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Comparison of 3D Versus 4D Path Planning for Unmanned Aerial Vehicles

Halil Cicibas[!], Kadir Alpaslan Demir[@,*], and Nafiz Arica[#]

[!]*Graduate School of Informatics, Middle East Technical University, Ankara, Turkey*
[@]*Turkish Naval Research Center Command, Istanbul, Turkey*
[#] *Graduate School of Applied and Natural Sciences, Bahcesehir University, Istanbul, Turkey*
[*]*E-mail: kadiralpaslandemir@gmail.com*

ABSTRACT

This research compares 3D versus 4D (three spatial dimensions and the time dimension) multi-objective and multi-criteria path-planning for unmanned aerial vehicles in complex dynamic environments. In this study, we empirically analyse the performances of 3D and 4D path planning approaches. Using the empirical data, we show that the 4D approach is superior over the 3D approach especially in complex dynamic environments. The research model consisting of flight objectives and criteria is developed based on interviews with an experienced military UAV pilot and mission planner to establish realism and relevancy in unmanned aerial vehicle flight planning. Furthermore, this study incorporates one of the most comprehensive set of criteria identified during our literature search. The simulation results clearly show that the 4D path planning approach is able to provide solutions in complex dynamic environments in which the 3D approach could not find a solution.

Keywords: Unmanned aerial vehicles, UAV, path planning, modelling, simulation, 3D path planning, 4D path planning

1. INTRODUCTION

Unmanned aerial vehicles (UAVs) have found many uses in both military and civilian operations. The application areas include surveillance, patrol, search and rescue, package transportation, etc. Although many researchers from different disciplines have made significant improvements in the development of these systems[6], new challenges emerge as UAV-involved missions and operations become complex.

An important research area is enabling UAVs with autonomous path planning. There are quite a number of studies, such as[2,18,19,21], that use a 2D or 3D approach in autonomous path planning. There are also some studies[5,15-17] using time dimension in addition to the spatial dimensions. In the studies using a 4D approach, although the researchers emphasize the superiority of the 4D approach, they do not support the superiority with an empirical comparison of their 4D approach with a 3D approach. In this study, our goal is to fill this gap by comparing 3D and 4D UAV path planning approaches. Unlike many studies either focusing on 3D or 4D, this research analyses simulation results obtained from both 3D and 4D path planning simulations. Our investigation yields that 3D autonomous path planning is inadequate especially if the environment is complex and dynamic. As a result, we contribute to the current literature by providing an empirical comparison of 3D and 4D (spatial and temporal) simulation of UAV path planning in complex dynamic environments consisting of an extensive set of criteria using different flight objectives.

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During the study, it is observed that the inadequacy of the 3D path planning reveals itself when the environment is dynamic and complex. A complex dynamic environment is the one that includes many constraints with different characteristics and various mission, flight, and environment related requirements. Even though, studies in autonomous path planning[1,3,20,21,32-51] address many challenges, domain-specific operational issues, such as utilisation considerations and aviation rules, did not receive adequate attention. This is important if the UAV under study is a medium altitude high endurance (MALE) UAV, because these types of UAVs are subject to aviation rules in addition to other criteria. There are different requirements and constraints for different types of UAVs. Naturally, a MALE UAV has different characteristics and requirements compared to a micro UAV has. In this study, the research model, consisting of mission criteria and objectives, is developed-based on the interviews with an experienced UAV pilot and mission planner to ensure the realism and relevancy of our research to UAV flight planning.

Realistic simulation models are essential for UAV research. Realism is achieved not only by modelling the UAV but also by modelling the environment. In previous studies[22-26], we discussed that modelling the operational environment is as important as modelling the UAV. In other studies[27,28] to take the realism a step further, we equipped the UAV with a ranged sensor limiting the knowledge of the UAV about the environment. Furthermore, we showed that these models are modular, therefore reusable for different studies for different purposes[29].

