

## Autonomous UAV Object Avoidance with Floyd–Warshall Differential Evolution (FWDE) approach

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**Abstract.** Unmanned Aerial Vehicles (UAVs) are recently focused significant research attention on commercial to military industries. Due to its wide range of applications such as traffic monitoring, surveillance, aerial photography, and rescue mission, many research studies were conducted related to UAV development. UAVs are commonly called ‘drones’ used to suit dull, dangerous, and dirty missions that can be suited by manned aircraft. UAVs can be controlled either remotely or using automation approaches so that they can be traveled into predefined paths. To make an autonomous UAV, the most complex issue that is faced by UAVs is obstacle/object avoidance. Obstacle detection and avoidance are important for UAVs, and it is the complex problem to solve due to the payload restriction. This will limit the sensor count mounted on the vehicle. A radar was used to find the distance between the object and the vehicle. This can help to detect and track the moving objects’ speed and direction toward the vehicle. This paper considered the object avoidance problem as a path-planning problem. There were many path planning methods related to UAVs that formulate path planning as an optimization problem to avoid obstacles. With this consideration, this paper proposed an efficient and optimal approach called the Floyd Warshall- Differential evolution (FWDE) approach to detect the frontal obstacles of UAVs. Finally, statistical analysis of the simulated environment reveals that the proposed evolutionary method can efficiently avoid both static and dynamic objects for UAVs. This efficient avoidance algorithm for UAVs can experiment with a simulation environment with three kinds of scenarios having different numbers of cells. The obtained accuracy and recall value of the proposed system is 95.21% and 91.56%.

**Keywords:** Unmanned Aerial Vehicles (UAV), Drones, Evolutionary, Differential Evolution, Genetic Algorithm, Floyd warshall, Object Avoidance.

### 1 Introduction

Unmanned Aerial Vehicles (UAVs) becomes the recent research focus from the civilian and military fields due to their terrific advantages including flexibility, strong mobility, good concealment, and lightweight [1]. Because of the wide range of applications such as traffic monitoring, surveillance, aerial photography, and rescue missions, many research studies on UAV development are done [2]. The growth of the applications of UAV technologies changes many industries’ development direction and also brings huge outcomes in economic and market benefits [3]. One of the major issues of UAVs with autonomous motion is to ensure the aircraft can explore space efficiently with the avoidance of collision of objects in a dynamic environment. With these complications of aircraft mission and usage scenarios, there is a need for technologies related to autonomous flight capabilities with intelligent UAVs and autonomous obstacle avoidance for UAVs [4]. The sudden improvement of UAVs in the commercial application of larger scenarios will increase the requirement for safe and reliable approaches for handling UAVs as efficiently [5-7]. Since UAVs were important for sensing technologies development such as thermal, hyperspectral, and multispectral they can change society with the creation of innovative applications and solutions [8-13]. The aircraft obstacle avoidance approaches are divided into two categories:

- I. This method's major goal is to convert the object avoidance problem into a path-planning problem [14]. With the advancement of UAV research, new path-planning systems have been developed, each with its own set of benefits and drawbacks. This algorithm includes graph theory-based Voronoi diagram [15], field theory-based artificial potential field approach [16], sampling theory-based RRT [17], heuristic information-based A\* algorithm [18], swarm intelligence-based optimization approaches [19-21], Graph based approaches not suited well for larger environments.
- II. Second category is related to the geometric relationship-based approaches for obstacle avoidance based on relative distance [25], angle [26], speed [27,28], and other related information [29] of aircraft and collisions. Compared to the first method related to path planning-based object avoidance, With the use of onboard sensors data from the scenario that comprises detection and avoidance, this method can avoid dynamic obstructions in the path.

This research work proposed a path planning-based dynamic object avoidance system. Aircraft path planning is a type of UAV operation that generates the best aircraft path from point A to point B. The route planning approaches for UAVs can formulate the path planning problem as an optimization problem by navigating the UAV in three dimensions with obstacles. To solve this problem, two groups of algorithms are used. They are heuristic and non-heuristic methods. Heuristic methods are providing the optimal solution with efficient computation time. Non-heuristic methods provide the optimal solution with expensive computational time and use mathematical principles. The path planning problem is solved from break down the detected area into computational domains with the help of technologies including tessellation or decomposition of matrix or combination of two. After the path generation, the UAV can travel that path with the smoothen process [30]. Differential evolution is a population-based evolutionary method that is frequently utilized in UAV path planning due to its real-world application optimization efficiency. It is also employed in non-linear and non-differential optimization problems. Due to its good convergence capabilities, DE is also employed in a variety of applications [31]. The contribution of this paper is as follows:

- Initially, object models are built in the aircraft waypoint. There are three kinds of object models have been constructed such as square, cylinder, circle, and hemisphere-based objects.
- The detected objects avoided in the aircraft path using the proposed path planning approach called the Floyd-Warshall method enhanced with the evolutionary algorithm called differential evolution.
- The proposed FW-DE-based path planning approach finds the aircraft path with the waypoints without obstacles and provides the UAV with safe travel from the origin to the destination. This evolutionary-based enhancement will make sure low computational complexity, flexibility, strong searching ability, and improved robustness.

The simulation results of the proposed UAV object avoidance system show efficient results with minimum computation time and error in avoiding the obstacles in the flight path.

The remaining section of this paper is as follows: Section 2 discusses about the literature related to UAV path planning and object avoidance. Section 3 introduced the proposed evolutionary-based algorithm for object avoidance. Section 4 simulated the environment to implement a proposed system and discussed the evaluated results. Section 5 concludes the proposed work with future work.

## 2 Related works

This section discussed the works of literature related to obstacle avoidance and path planning for UAVs. In terms of optimal solutions with reduced computation time, papers [14] and [32] compared the path-planning approaches in various scenarios and object layouts. They conclude that in terms of optimality, the path-planning approaches often conflict with each other. Sasongko et al., [27] developed an obstacle avoidance approach by calculating a group of waypoints to avoid the obstacles according to the obstacle model and UAV speed vector.

Al-Kaff et al. [28] devised an avoidance strategy that involved tracking a group of obstacle feature points in the flight boundary and determining the link between aircraft and obstacle coordinates. Based on the aircraft's forward speed and the difference between the obstacle and the vehicle, Zheng et al. [25] designed a fuzzy rule-based avoidance system. For UAV path planning, BesadaPortar [33] compared evolutionary methods. The control parameter for those evolutionary algorithms is not discussed in detail in this study.

By discovering the region of an item, Levente Kovacs et al. [34] devised a deconvolution approach to build a feature map called D-map. The obstacle is captured using the monocular camera with less collision ratio. The method used in this paper can be used in surveillance, navigation system, and odometry. Jacob engel et al., [35] discussed UAV navigation in GPS (Global Positioning System) based surroundings. This system is based quadcopter with a SLAM approach, Extended Kalman filter for sensor fusing. This system can be helpful for

outdoor surroundings having a location accuracy of 18 cm and for indoor surroundings with a position accuracy of 4.9cm. It provides navigation estimation accurately.

