presents an enhanced particle swarm optimization (PSO) for the path planning of unmanned aerial vehicles (UAVs). An evolutionary algorithm such as PSO is costly because every application requires different parameter settings to maximize the performance of the analyzed parameters. People generally use the trial-and-error method or refer to the recommended settings from general problems. The former is time consuming, while the latter is usually not the optimum setting for various specific applications. Hence, this study focuses on analyzing the impact of input parameters on the PSO performance in UAV path planning using various complex terrain maps with adequate repetitions to solve the tuning issues. Results show that inertial weight parameter is insignificant, and a 1.4 acceleration coefficient is optimum for UAV path planning. In addition, a population size between 40 and 60 seems to be the optimum setting based on case studies.

Keywords: Particle Swarm Optimization, Evolutionary Algorithm, UAV, Drone, Path Planning

1. INTRODUCTION

Unmanned aerial vehicles (UAVs) have undergone great development, and an abundance of research is being conducted to improve the various systems in these vehicles [1, 2]. UAVs were initially developed because of their vast potential in military missions [3]. The use of UAVs in various dangerous missions instead of soldiers may save lives and reduces costs drastically [4, 5]. Some designs are also capable of extreme manoeuvrability that enables countless types of missions in the military field, especially aerial surveillance, search and rescue, reconnaissance, and armed attacks [6]. Currently, UAVs are also applied in the commercial field, including crop spraying, cargo transport, and motion picture filmmaking.

Given such advantages, developing fully autonomous UAVs is highly desired. Recently, a survey has been done on coverage path planning using UAVs [7]. This study, however, focuses on achieving prompt and accurate decision making in UAV path planning. Generally, path planning is done to figure out the optimum path between starting destination points [8]. Unlike coverage path planning, which determines routes based on several flight patterns to explore every point in a target area, in this paper, we are also analysing the performance of the algorithm in estimating good solutions from a starting point to a destination point.

The evolutionary algorithm is commonly used to solve the optimization problem in path planning [9]. It has the advantage of searching a large space to obtain an optimum solution with the minimum computation time. Although determining the optimum solution may not guarantee low computational cost, it is crucial to ensuring the UAV can respond to any uncertainty instantaneously. Several types of evolutionary algorithms exist, such as genetic algorithms, differential evolution, ant colony optimization, and particle swarm optimization (PSO). Anyway, each evolutionary algorithm involves different techniques to find an optimal solution. For example, the genetic algorithm and differential evolution involve selection, crossover and mutation, while the PSO is using particle movement and velocity based on local and global best-known positions.

As mentioned in this survey paper [8], previous work has improved the PSO algorithm through adding a Bezier curve strategy and the Chaotic method into the algorithm, while the input parameters of the PSO algorithm are constant values throughout the analysis. However, the chosen input parameter settings in their analysis is vague [8]. Thus, this study aims to investigate, using a thorough analysis, the impact and influence of the PSO input parameters. This was done in order to estimate a suitable parameter setting for the algorithm in path planning. Developed by Kennedy [10], the PSO algorithm has become one of the most popular methods for solving optimization problems because it does not require the problem to be differentiable and the gradient of the problem is not needed either. The computational cost using the PSO algorithm is also shorter [11], and it has more stable convergence than those of other evolutionary algorithms[12]. Furthermore, PSO has a high convergence speed [13, 14] and consistent performance [15].

Despite the advantages of PSO, it is not easy to use and obtain maximum performance in applications

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because it requires the input values of several parameters, including population size, inertial weight, and an acceleration coefficient. Similar to other types of evolutionary algorithms, PSO still uses trial and error to obtain the desired solutions. However, tuning the parameter settings is costly, and no one solution is suitable for all applications [16-18]. Despite the numerous studies on UAV path planning using PSO, these studies either use trial-and-error methods or refer to other general parameter values [19-21].

The focus of this study is to obtain an optimum input parameters for the PSO algorithm in path planning, so that this setting can be used as a future reference in the research of the PSO based algorithm in path planning. In order to ensure findings are significant, this study used 9 different real terrain maps with various combinations of PSO input parameters. Each performance of the PSO algorithm was simulated 100 times to obtain the average performance. Thus, the optimum parameter settings recommended at the end of this study are not merely a local optimum.

2. PROBLEM MODELING

In this study, the terrain map information is predetermined before the flight. Path planning using the PSO will begin to generate an optimum flight path with the input of a waypoint number. However, trouble may occur if the waypoints are scattered randomly over the map, leading to reduced efficiency in obtaining an optimum flight path.

Therefore, to increase the search speed and maintain the performance of the developed PSO, a virtual line connecting the initial and final locations and each waypoint is defined to have the same distance as the adjacent waypoints. This line acts as the x-axis. A virtual y-axis is formed at each waypoint, and the location is adjusted along the virtual y-axis[4]. Fig. 1 displays this concept of path planning [22] and illustrates the 3D visualization of path planning using PSO, where the dotted line is the virtual x-axis, and the dashed line is the virtual y-axis.

2.1 Function Cost

Many aspects can be considered in UAV path planning in terms of cost, such as maximum path length, minimum turning radius, power consumption, and the danger zone. However, path length and computational cost are the only aspects considered in this research, which assumes the power source is adequate for to-and-fro flight regardless of the path length. Some UAV models are required to include other function costs such as turning radius and power consumption in the analysis. However, those results are only applicable to a particular UAV model. Therefore, only the path length and computational load are considered in this paper to ensure impartial comparison, whereby the results can be applied to other types of UAV as well.

The path cost formula is shown in Eq. 1 below, where w is the number of waypoints, and l is the length between current and previous waypoints.

$$j = \sum_{i=1}^{w-1} l_i \tag{1}$$

The UAV is set to maintain an altitude of 100 m from the ground at each waypoint, so it is unlikely that the UAV will hit the terrain along the flight path.