To aid UAV path planning, we developed a simulation model used to create flight paths in 4D environment. The simulation model is more applicable and realistic compared to other studies examined during the literature review. The study includes the most comprehensive set of requirements including the ones overlooked in a wide range of studies. This study extends existing literature[1,3,20,21,32-51] by placing a special importance on aviation rules and utilisation considerations. The model generates suitable paths that address UAV performance limitations, environmental factors, basic aviation rules, flight dynamics, UAV utilisation considerations and user requirements. It helps in online and offline planning of optimal paths based on distance, fuel consumption, or time objectives, while implementing the described flight criteria. To build the simulation model (SM), we first built a conceptual model (CM) to structure the problem[68]. In the simulations, for each objective, various scenarios are created by changing the number of static and dynamic obstacles and target types. In each scenario, the path planning approach found the shortest and least costly flight paths. The path search is performed by A* heuristic algorithm proven to be complete and optimal. Additionally, in the experiments, A* algorithms with different heuristic parameters are compared using various scenarios in static and dynamic environments under different constraints. Since current UAVs have to make predictions and estimations about the possible future locations of mobile objects, the simulations also include path searches in time varying environments represented with a 4D grid. The 4D grid is constructed using a combination of 3D grids. Each 3D grid is a possible configuration of the world space at a specific time. A time-dimensional search space considers dynamic elements and changing factors in an operational environment.

2. LITERATURE REVIEW

The UAV path planning problem is a type of vehicle motion planning problem under differential constraints. This problem is significantly different from the problems related to traditional mobile vehicles and manipulator robots[11]. A previous study[12] defines the 'UAV path planning problem' as 'a multi-objective decision making problem that takes into account of mission efficiency, flight rules, flight limitations, operational constraints, and environmental conditions'.

In UAV path planning studies, world space is a physical space containing the UAV, the start location, the target or goal location, and the obstacles defined for this world. The physical space is basically divided into two main regions: free-space and obstacle space. Obstacle space are the regions filled with obstacles[13,14] or a set of points leading to a UAV collision with the obstacle[7]. A 'configuration' is a vector of parameters that defines the shape of the UAV in the world space. The configuration coupled with its rate of change is called a 'state'.

The constraints that must be satisfied in the path-planning problem are generally divided into two main groups: motion and environmental. The motion constraints consist of maneuver limitations of the UAV such as turn, climb, and acceleration rate. The environmental constraints include physical obstacles, restricted areas, and meteorological factors such as clouds or winds. In the paper, the terms, 'flight objective' and 'flight criteria', are used instead of the common term, 'constraints'.

Planning methods in the robotics domain fall into two groups: sample-based planning and combinatorial planning[14]. Although combinatorial planning methods are complete and optimal, they are impractical for solving real problems because of their computational complexity[14]. Furthermore, the computation times of combinatorial algorithms also grow quickly with the number of primitives in the obstacle and configuration space[53]. Therefore, sampling-based planning emerges as a suitable way in motion planning with its practicality, simplicity, and efficiency in multi-dimensional environments. In this study, sampling based planning is chosen because of its applicability.

Grid based sampling is a well-known sampling method in which each cube of the grid refers to a point in the world space. Grid based sampling decomposes the space into arrays of cells that represent the obstacles and free space in the world space[56]. The possible connections between these cells construct a search graph in which search algorithms traverse for solutions. Multi-resolution techniques[54-56] are commonly used to reduce the complexity of a graph. In addition, decomposition methods are also used to reduce the number of samples in the generated graph by dividing the world space into regions[30,31].

UAV path planning studies addresses multiple flight objectives under several flight criteria[12,20,21,32-51]. In this study, we try to address an extensive set of criteria (see Table 1) in online path planning by implementing multiple constraints to provide more effective and safer UAV paths. We defined cloud criteria and implemented cruise level rule, air classes, mobile targets, and approach angle in addition to the criteria used commonly in earlier studies. Moreover, the target is mobile to make the model more realistic.