Drone collision avoidance algorithm developed by Omid esrafilian et al., [36]. (Aerial Quadrotor). The front camera records video feeds, and the Drone's data navigation is communicated to the ground station via wireless networks. SLAM (Simultaneously localization and mapping) was utilized for navigation and mapping. To generate a 3D map, the data is processed using an Oriented fast and rotate brief (ORB). Using linear filtering, the monocular SLAM scaling parameter is computed. Roghair et al.,2021 [37] proposed a deep reinforcement algorithm called Deep Q network for UAV object avoidance. UAV exploration of obstacle avoidance was improved using two methods a convergence-based and a guidance-based approach which is implemented in the 3D simulation environment. Compared to state of art methods, this secured two-fold improvement in avoiding UAV obstacles.

Wang et al., 2020 [38] developed deep-learning-based object detection, RGB-D information fusion, and Task Control systems (TCS) for UAV obstacle avoidance. The simulation results show the detection accuracy of CNN as 75.4% and the processing time of the single image is 53.33ms and it depends on the distance between the camera and the object. The outcome of this experiment indicates that the proposed system autonomously performs the obstacle avoidance policy and explores the minimum distance flight path according to RGB-D fusion information.

Guo et al., 2021 [39] proposed a circular arc trajectories method to avoid obstacles in UAVs. Using the onboard system, the obstacles that are irregular are detected. The circular arc trajectory for obstacle avoidance was generated using convex bodies. The suggested system can avoid both static and dynamic impediments in the route of the UAV, according to numerical simulation findings. Radmanesh et al., 2018 [40] did a comprehensive survey with the comparison of existing UAV path planning algorithms for heuristic and non-heuristic methods. To test the performance of the UAV path planning method, three kinds of obstacle layout has been used. They concluded that the Genetic algorithm secured low sensitivity to time and MSLAP secured the fastest solution.

Lee et al., 2021 [41] developed a deep learning-based monocular obstacle avoidance approach for UAV-based tree plantations using Faster Region-based Convolutional Neural Network (Faster R-CNN). Faster RCNN has been used here to train tree trunk detection. To avoid collision with trees, the control strategy is used. This can be used to travel the UAV in the safest area. The simulation has experimented with 11 flights in real tree plantations in two various locations. An evaluated result proves that the proposed system is accurate and robust.

Pedro et al., 2021 [42] proposed neural network pipelines and flow clustering-based collision avoidance on UAVs. This deep learning-based model is incorporated for real-time dynamic obstacle avoidance using off-the-shelf commercial vision sensors. A video dataset was created and made available. Transfer learning also tested and obtained positive results on computational processing and consumption of power. Yasin et al., 2020 [43] reviewed about the collision avoidance approaches used in UAVs. Various collision avoidance methods are explained with a comparative study based on different technical and scenario aspects. They also discussed about the sensors that may be used for efficient collision avoidance on UAVs. However, the reviewed object avoidance approaches are not applicable to small aerial vehicles due to the cost, weight, and energy consumption issues. Most UAV avoidance systems can support only static objects. To overcome these issues, the proposed evolutionary algorithm-based approach has been developed to support a robust object avoidance system that can support static and dynamic objects. In another study, UAV flight path planning was made to take into account how the particle swarm may be made to avoid obstacles. The use of swarm dynamics improves optimization difficulties. By explaining avoiding obstacles and modifying course planning for UAVs, this is meant. To avoid both static impediments, the idea of concurrent restructuring has been incorporated into the path design process. This optimization method seeks to save processing time and find the shortest path possible during path planning [59].

### 3 Proposed Methodology

This paper aimed to propose an object avoidance approach for real-time autonomous UAVs based on an evolutionary algorithm according to find the best path between UAV and object through object modeling. The overall schematic of the proposed system is shown in Fig 1. The object model is built with a waypoint path. Once the object model is built, the objects are detected. Detected objects are avoided using the proposed Floyd warshall enhanced with an optimization algorithm called the Differential Evolution approach. Using this approach, the shortest path between the origin and destination is found without obstacles. Once the path has been found without object then waypoint gets tracked for movement. Or else the objects are avoided by executing the object avoidance algorithm again. Once the waypoint path tracking ends the UAV also stopped.

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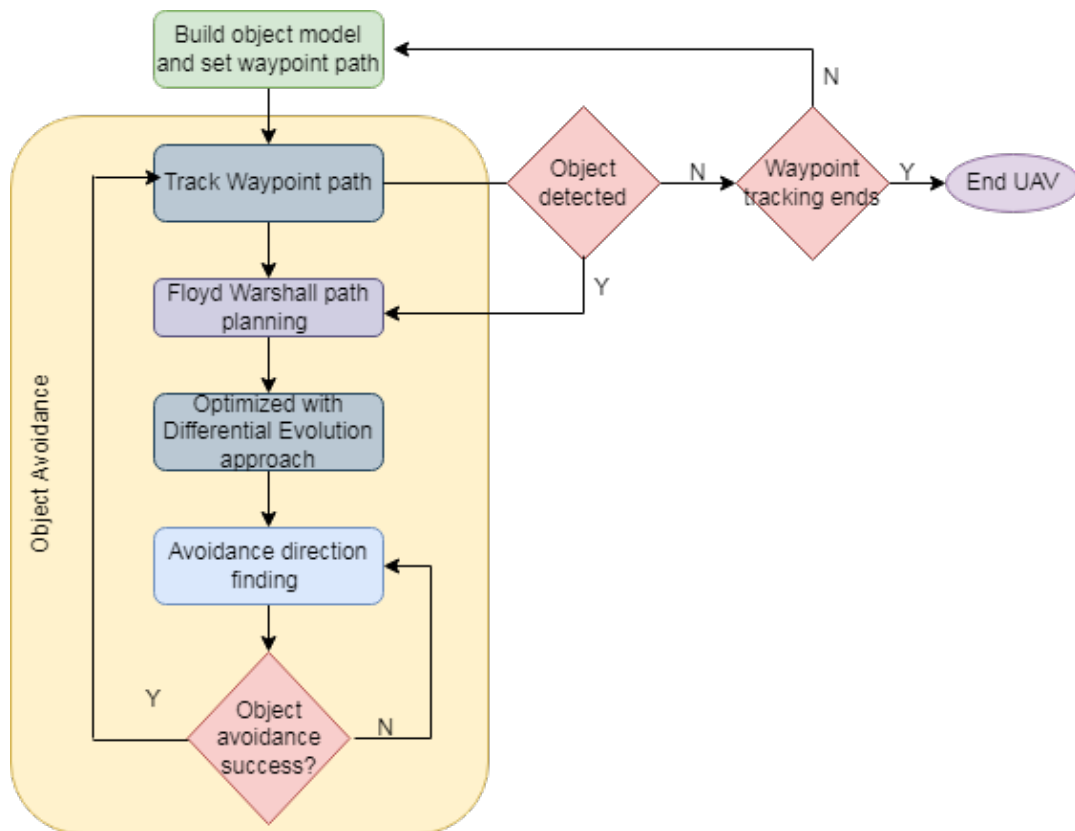


Figure 1: Proposed UAV guidance architecture

### 3.1 Mathematical modelling of Object avoidance

#### 3.1.1 Object modelling

When the UAV is flying, there are numerous potential things on the path, such as buildings, trees, and mountains. It's difficult to handle this irregular object directly, and the things recognized by the onboard sensors aren't complete. The complexity and efficiency of the object avoidance strategy will be harmed if you pay too much attention to finding the object shapes. Objects have the most round, square, and cylinder shapes based on the sampling sites observed by aircraft. For square objects, the location and sectors are classified and for a cylindrical object, the centre and radius give the objects information.