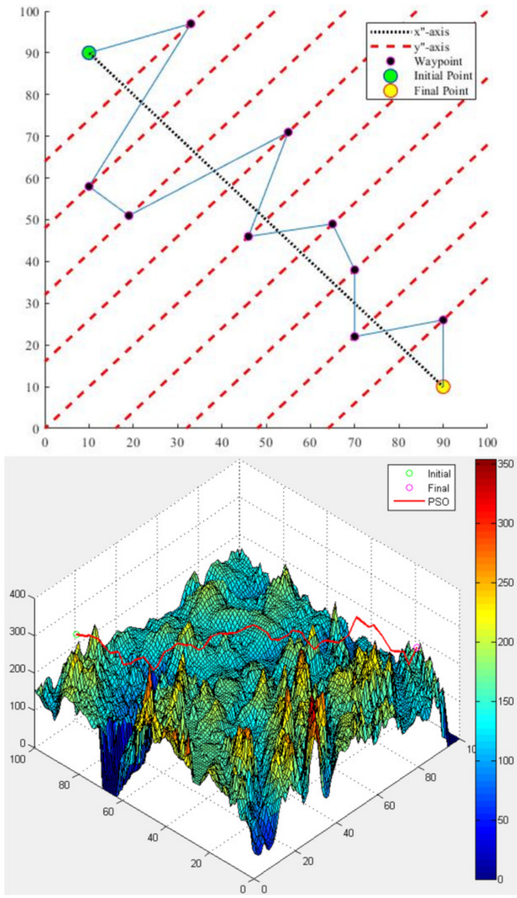


Fig.1: *Concept of Path Planning (Top) and 3D Visualization of Path Planning Map using PSO.*

2.2 Computer Performance

A computer with an Intel Core i5-4460 CPU@ 3.20 GHz and 16.0 GB RAM was used in this research.

3. PSO CONCEPT

Like other evolutionary algorithms, PSO begins by initiating a population of random solutions. Each point in the solutions is treated as a particle that can move to other locations by using a certain formula. Prior to this step, a cost evaluation on each solution in the population is required to obtain the local and global best points in each waypoint along with the solution. The local best point is the current generation's best location, whereas the global best point is the best location so far. The velocity for each particle can be calculated using the formula shown in Eq. 2 [23, 24].

$$\begin{aligned} v_{i,k}^{G-1} = w v_{i,k}^{G} + c_1 r_g (g_{best,k} - x_{i,k}^{G} + \\ c_2 r_p (p_{best,k}^{G} - x_{i,k}^{G}), \end{aligned} \tag{2}$$

where v is the velocity, w is the inertial weight, c_1 and c_2 are the acceleration coefficients, r_g and r_p are the random numbers within [22], g_{best} is the global best point, p_{best} is the local best point, x is the current location, i is the particle from the population, k is the waypoint, and G is the generation.

Velocity for the first generation is initialized to 0, while inertial weight and acceleration coefficients are set as constant values. The acceleration coefficients usually have the same value. Inertial weight is the weightage coefficient of the previous velocity on the current velocity. Acceleration coefficient is the weightage coefficient of the distance difference between current and best locations on current velocity. In other words, a high inertial weight will alter the current velocity to be closer to the previous velocity, while a high acceleration coefficient will increase particle movement significantly. The location of each particle is updated using Eq. 3 [24].

$$x_{i,k}^{G+1} = x_{i,k}^{G} + v_{i,k}^{G+1} \tag{3}$$

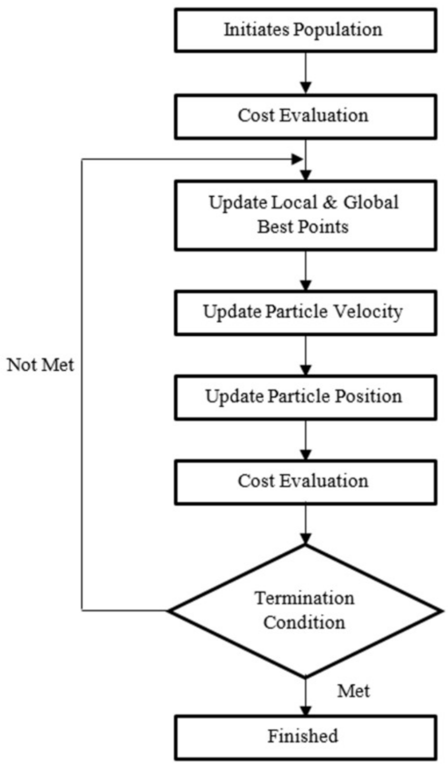


Fig.2: *PSO Algorithm Flow Chart.*

The cost of each new solution is examined again, and the process is repeated to update the local and global best points until the termination condition is met. The termination condition might be reaching maximum generation number or the cost function converging near enough to an optimal solution. However, an improved flight path might be replaced with a higher cost flight path in the next generation, an outcome that should be avoided at all costs. This problem can lead to the path cost continuing to fluctuate even when the algorithm hits the maximum generation setting. Therefore, for this research, an extra condition is added in the PSO algorithm so that the best solution from the previous generation will not be replaced unless a better solution occurs in the current generation.

Fig. 2 presents a flow chart of the developed PSO for path planning. Control parameters, including population size, inertial weight, and an acceleration coefficient will affect the updated solutions every generation. There exists no prior particular study on control parameters selection in PSO for UAV path planning previously, so a thorough analysis is done in this paper to find the optimum range of the control parameters in UAV path planning.