In addition to the studies presented in Table 1, there are also cognitive-based studies[4,66-72] that aim to manage challenges between human and command and control (C2) systems in UAV domain. Several researchers highlighted human factors on C2 systems to increase the effectiveness of UAV operations. Focusing on dynamic UAV route re-planning during missions[67-69], allocating air space[66,70], and 3D space perception[71-72] are some of the research areas in human controlled UAVs.

3. CONCEPTUAL MODEL

3.1 World Space Representation

In the study, the operational environment is modeled using a classic grid sampling method[5] in which samples are represented by a cube or an instance in the world space. Each sample includes data relating to the operational environment such as wind speed and geographic location. UAV flight performance parameters and manoeuver limitations determine the size of the sample cubes. Horizontal and vertical length of sample cubes are determined based on the turn radius and ascend/descend angle of real UAVs. Vertical distances are determined based on the climb and descent angle of the aircraft. In the model, using realistic UAV flight performance limitations is important for two reasons. First, it increases the realism. Second, it prevents generating unnecessary samples and reduces computation time while ensuring collision-free paths.

Table 1. Overview of related path planning studies

Flight Criteria \ Authors	Sinopoli[47], *et al.*	Yang & Kapila[51]	Nikolos[20], *et al.*	Zheng[49], *et al.*	Pfeiffer[33], *et al.*	Tooroella[38]	Petterson& Doherty[40]	McManus[35], *et al.*	Qu[50], *et al.*	McGee & Hedrick[45]	Kim[32], *et al.*	Ma[17], *et al.*	Ceccarelli[46], *et al.*	Mittal[48]	Lamont[34], *et al.*	Helble & Cameron[39]	Ruz[41], *et al.*	Cruz[43], *et al.*	Gonzalez[42], *et al.*	Wu[12], *et al.*	Xia[36], *et al.*	Qi[21], *et al.*	Jun[37], *et al.*	Authors Study
Geographical structure	✓		✓	✓			✓	✓				✓		✓	✓			✓	✓	✓	✓	✓		✓
Buildings and architectures	✓						✓	✓								✓	✓							✓
Treated zones	✓	✓		✓				✓	✓		✓	✓						✓		✓	✓	✓	✓	✓
Above ground level rule				✓	✓		✓	✓						✓				✓	✓	✓		✓		✓
Air classes								✓											✓	✓				(1)
Cruise level rule																				✓				✓
Mobile objects	✓		✓	✓*			✓	✓			✓*					✓	✓*	✓*		✓				✓
Cloud																								✓
Mobile targets		✓								✓			✓			✓								✓
Mobile threats	✓	✓	✓	✓							✓						✓	✓		✓				✓
Wind						✓				✓		✓	✓							✓				✓
Space dimension	3D	2D	3D	3D	2D	3D	3D	3D	2D	2D	3D	2D	2D	3D	3D	3D	3D	3D	3D	3D	3D	3D	2D	3D
Approach angle				✓																				(2)
Flight dynamics		✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓		✓		✓
Icing						✓																		(3)
Flight objectives																								
Distance	✓	✓	✓	✓		✓		✓	✓		✓			✓	✓	✓		✓	✓	✓	✓	✓	✓	✓
Time				✓	✓		✓	✓		✓	✓	✓	✓	✓			✓	✓		✓				✓
Fuel consumption				✓		✓		✓				✓					✓	✓		✓				✓
Risk/threat			✓	✓	✓				✓		✓	✓		✓	✓		✓	✓		✓	✓	✓	✓	(4)
Path smoothness			✓																				✓	(3)
Hidability				✓	✓										✓			✓						(4)

* Referred as pop-up elements, (1)Environment is close to air traffic,(2) Assumed no need to approach angle, (3) Approximated, (4) Never enter risky zones

The path planning of a moving UAV in a dynamic environment can be simply performed by applying a search at each location of the UAV in a 3D grid iteratively. After each UAV move on the previously calculated path, the path is recalculated on the updated grid regenerated due to the changes in the operational environment. This process is repeated iteratively until the vehicle reaches the goal state. Even though, this approach seems to run fast, it does not investigate the future status of the search space. As a result, it generates inconsistent and non-optimal paths in dynamic environments. At each iteration, the search algorithm calculates the path based on the current location of moving objects in the environment. Therefore, it might not find optimal solutions.