##### (i) Square Objects

From the laser scanning radar, one or two sides of the square objects can be seen at the same time. If one side of the object gets detected, then the object is located in one sector boundary. Vertical length is calculated by the shortest distance from the UAV's current position to the object side. The remaining two sectors' distance is declared as infinity. Figure 2 shows the square object detection with one boundary and two boundaries.

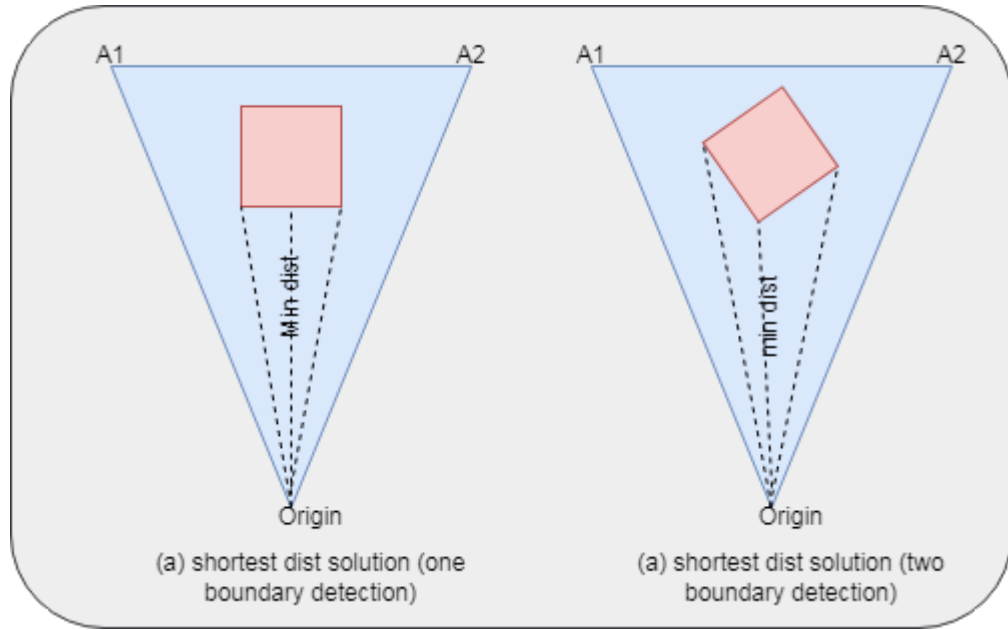


Figure 2: Square Object detection with shortest distance solution

When two boundaries of a square object are in the same sector, the distance between the two boundaries endpoints and UAV position are compared by the sensor. The minimum distance is considered as output. If there is any intersection between sectors and object boundary, need to find the distance between the terminal point and UAV’s current position of the sector with the intersection point. The value with less value is considered.

**(ii) Circle objects**

The circle objects with the sampling points are fitted using fitting algorithm such as least square method. For an object in circle shape, the radius  $r$  is calculated as in Equation (1) with the centers  $[O_x, O_y]$  T of an object as in Equation (2)

$$r = \frac{1}{2} \max_{i=1}^{n-1} \min_{j=1+1}^n \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{1}$$

$$\begin{bmatrix} O_x \\ O_y \end{bmatrix} = \frac{1}{2} \begin{bmatrix} x_{i,id} - x_{j,id} \\ y_{i,id} - y_{j,id} \end{bmatrix} \tag{2}$$

Where,  $(x_i, y_i)_{i=1,2,\dots,n}$  – convex hull of the sampling point,  $id$  – index value of Equation (1). Thus, the way the object in a circle shape is fitted and cover key parts or whole parts of the object. This will make the object avoidance algorithm easier to use. In certain circumstances, the UAV detects object models that are greater than the distance between the UAV and the item, while in others, the system is unable to capture the entire object or a crucial part of it due to its limitations. These cases are avoided with multiple circles have been used for larger objects as shown in Figure 3.

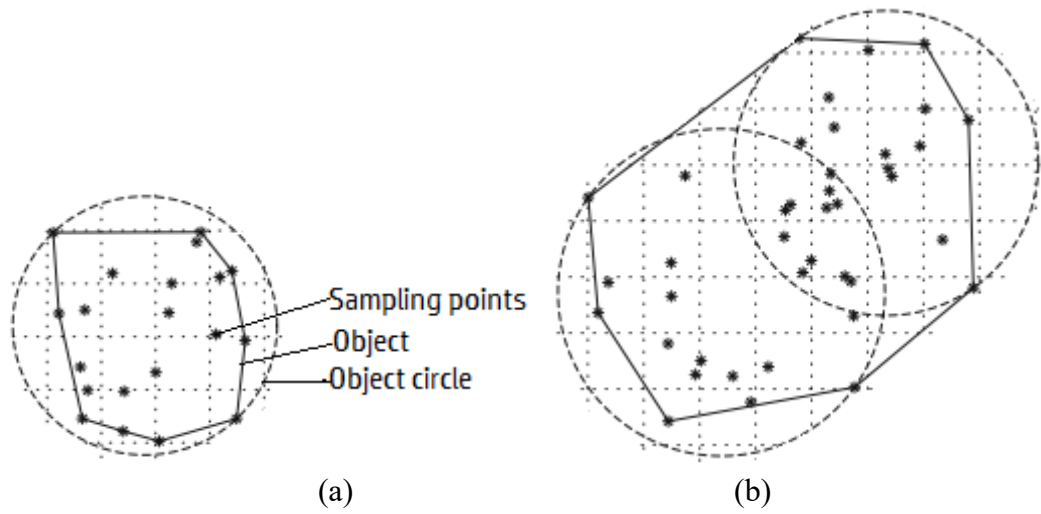


Figure 3: Object model of circle shape (a) simple circle object (b) complex circle object