4. RESULTS AND DISCUSSIONS

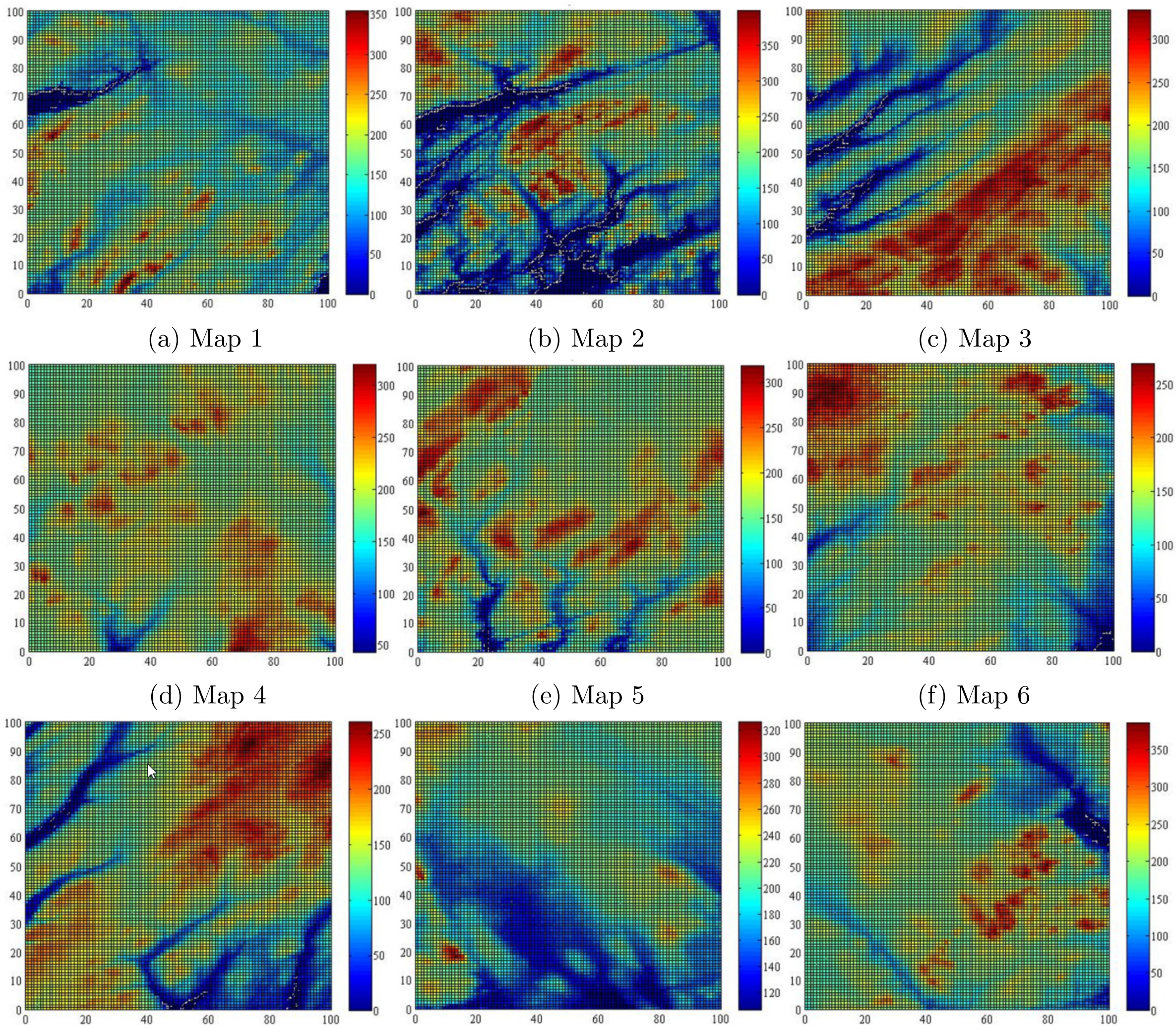
To obtain sufficient data for optimization of the parameter settings in PSO, specifically for UAV path planning, nine maps were studied (Figure 3). A variety of complex terrain maps provides more promising data, which, in turn, enables an improved estimation of an optimum parameter settings for path planning. The range of parameter settings in this analysis is given in Table 1.

Table 1: *Parameter Setting.*

No	Parameters	Value Range
1	Generation Number	1 – 500
2	Population Size	10 – 100
3	Inertial Weight	0 – 0.5
4	Acceleration Coefficient	0.2 – 2.0
5	Waypoint Number	50

In addition, each parameter setting for all case studies was tested 100 times, to calculate the average performance. This step is essential because an evolutionary algorithm depends on a certain degree of probability so that the output for the same parameter settings is unlikely to be the same when the simulation is repeated. Thus, obtaining the average result from 100 simulations for each parameter setting is needed to acquire robust data interpretation.

The initial and final locations for each case study are also fixed at {10, 90} and {90, 10}, respectively. These location settings enable full utilization of the map space during the search for the optimum flight



(a) Map 1 (b) Map 2 (c) Map 3

(d) Map 4 (e) Map 5 (f) Map 6

(g) Map 7 (h) Map 8 (i) Map 9

Fig.3: *The 9 Complex Terrain Maps Studied.*

path of the UAV. Except for the fixed number of waypoints, the impact of other parameters on the performance of the PSO on UAV path planning is analyzed within the ranges defined in Table 1. An example flight path obtained from PSO for each terrain map is illustrated in the Appendix.

4.1 Impact of Population Size, Inertial Weight, and Acceleration Coefficient

Figure 4 shows the average path cost and computational cost analyzed for Map 1 at population sizes of 10, 30, 50, 70, and 100, respectively. These results are calculated using the inertial weight ranging from 0 to 0.5, and the acceleration coefficient ranging from 0.2 to 2 at the 500^{th} generation. Overall, increments of the inertial weight or acceleration coefficient increase the average computational cost. On the other hand, a trend is observed for the minimum value of average path cost among these population sizes at several good combinations of inertial weight and acceleration coefficient.

Moreover, a similar trend is exhibited for the computational cost, where the minimum point is also close to the minimum level. Hence, the optimum setting of inertial weight and acceleration coefficient can be selected for each population size and generation number.