The CM developed aims at creating least cost paths in time varying environments represented by a 4D grid (3 spatial 1 time dimension). 4D grids consist of future status of mobile objects in the operational environment. 3D grids, each of them can be defined as an instant status of world space in a time moment, form a 4D grid. A time interval (Δt) between two instances is determined by the UAV performance specifications. The time interval is measured as the time elapsed during the travel from one node to another in the search tree.

In the estimation process, it is assumed that UAV has the ability to sense and detect the mobile objects and their movement during flight time (online) planning. In our CM, mobile objects move with constant speed on a steady course. Their future location $(l_m^{'})$ are calculated using the mobile object speed (v_m), time interval (Δt) between two instances and the current location of mobile object (l_m).

$$\Delta d = v_m \times \Delta t \quad (1)$$

$$l_m^{'} = l_m + \Delta d \quad (2)$$

The generation of the 4D grid and path planning processes can be summarised with the following steps (Fig. 1):

Step 1	Detect the movements of mobile objects and sense environmental factors
Step 2	Estimate the future locations of mobile objects
Step 3	Load the estimated data into the 3D grids based on its time instant
Step 4	Combine 3D grids and generate a 4D grid
Step 5	Calculate the least cost path using 4D grid
Step 6	Proceed one node forward on the path
Step 7	If the current node is not the target location, repeat the previous steps from the start

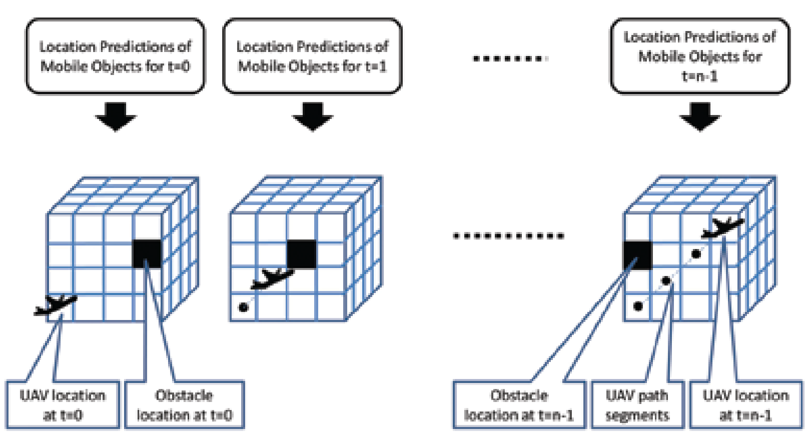


Figure 1. 4D grid generation procedure.

3.2 Roadmap Generation

After spatially adjacent nodes are connected on a multi-resolution grid, the links containing any obstacle such as buildings, structures, or other vehicles are removed to avoid collision. Finally, the adjacent nodes in time dimension of the 4D grid are created.

The grid is divided into several regions. Then, all nodes in each region are checked whether it is an obstacle node or not. If a node in a region is recognised as an obstacle node, the region is marked with a flag indicating that it is a high-resolution region. Regions without obstacle nodes are marked as low-resolution regions. In low-resolution regions, the border nodes are linked with the nodes existing in the border of other regions. This method uses a variable length successor to provide connectivity between the nodes that belong to different regions. In addition, this method creates adjacencies between nodes that are away from each other. Adjacencies in low-resolution regions provide an enhanced capability for the model to generate more smooth paths compared to classical adjacencies with a 45° angle.

The model checks for collisions between node pairs before generating adjacencies. Collision detection is handled implicitly with the help of obstacle identifier flag in a node object. If any node of the pair has an obstacle flag, the model cancels the links between these node pairs. Using obstacle identifier flags prevents additional collision control. The model ensures creating adjacencies between nodes, which exists in different time instants. Each node in the UAV path belongs to consecutive time instants. In a 4D grid, the time instant of the parent node is smaller than the child nodes.