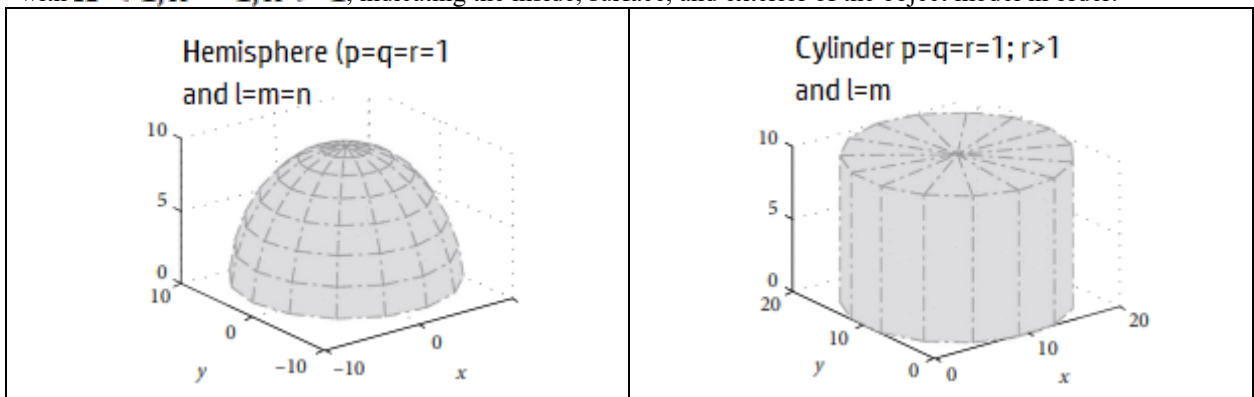
**(iii) Cylinder shape objects**

It is possible in some situations that an object has been modelled with other convex bodies such as cylinder, cone, hemisphere and circular table based on detection system. The computation for this kind of objects is expressed as in Equation (3) [39].

$$K = \left(\frac{x-x_c}{l}\right)^{2p} + \left(\frac{y-y_c}{m}\right)^{2q} + \left(\frac{z-z_c}{n}\right)^{2r} \tag{3}$$

Where, (x,y,z) – arbitrary points of the object, (x<sub>0</sub>,y<sub>0</sub>,z<sub>0</sub>) – coordinates of object center point, (p,q,r,l,m and n) – constant of shape and size of the object model. Figure 4 represents the various kinds of convex bodies of objects with  $K < 1, K = 1, K > 1$  indicates the inside, surface and outside of the object model sequentially.

The object model's shape and size remain fixed. Figure 4 depicts the several types of convex bodies of objects with  $K < 1, K = 1, K > 1$ , indicating the inside, surface, and exterior of the object model in order.



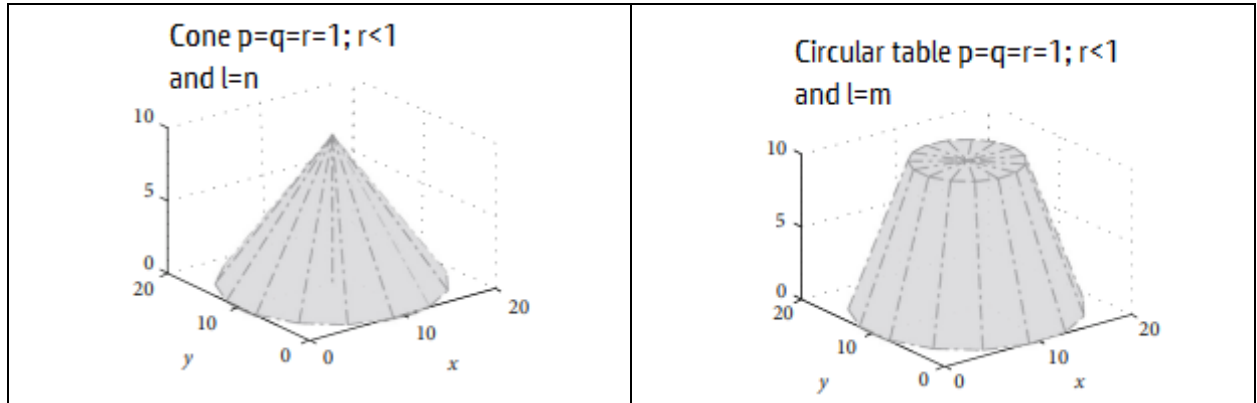


Figure 4: Various convex body of object models

Based on these object models, while UAV detect objects in its path simple objects are modelled with single convex body and complex objects are modelled with combination of various convex bodies. This model is implemented using the proposed object avoidance approach called Floyd–Warshall Differential evolution algorithm, based on this best path is find without obstacles.

### 3.1.2 Description of the difficulty of Object avoidance

This model considered the surface and inside of the object sector as no-fly zone or threat zone that is  $K > 1$ . The problem of UAV object avoidance is described by how to keep UAV outside of no-fly zone during the travel.

Assume the UAV mission as  $M$ ,  $M_t$  is a threatened or object area that is  $K \leq 1$  and  $M_s$ - safety area that is  $K > 1$ . The relationship between safety and threaten zone are declared as in Equation (4). The UAV waypoint path to target is expressed as in Equation (5).

$$\begin{cases} M = M_t \cup M_s \\ M_s \cap M_t = \emptyset \end{cases} \quad (4)$$

$$W = W_{target} + \cup_{i=1}^m W_{avoid}^i, W_{avoid}^i = \{K > 1\} \quad (5)$$

Where, m- number of objects,  $W_{target}$ - UAV target path,  $W_{avoid}^i$  - object avoid at stage i.

### 3.2 Proposed Floyd–Warshall Differential evolution (FWDE) object avoidance algorithm

The key idea of FWDE is transform the object avoidance problem as path palling problem based on the swarm searching behaviour of UAV towards object. This approach is contrary to the standard path planning approach called potential field approach where continuous and differential, the FW use pre-declared discretized cells to find the path. FW can obtain shortest path using weighted graph where each cell has its own weight and cost. Rather than the traditional weighted graph associates cell cost or weight [44], FW associates negative and positive edge weights. Vertex of the graph represent environment physical space and edge represents the distance between two vertices. FW can solve all paths shortest problem (APSP) and can be suited for offline path planning and not good for dynamic path planning [45]. The other variance of FW in [46] shows robustness performance for location problem. The main objective of FW is to minimize the Equation (6) for shortest path finding from vertex i to vertex j from the set 1,2,...,p as the intermediate points. p is the possible points that an UAV can cover [47, 48].

$$P(i, j, p + 1) = \min (P(i, j, p), P(i, p + 1, p) + P(p + 1, j, p), where P(i, j, 0) = w(i, j) \quad (6)$$

To make FW as dynamic path planning approach, it has been optimized with evolutionary algorithm called Differential Evolution (DE). This FW with DE provides the path planning of UAV as efficient from initial to target points which is connected using virtual x-axis. Based on the count of waypoint in UAV path, virtual x-axis is divided into intervals of same number and form virtual y axis at same interval. This proposed FW-DE approach can optimize the path planning and the computational time. DE was first proposed by Storn and Price [49]. There are five parameters in DE approach. They are maximum generation number, length of waypoints, weight (differential), population size and crossover. While increasing the generation number, the solution may evolve.