4.2 Impact of Generation Number

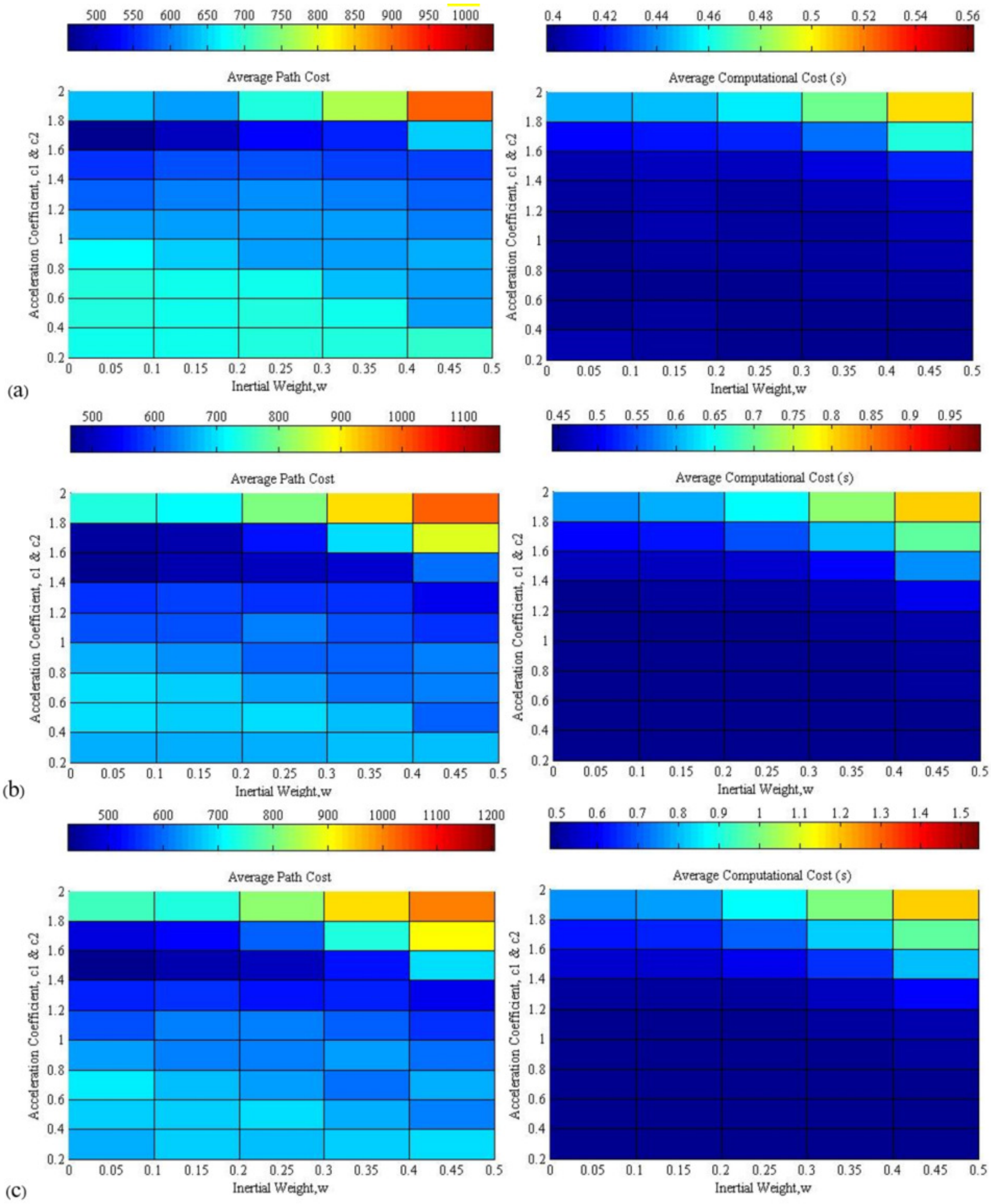
In this section, the optimum settings of inertial weight, acceleration coefficient, and population are studied for a range of generation numbers. The final results of the average path and computational cost in relation to the generation number with an independent parameter setting to give the lowest average path cost are plotted in Figure 5 in the respective order.

Most case studies indicate that path cost converges to a minimum level within 100 generations. In this simulation, the computational cost for 100 generations is less than 0.15 s, which is considered low. Thus, a computational cost of less than 1 s can be achieved even when a lower performance device is used given the same number of generations.

Inertial weight, acceleration coefficient, and population size in relation to generation number are also plotted in Figures 6 to 8, respectively. Most test cases show that the optimum inertial weight remained at 0 throughout the simulation for UAV path planning, except for Map 4 at 0.2. Therefore, the optimum inertial weight for UAV path planning can be safely concluded to be 0. This finding means that the influence of velocity from the previous generation on the current velocity does not improve path cost. Computational cost can then be further reduced slightly by ignoring the influence of the previous velocity.

Surprisingly, the trend of the optimum acceleration coefficient is quite similar to that of the inertial weight data. In general, six (Maps 1, 2, 3, 4, 5, 7) of the nine test cases studies show almost the same plot data. Specifically, the optimum acceleration coefficient, in the beginning, is approximately 0.6 but increases eventually to 1.4. In addition, all these changes happen within 100 generations. The optimum acceleration coefficient from the 100$^{\text{th}}$ generation onward remains at 1.4.

Although the rest of the test cases do not have this trend, two out of the three remaining test cases stud-