In the calculation of time instant of the child node i_c, first we find the number of hop (h) which can be described as 'UAV's pass during its flight from a parent node to a child node'(Eqn (3)). We use the physical distance between the parent node and the child node (d_{pc}) and find average the distance $(avg(d_h))$ in the calculation of (h). We can find i_c, with summing parent node instant i_p and h (Eqn (4)). In the subsequent planning iterations, the model updates $(avg(d_h))$ with Eqn (5).

$$h = \frac{d_{pc}}{avg(d_h)} \quad (3)$$

$$i_c = i_p + h \quad (4)$$

$$avg(d_h) = \frac{d_{pc}}{h} \quad (5)$$

Adjacencies between nodes in different time dimensions provide a continuous, realistic, and safe navigation for the UAV. By determining each node's status (obstacle or not) for every time dimension, UAVs can fly over non-obstacle nodes.

3.3 Multi-Criteria Path Planning Model

Strategies and methodologies used in criteria and objectives modelling, world space representation, graph generation, and searching in CM are presented here. In the study, we implement several flight criteria and flight objectives to plan safer flight paths. The criteria and objectives are selected based on environmental factors, UAV performance limitations, basic aviation rules, and requirements stated by domain experts.

3.3.1 Flight Criteria

Flight criteria are requirements that should be met during flight. They do not influence the flight cost but affect flight safety and mission effectiveness. The flight criteria can be categorised as static and dynamic criteria. The information regarding the criteria and their implementations in the model is presented in section 3.3.1.1 and 3.3.1.2. The locations and properties of static criteria do not change over time, whereas the locations and properties of dynamic criteria may change.

3.3.1.1 Static Criteria

Buildings and Architectures: Buildings and architectures are represented with polygons. They are defined as obstacles in our world space (Fig. 2(a)).

Danger Areas: A danger area is a land region that poses any kind of threat to the UAV flight. For example, an anti-air defense system is a kind of threat to military UAVs. We make a distinction between the aerial threats and land based threats. In our model, we draw a half-sphere on the location of the threat. The center of this virtual sphere corresponds to the location of the threat (Fig. 2(b)).

Geographical Structures: Terrain is a natural obstacle that must be taken into account in low altitude flights. In our model, the terrain or in other words, a geographical structure, is represented as an obstacle. Therefore, the UAV cannot go through this terrain. The terrain elevations are obtained from digital terrain elevation data level 1 (DTED L1) maps from National Aeronautics and Space Administration (NASA)[57]. The environment model is inherently developed based on the geography of the operation area.

Above Ground Level (AGL) Rule: Pilots follow this rule to prevent aircraft from colliding. In our model, we identified a minimum altitude level above from ground level to ensure collision-free flights. Areas below the AGL altitude are defined as the obstacle space. This rule is inherently integrated into the model.

Cruise Level Rule: Cruise level rule is another rule that provides a safe flight for aircrafts. This rule forces aircrafts to fly in specific allowed altitudes for certain defined courses. In this study, Turkish Air Regulations in cruise level separation is implemented. Odd multiples of 1000 ft Above Mean Sea Level (AMSL) (e.g. 1000 ft, 3000 ft, 5000 ft AMSL) are permissible for aircraft with headings between 0° to 179°. For headings between 180° and 359°, aircraft should cruise at even multiples of 1000 ft AMSL (e.g. 2000 ft, 4000 ft, 6000 ft AMSL). We believe that cruise level rule would reduce air space collision and near miss problems discussed in[69,70]. This rule is inherently integrated into the model.