This solution length will decide the system complexity and also weight, crossover and population size will change the performance. This approach can decide the population size, crossover and differential weight with FW to optimize the parameters. So that, UAV can move in a safe path with sufficient energy in the map. At each coordinate of waypoint, the UAV can also maintain 100 m distance from the ground. The standard cost function is defined in Equation (7)

$$C = \sum_{i=1}^W l_i \quad (7)$$

Where, W- number of waypoints and l- length of previous and current location of UAV. It is similar to Genetic algorithm and involves the steps such as selection, crossover and mutation with different sequence. The population initialization started with random individuals in the search space. This population goes to mutation and individual  $V_i^{g+1}$  is generated as in Equation (8) [50-54].

$$V_i^{g+1} = x_{h1}^g + DW(x_{h2}^g - x_{h3}^g)h1 \neq h2 \neq h3, i = 1, 2, \dots, N \quad (8)$$

Where x – individual in the population  $h \in (1, N)$ , g – number of iteration or generation, N – size of the population and DW – differential weight. Based on the probability of crossover, not all the individuals in the mutation used for next iteration. Trial individual in the population called  $u^{g+1}$  is produced by the crossover operation with the condition stated in Equation (9)

$$u_{ij}^{g+1} = \begin{cases} V_{ij}^{g+1}, r_{ij} \leq \text{crossover} \\ x_{ij}^g \text{ otherwise} \end{cases} \quad (9)$$

Where  $j=1,2,\dots,D$ ,  $r_{ij}$ - random value lies between 0 and 1 for jth particle of ith individual. For selection process, this trial population is forwarded. Compare to GA, DE selection process compares trial and current population. Individual with lowest cost found in Equation (6) will replace the current population individual as in Equation (7). The process is repeated until termination condition met from mutation and selection.

$$x_i^{g+1} = \begin{cases} u_i^{g+1}, f(u_i^{g+1}) \leq f(x_i^g) \\ x_i^g \text{ otherwise} \end{cases} \quad (7)$$

The algorithmic steps of FWDE is as follows.

**Algorithm: FWDE object avoidance**

Input: Population initialization, maximum iteration (max).

Output: Best possible path for UAV without object

Step 1: while (t<=max)

Step 1: for each vertex v in the graph do

Step 2: distance (v,v) ← 0

Step 3: end

Step 4: for p in the cells of map do

Step 5: for i in the cells of map do

Step 6: for j in the cells of map do

Step 7: if (dist(i,j) > dist(i, p)+dist (p, j)) then

Step 8: x= dist(i,j) ← dist(i,p)+dist(p,j)

Step 9: end

Step 10: end



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Step 11: end
Step 12: end
Step 13: Mutation using Equation (8)
Step 15: Crossover using Equation (9)
Step 16: Selection using Equation (10)
Step 17: t=t+1
Step 18: end while

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## 4 Results and Discussion

This section describes about the evaluated results using proposed object avoidance algorithm implemented using Matlab. This proposed approach used UAV-viewed dataset [55] for object detection for simulation of object avoidance. Based on the type of object models and number of waypoints the evaluation is carried and the results are discussed. The data collection contains 50 video sequence of 70250 frames with the frame rate of 30 frames per second. A GoPro3 camera sensor is installed in the aircraft to capture the action. The target UAV in every movie is varies with appearance and shape. The dataset is split in 80:20 as training and testing dataset. The sample and object detected video frames are shown in Fig 5.

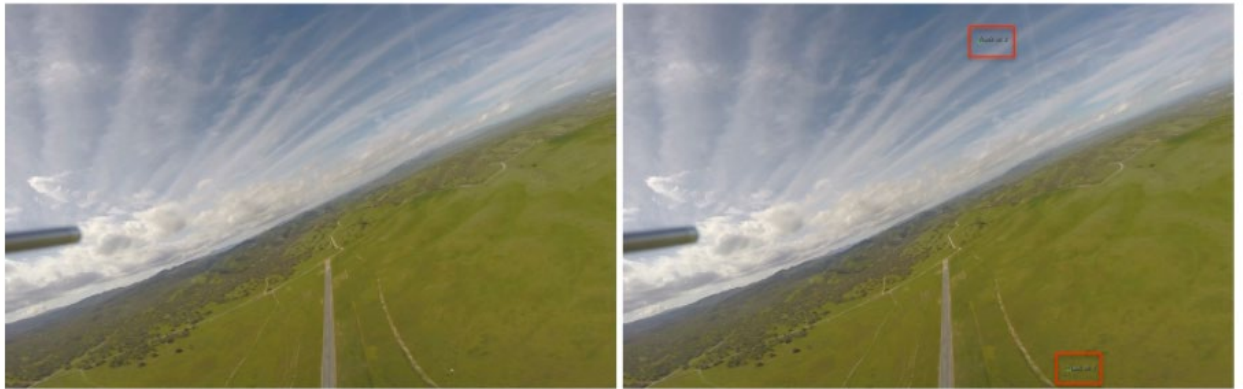


Figure 5: Sample video frame (left) and detected objects (right)

Evaluation of proposed object avoidance approach is carried with three object models in terms of computation time and optimal solution. This comparative analysis will differ in terms of different kind of scenarios based on object shape and complexity. Fig 6 shows the optimal path of three objects using proposed algorithm. Each object layout experiences cell with different resolution and the scenario is Scenario 1 – 900 cells, Scenario 2 – 90,000 cells and Scenario 3 – 9000000 cells. This will help to analyze the scalability of the proposed approach. The proposed approach is executed at three times and average outcome is tabulated. The error values of this execution is computed using Equation (8) and worst case results for the algorithm is calculated based on this error value.

$$E = \frac{\text{lengthofpath} - \text{optimalpathlength}}{\text{optimalpathlength}} \times 100 \quad (8)$$