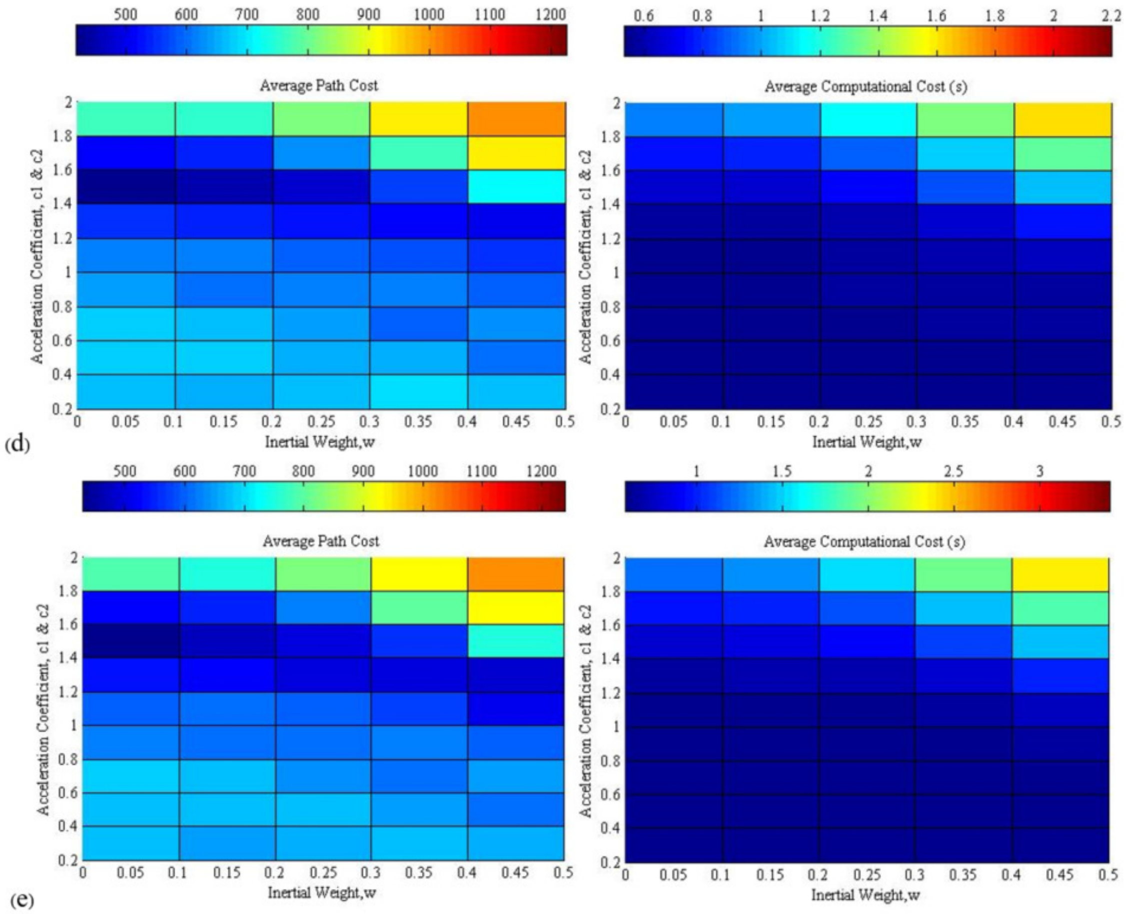


Fig.4: *Average Path and Computational Cost at (a) 10, (b) 30, (c) 50, (d) 70 and (e) 100 Population Sizes.*

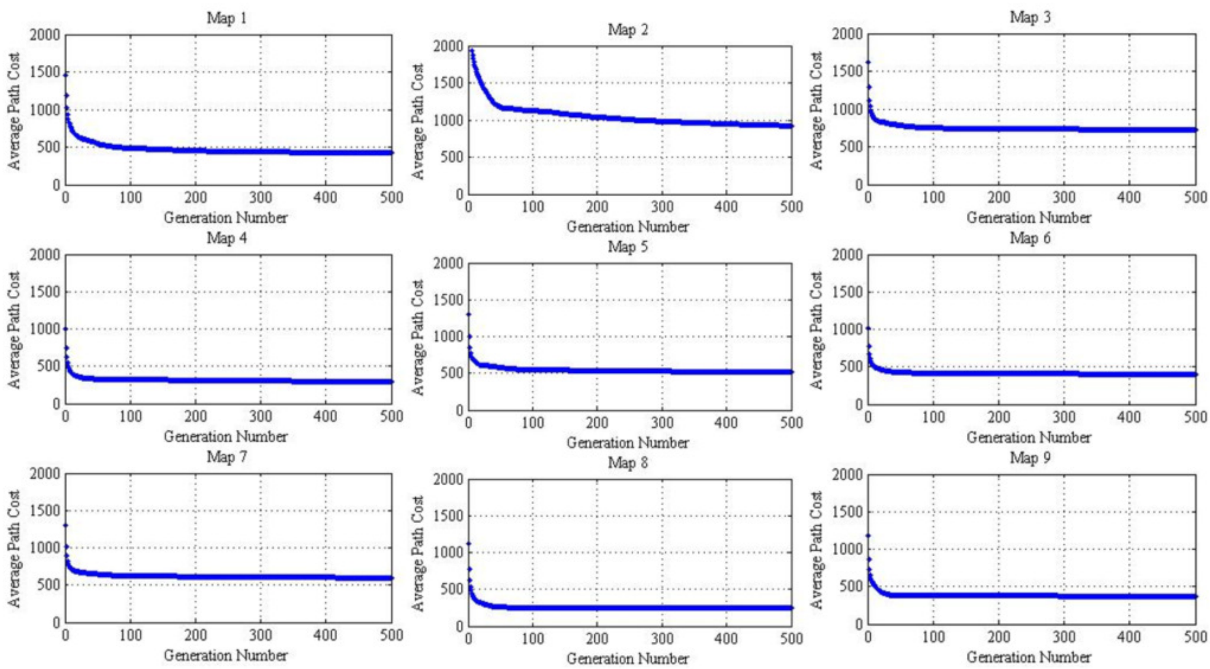


Fig.5: *Average Path along Generation Number.*

ies (Maps 6 and 8) still converge to 1.4 from around the 150th and 300th generations onward.

Only one (Map 9) out of the nine test cases converges to 1.6 from the 250th generation onward. Therefore, a 1.4 acceleration coefficient is considered as the optimum value because the lowest average path cost becomes stable from the 100th generation onward. This acceleration coefficient value can converge to the lowest path cost at high processing speed for most UAV path planning.

Figure 8 presents the population size for the lowest average path cost, along with a generation number for the nine case study maps. Generally, no common trend for the optimum population size occurs to obtain the lowest path cost. Some test cases, such as Maps 1, 5, and 7, do exhibit the lowest path cost with high population size in the beginning. However, the big population size is needed to obtain the smallest average path cost after around 100 generations.

The optimum population size is at the minimum level for Maps 8 and 9 as the generation increases. Other test cases also have different trends. Thus, given that a high population leading to a high computational cost and a low population cost may not provide enough diversity to the solution, based on these test cases, a moderate size between 40 and 60 seems to be the most reasonable setting.

The performance of the PSO algorithm with optimum parameters obtained from the preliminary analysis is shown in Appendix B under various numbers of waypoints and generation numbers. It can be observed that the average path cost is decreasing when the number of waypoints is reduced, as the complexity of the problem becomes smaller. Nevertheless, the trend of the path cost by varying the number of waypoints is consistent, which indicates that the number of waypoints will not affect the optimum value of the input parameters obviously, but mainly has an effect on the computational cost.

5. CONCLUSIONS

Reasonable parameter settings for the PSO for UAV path planning were obtained after numerous simulations and analysis using various terrain maps as case studies. The initial point and final point can be changed according to different situations, in which the PSO can be used even if there are moving obstacles or disturbances, given that the processing speed is fast enough to get updated solutions in real-time. The optimum inertial weight is 0. The best acceleration coefficient is 1.4. A population size between 40 and 60 seems to be the most reasonable setting according to the results. These values achieve the minimum path and computational cost. Thus, the velocity formula can be further simplified by ignoring the previous velocity component because the inertial weight is 0. In conclusion, the trial and error steps for obtaining the optimum parameter settings in UAV path planning using PSO can be omitted.

ACKNOWLEDGEMENTS

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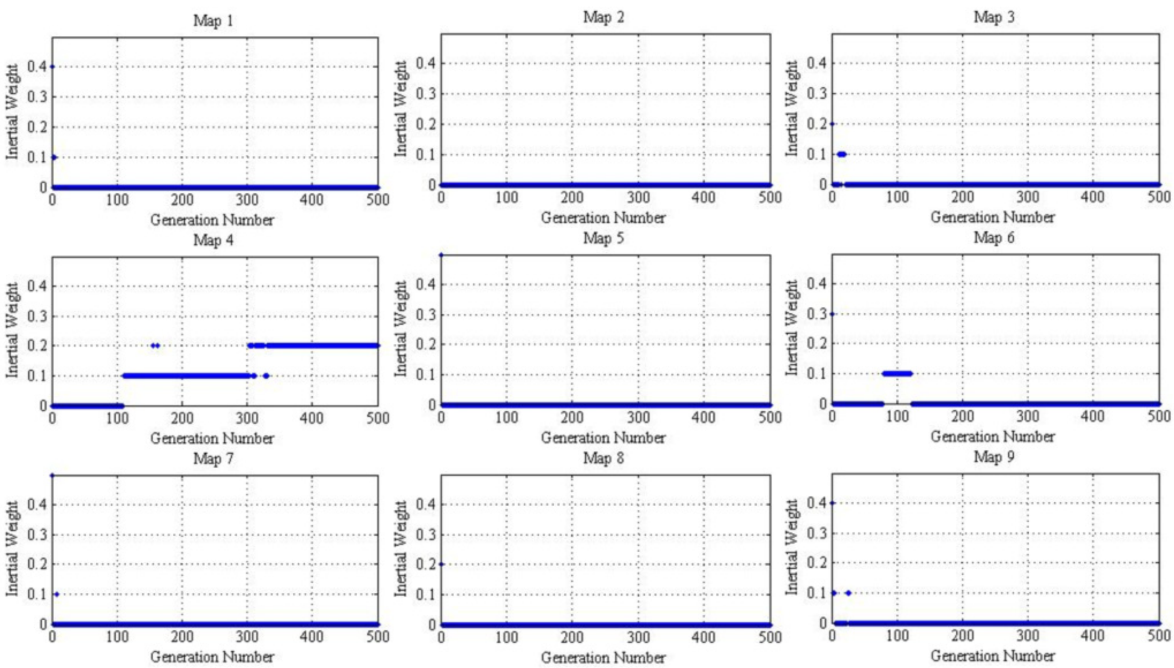