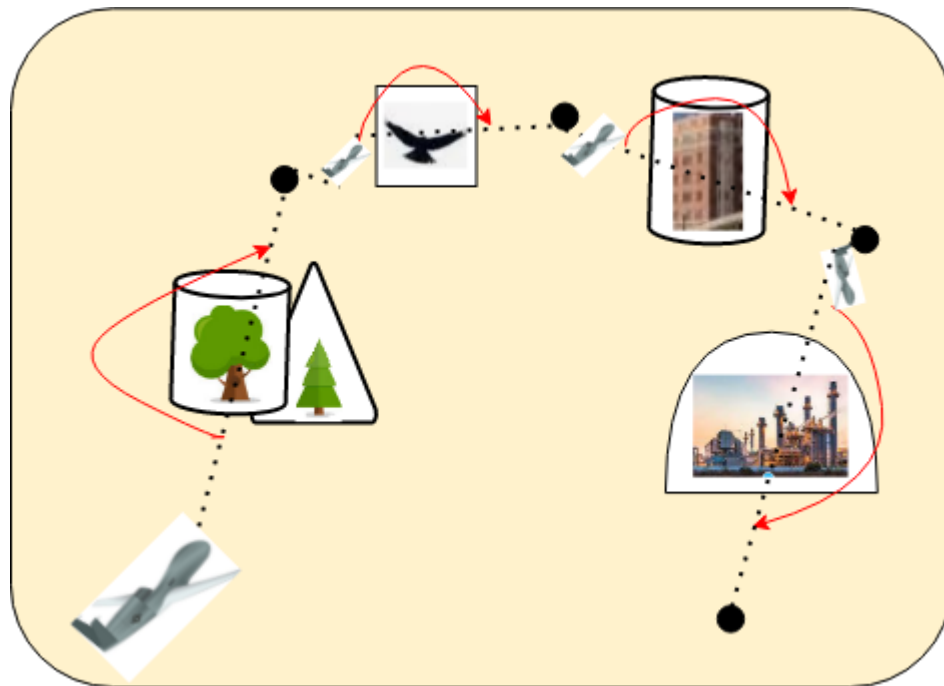


Figure 6: Simulation illustration of UAV avoid objects using proposed FEDE with three object models  
**4.1 Object layout 1 (Square shape objects)**

The algorithmic output of the first layout of square object layer is shown in Table 1 with the comparison to existing approaches such as Circular Arc Trajectory Geometric Avoidance (CTGA) [39], Floyd Warshall, fuzzy logic [25] based UAV object avoidance. The maximum error obtained by Floyd Warshall algorithm compared to other approaches of 1.4% and time as 2.53seconds. The standard deviation (std) of proposed work is 0.0031. The proposed FWDE approach secured minimum error percentage of 0.0012% and avoids the objects with less time as 0.2341seconds. compared to other approaches, proposed model performance is superior to other approaches in terms of Error, computation time and standard deviation. This demonstrates that the proposed system is more efficient than alternative methods. In Figure 7, the error value comparison of object layout 1 is illustrated. This graph illustrates that proposed FWDE secures minimum error for all the scenarios with different cells.

Table 1: Object avoidance methods comparison in terms of computation time and error for object layout 1

Methods	Scenario 1			Scenario 2			Scenario 3		
	CT (s)	Error (%)	Std	CT (s)	Error (%)	Std	CT (s)	Error (%)	Std
CTGA	1.4301	0.912	0.035	7.5261	3.12	0.0453	1029.12	3.152	0.0461
Floyd Warshall	2.5351	1.431	0.0367	11.8928	6.342	0.0426	5981.929	5.925	0.0418
Fuzzy logic	3.7124	0.9913	0.0389	8.2913	5.827	0.0371	3293.11	4.203	0.0397
<b>Proposed FWDE</b>	<b>0.2341</b>	<b>0.0012</b>	<b>0.0031</b>	<b>6.0283</b>	<b>0.011</b>	<b>0.0034</b>	<b>541.92</b>	<b>0.0101</b>	<b>0.0035</b>

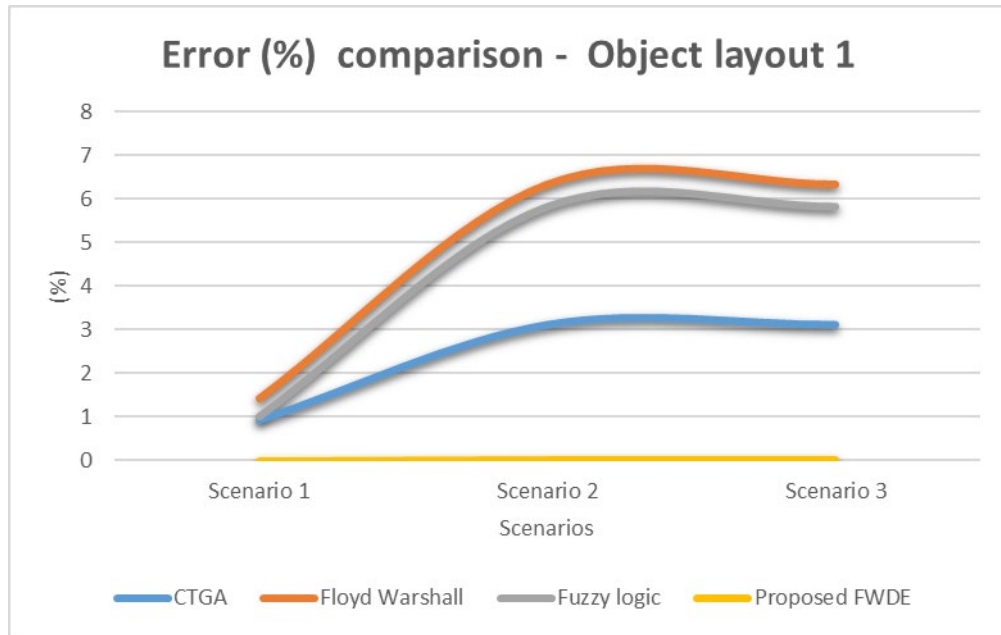


Figure 7: Error value comparison of UAV object avoidance methods – object layout 1

**4.2 Object Layout 2 (Cylinder shape objects)**

The algorithmic output of the second layout of square object layer is shown in Table 2 with the comparison to existing approaches such as Circular Arc Trajectory Geometric Avoidance (CTGA) [39], Floyd Warshall, fuzzy logic [25] based UAV object avoidance. The maximum error obtained by Floyd Warshall algorithm compared to other approaches of 1.53% and time as 6.3352 seconds. The proposed FWDE approach secured minimum error percentage of 0.0002% and avoid the objects with less time as 0.4342seconds with reduced standard deviation. This demonstrates that the proposed system is more efficient than alternative methods. The error value comparison of object layout 2 is shown in Fig 8. This graph illustrates that proposed FWDE secures minimum error for all the scenarios with different cells.

Table 2: Object avoidance methods comparison in terms of computation time and error for object layout 2

Methods	Scenario 1			Scenario 2			Scenario 3		
	CT (s)	Error (%)	Std	CT (s)	Error (%)	Std	CT (s)	Error (%)	Std
CTGA	4.6302	0.8122	0.0352	11.5211	5.11	0.0411	1221.11	4.112	0.0352
Floyd Warshall	6.3352	1.533	0.0412	16.8921	7.342	0.0397	6982.92	5.181	0.0462
Fuzzy logic	5.7114	1.2313	0.0356	10.2213	6.871	0.0381	5291.12	5.131	0.0472
<b>Proposed FWDE</b>	<b>0.4342</b>	<b>0.0002</b>	<b>0.0025</b>	<b>8.0281</b>	<b>0.0012</b>	<b>0.00288</b>	<b>623.81</b>	<b>0.0111</b>	<b>0.0362</b>

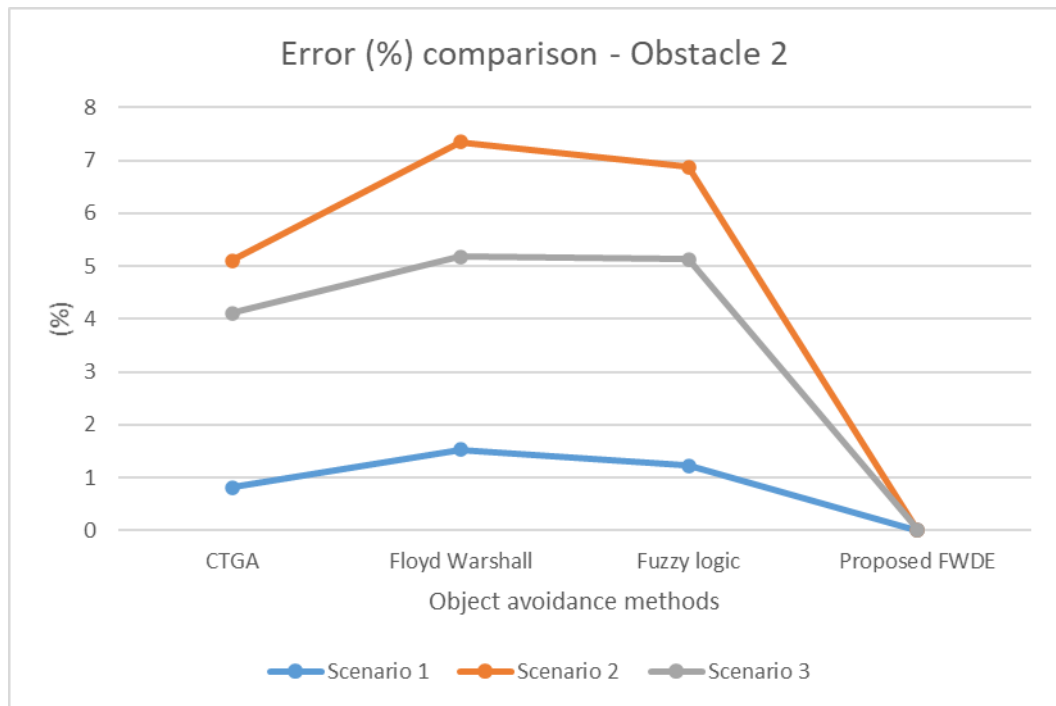


Figure 8: Error value comparison of UAV object avoidance methods – object layout 2

#### 4.3 Object Layout 3 (Circle, Hemisphere shape objects)

The algorithmic output of the third layout of square object layer is shown in Table 3 with the comparison to existing approaches such as Circular Arc Trajectory Geometric Avoidance (CTGA) [39], Floyd Warshall, fuzzy logic [25] based UAV object avoidance. The maximum error obtained by Floyd Warshall algorithm compared to other approaches of 1.23% and time as 6.29seconds. The proposed FWDE approach secured minimum error percentage of 0.0001% and avoids the objects with less time as 0.38121seconds and reduced standard deviation. This demonstrates that the proposed system is more efficient than alternative methods. The error value comparison of object layout 3 is shown in Fig 9. This graph illustrates that proposed FWDE secures minimum error for all the scenarios with different cells.

Table 3: Object avoidance methods comparison in terms of computation time and error for object layout 2

Methods	Scenario 1			Scenario 2			Scenario 3		
	CT (s)	Error (%)	Std	CT (s)	Error (%)	Std	CT (s)	Error (%)	Std
CTGA	4.1271	1.8211	0.042	11.1281	5.82	0.038	1212.131	4.152	0.037
Floyd Warshall	6.2912	1.2312	0.043	16.2631	6.231	0.037	6837.221	5.625	0.036
Fuzzy logic	5.1121	1.4123	0.038	10.2121	5.311	0.032	5592.15	4.727	0.039
<b>Proposed FWDE</b>	<b>0.3812</b>	<b>0.0001</b>	<b>0.003</b>	<b>8.1271</b>	<b>0.0011</b>	<b>0.0028</b>	<b>589.287</b>	<b>0.00142</b>	<b>0.0028</b>

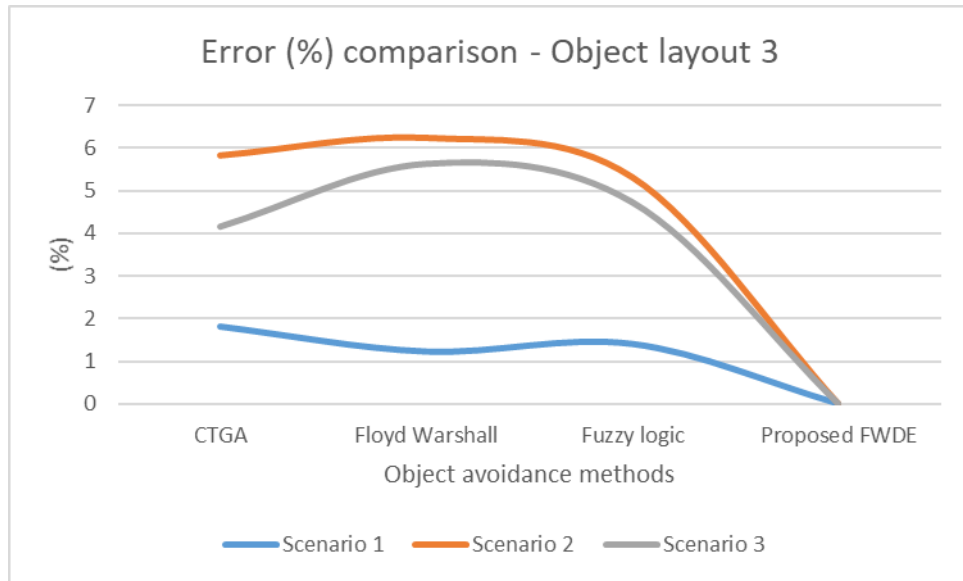


Figure 9: Error value comparison of UAV object avoidance methods – object layout 3

The evaluated results using various object avoidance approaches applied on three object layers as per the simulation. While problem complexity increases, the computation time also increases [56]. In the existing studies, the algorithms such Floyd Warshall, fuzzy logic were consuming more time to find the object path while size of the problem increased [57]. With the implementation of evolutionary algorithms, the consuming time and error rate are decreased, and objects are avoided which helps the UAV to travel in safety path. The parameter setting of DE also plays vital role to find the objects in front of UAV. The optimal parameter of DE for maximum generation of 1000 is shown in Table 4.