Fig.6: *Optimum Inertial Weight along Generation Number.*

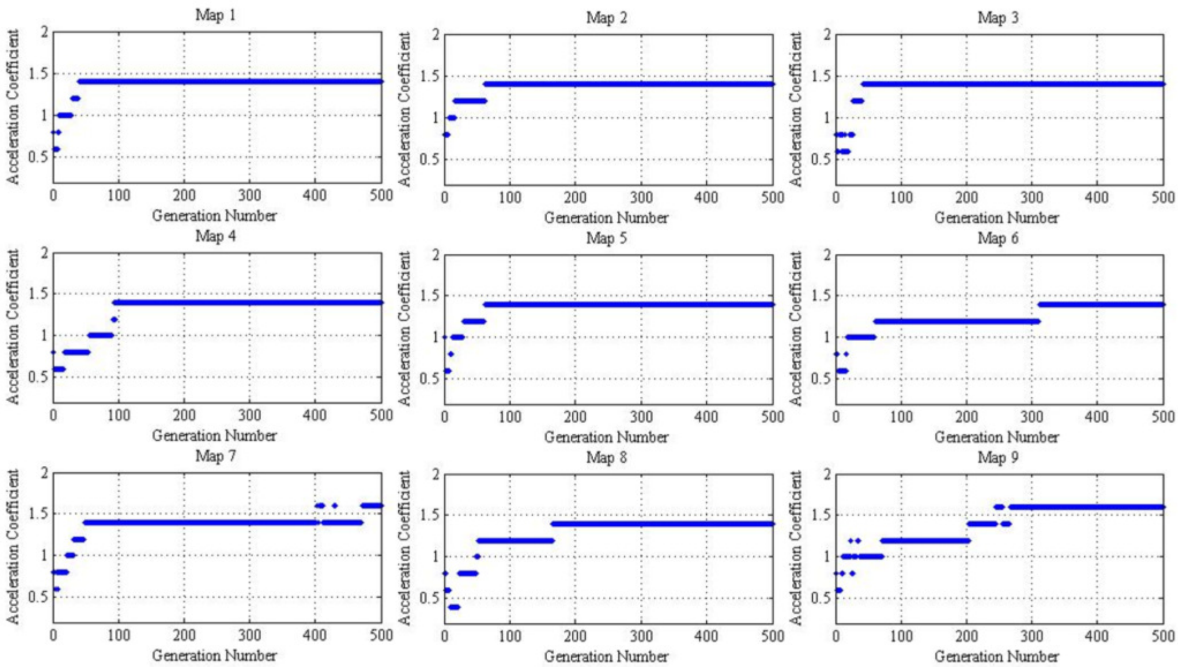

Fig.7: *Optimum Acceleration Coefficient along Generation Number.*

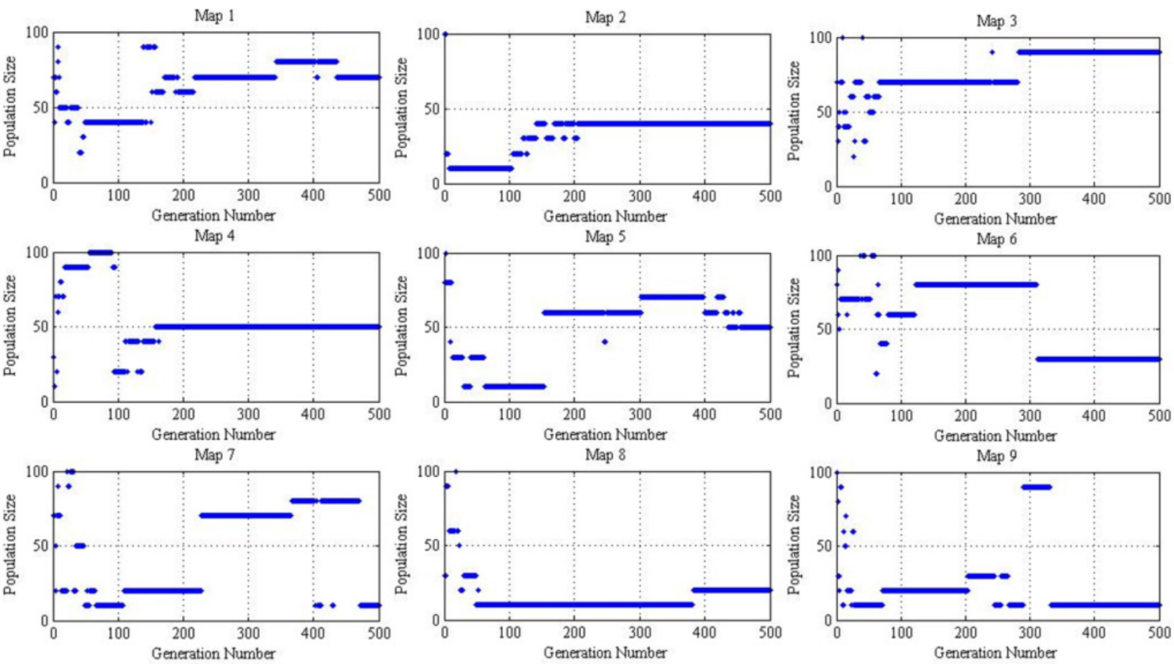

Fig.8: *Optimum Population Size along Generation Number.*

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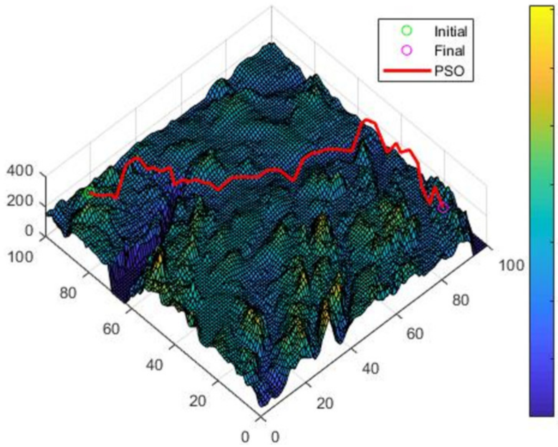
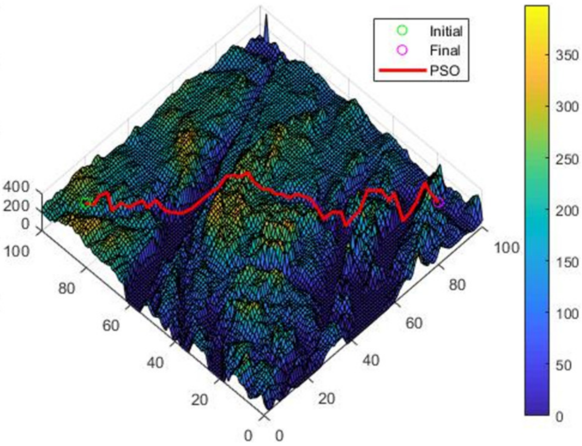
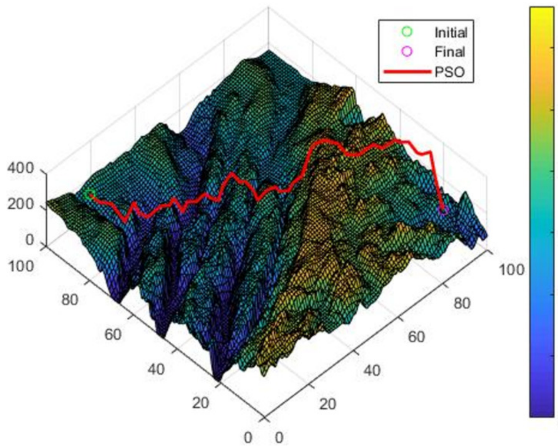
Appendix A



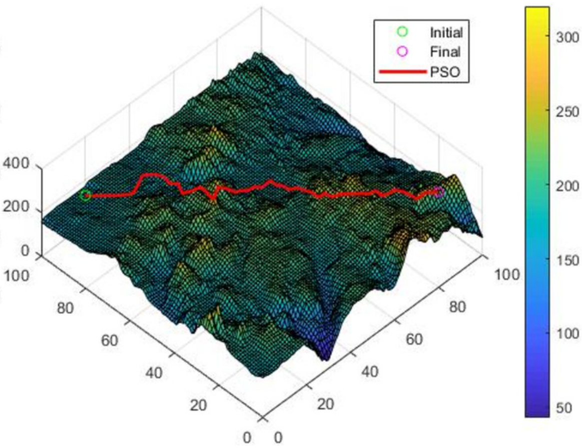
(a) Map 1



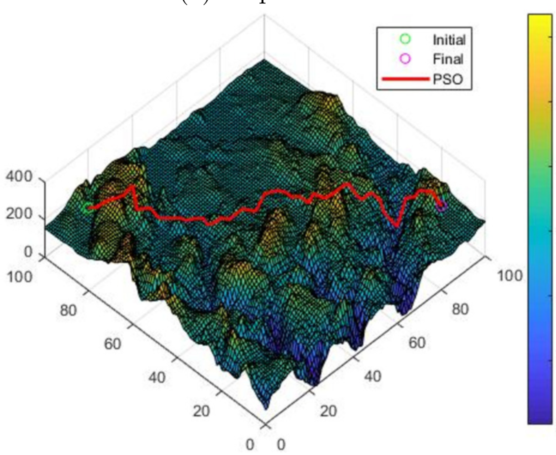
(b) Map 2



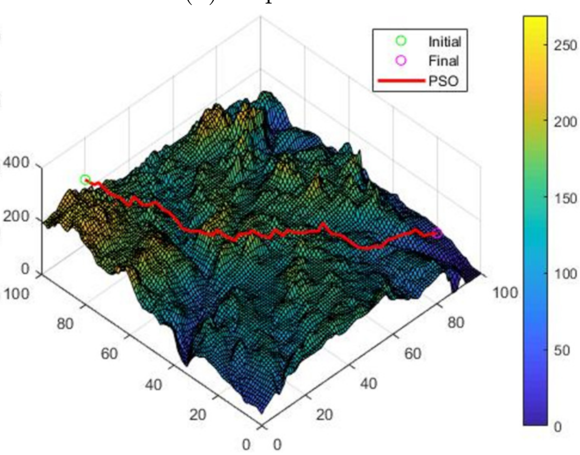
(a) Map 3



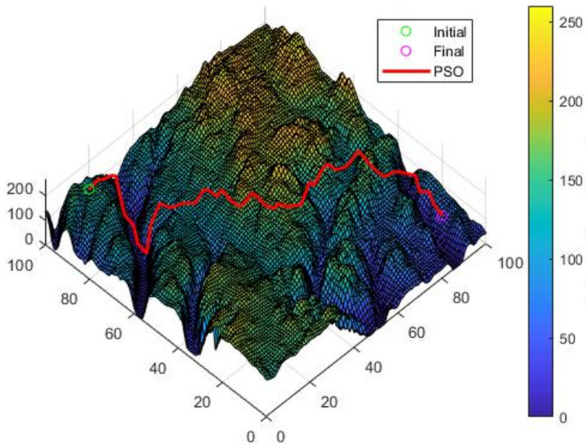
(b) Map 4



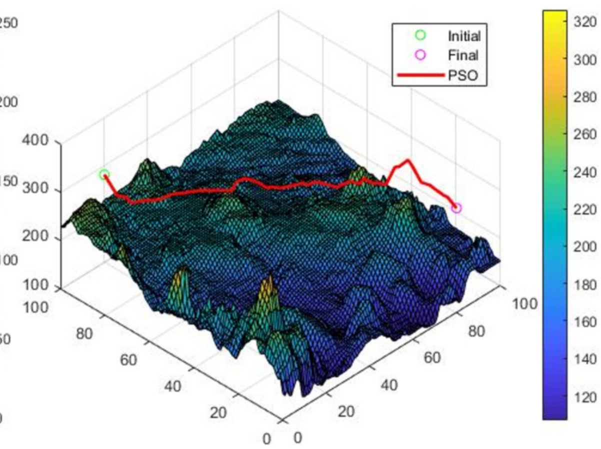
(a) Map 5



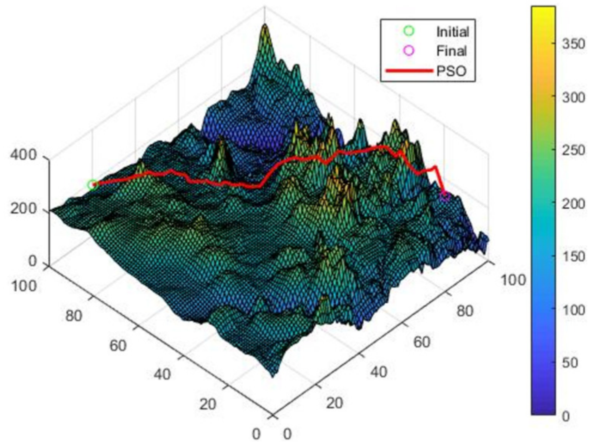
(b) Map 6



(a) Map 7



(b) Map 8



(a) Map 9

Appendix B

Table 2: *Performance of PSO with various numbers of generations and waypoints.*

Waypoints	Generation Number	Average 9-Maps Data	
		Path Cost	Computational Cost (s)
10	100	234.7	0.027
	200	231.3	0.052
	300	230.2	0.078
	400	229.5	0.104
	500	229.2	0.129
20	100	355.1	0.047
	200	350.9	0.093
	300	349.3	0.139
	400	347.7	0.185
	500	346.7	0.231
30	100	450.2	0.065
	200	436.2	0.129
	300	428.4	0.193
	400	423.7	0.257
	500	419.7	0.321
40	100	508.9	0.083
	200	495.5	0.165
	300	489.0	0.246
	400	485.5	0.328
	500	483.0	0.409
50	100	559.9	0.102
	200	533.3	0.202
	300	522.9	0.301
	400	517.9	0.400
	500	513.7	0.499

Kai Yit Kok received the B.Eng. (Hons.) in aerospace engineering from Universiti Sains Malaysia in 2014 and the M.Sc. degree in aerospace engineering from Universiti Sains Malaysia in 2016, where he is currently pursuing the PhD degree with the School of Aerospace Engineering. His research includes aircraft control, UAV path planning, image processing and stereo vision.

Parvathy Rajendran is currently an academic in the School of Aerospace Engineering at Universiti Sains Malaysia since 2013. She completed her PhD in Aerospace Engineering from Cranfield University, United Kingdom in October 2012. There, her research includes UAV design, development and flight testing and UAV's systems development and testing. Rajendran has produced many high-impact publications and served as an editor-in-chief, guest editor, international advisor and reviewer. She has been the chairman and member of the technical conference committee of various international conferences. In addition, she has maintained various grants worth more than RM 1 million.