Table 4: Optimized parameter settings at various generation number

Generation	200	400	600	800	1000
Population	34	36	38	39	40
Weight	0.11	0.12	0.12	0.14	0.14
Crossover (%)	64	51	40	31	26

The evaluated computation cost and error of three object layouts after parameter settings is shown in Table 5 for scenario 1. The optimized parameter setting of the execution of proposed system will decrease the computation cost, error percentage and standard deviation.

Table 5: computation time and error comparison of three layouts for scenario after optimized parameter settings

Methods	Object layout 1			Object layout 2			Object layout 3		
	CT (s)	Error (%)	Std	CT (s)	Error (%)	Std	CT (s)	Error (%)	Std
CTGA	0.4311	0.6021	0.028	3.3102	0.621	0.0323	3.1722	1.8211	0.034
Floyd Warshall	1.5151	1.1311	0.0276	5.1316	1.033	0.0372	5.2122	1.2312	0.026
Fuzzy logic	2.1124	0.8132	0.0341	4.6141	1.113	0.0289	4.1013	1.4123	0.032
<b>Proposed FWDE</b>	<b>0.1341</b>	<b>0.0001</b>	<b>0.00276</b>	<b>0.3121</b>	<b>0.0001</b>	<b>0.00312</b>	<b>0.2812</b>	<b>0.0001</b>	<b>0.0021</b>

The accuracy and recall of avoiding the objects in the path of UAV is evaluated and the results are shown in Fig 10 using the Equations (9) and (10). True positives (TP) are a collection of successfully identified things, whereas false positives (FP) are a group of wrongly discovered objects [58].

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

The set of items that the detector does not detect is referred to as false negatives (FN). The value of recall is then calculated by dividing the number of detected items (TP) by the total number of data set objects as follows:

$$Recall = \frac{TP}{TP+FN} \tag{10}$$

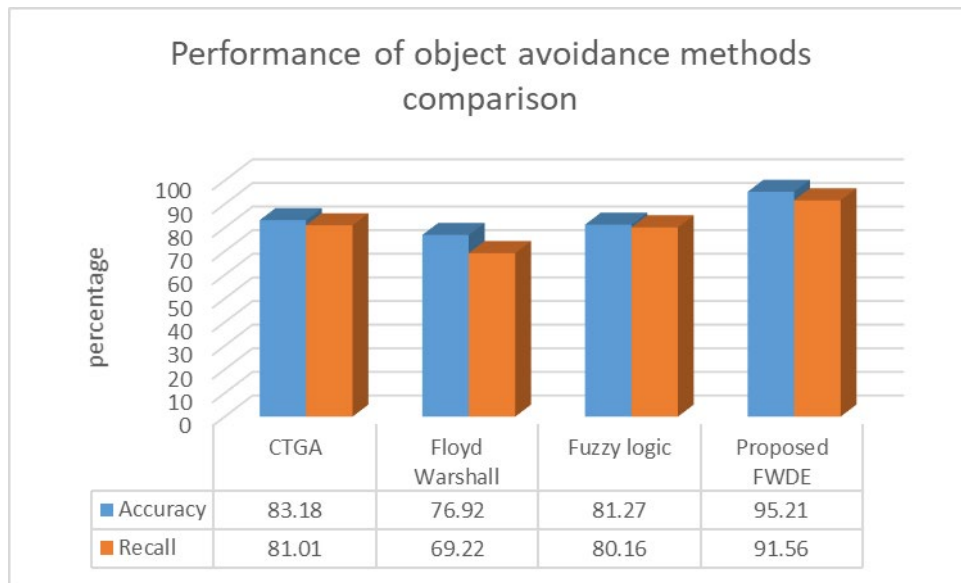


Figure 10: performance comparison of proposed vs existing approaches in terms of accuracy and recall

From the illustration of Fig 8, the proposed FWDE secures improved accuracy on avoiding the objects in the aircraft path compared to other traditional approaches. FWDE secures the accuracy and recall of 95.21% and 91.56%. Various the other approaches such as CTGA, Floyd Warshall and Fuzzy logic obtained 83.18%, 76.92% and 81.27% sequentially.

**4.4. Statistical Analysis**

After analysing the performance of the proposed model, the statistical analysis of the proposed FWDE model is performed. Table 6 shows the Friedman Test results that shows the global ranking of the considered models. The proposed FWDE leads the ranking compared to other approaches. The p value of the Friedman test is less than 0.0001 and the null hypothesis are rejected.

Table 6: Friedman test ranking

Methods	Rank
CTGA	2.12
Floyd Warshall	3.62
Fuzzy logic	3.87
<b>Proposed FWDE</b>	<b>1.02</b>

Once, the statistical difference between the methods is verified, the Holm’s post hoc analysis is performed. We set FWDE is the best method and compared it with the other approaches. The p value and Holm’s adjusted  $\alpha$  are

showed in Table 7. From these values, the null hypotheses are rejected and the p value is smaller than  $\alpha$ . Therefore, it stated that there is statistical difference between the proposed and existing models. The proposed model obtained the best result for our experiments.

Table 7: Holm's Post hoc Analysis

Methods	p	z	Holm $\alpha$
CTGA	0.0016	5.256	0.0346
Floyd Warshall	0.0019	6.287	0.0562
Fuzzy logic	0.0018	7.291	0.0352
<b>Proposed FWDE</b>	<b>0.0001</b>	<b>8.253</b>	<b>0.0100</b>

Holms analysis is performed on final results on selected paths are good or bad over each other path comparison. The raw value is assumed as p-value and selected with smallest value for adjustment. After adjusting the p-values, the number which is biggest is taken for consideration. In CTGA, Floyd warshall, fuzzy logic, post hoc Holm analysis, the selected final paths are compared, p adjustment is 0.0016, .0019,.0018 and statistical analysis z is 5.25, 6.28,7.29, Holm values (probability of least 1 error rate) is 0.0346,0.0562,0.0352 which higher than proposed Holm value of 0.0100. This shows proposed path prediction obtains less error rate.

## 5 Conclusion

A novel autonomous object avoidance algorithm called Floyd Warshall with Differential Evolution (FW-DE) for UAVs has been proposed and discussed in this paper. Initially, the object model is derived based on the shape of objects based on convex bodies such as circle, square, cylinder and more shapes of the object detected. The proposed algorithm is implemented with this object model that not only transforms the object avoidance as path planning but also simplifies the avoidance problem. The developed model is suitable for static and dynamic objects according to the geometric relationship between UAV and objects. The evolutionary algorithm can improve the performance of Floyd warshall avoidance to obtain less computation time, error and improved accuracy. This efficient avoidance algorithm for UAV can be experimented with simulation environment with three kinds of scenarios having different number of cells. For object layout 1, the proposed algorithm secured the time of computation as 0.2341s, 6.0283s and 541.928s for scenario 1, 2 and 3. It is suitable for practical engineering. Likewise, the proposed system is evaluated in object layer 2 and 3. The accuracy and recall value of proposed system is 95.21% and 91.56%. Our future work includes applying the simulation environment into real UAV tests.

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