3.3.1.2 Dynamic Criteria

Mobile Obstacles: Mobile obstacles can be other aircraft or other flying objects such as helicopters, or drones in the operational environment. These mobile objects are marked as 'obstacle space' in the world space. Therefore, the model inherently prevents the UAV from collisions with the mobile obstacles. The mobile obstacles are represented with the approached detailed in[12]. In this approach, flying objects are characterized as cylindrical shapes (Fig. 2(c)). The dimensions of these cylinders representing the mobile objects are calculated in such a way that UAV is able to maneuver safely avoiding a collision with the mobile target.

Mobile Targets: Our model generates the least cost paths enabling UAVs to reach the mobile target. In this procedure, the model calculates the future locations of mobile targets and generates the optimal paths. Any movement model can be defined and implemented for the mobile targets. They can move at constant or random course and speed. In addition, predefined navigation paths can be fed into the simulation model (Fig. 2(c)).

Clouds: In the operational environment, clouds are likely to prevent UAVs from completing certain missions such as reconnaissance via photographing or video capturing. In such circumstances, to complete the missions, UAVs should descend to lower altitudes below the clouds. Our model enhances mission efficiency by enabling UAVs to go under clouds when the weather is cloudy above the target location. At other times during flight, the UAV can fly through clouds. We represent the clouds with polygonal and cylindrical shapes as shown (Fig. 2(d) and 2(e)).

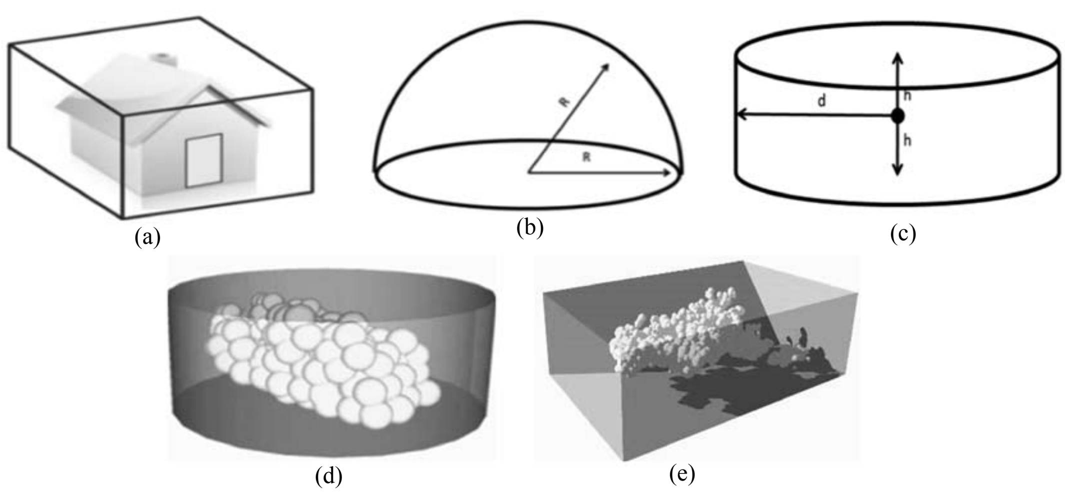


Figure 2. Static and dynamic criteria.

Wind: In the calculation of flight time and fuel consumption, wind is a major parameter that changes the UAV relative-to-ground speed. Thus, wind poses quite a challenge in path planning for UAV simulations. In our model, there are wind fields with various speeds and directions in the operational environment. The effect of wind is accounted for in the calculations.

3.3.2 Flight Objectives

Flight cost is the total cost of trajectories between nodes that construct the path from start to goal. It is measured based on time, distance, and fuel consumption. One of these flight objectives is chosen for the calculation of the flight cost before the simulation starts. A search algorithm then finds the optimal path with respect to the selected flight objective.

Let us define the roadmap as a search graph, $G=(N,E)$ where the node $s_i \in N$ represents a cube in the grid in the world space representation, and the edge $e_{ij} \in E$ is the edge (s_i, s_j) connecting two adjacent nodes s_i and s_j in the roadmap. Then any path, P_i, between the start (s_{start}) and target nodes (s_{target}) can be shown as,

$$\Gamma_{pi}(s_{start}, s_{target}) = \{(s_{start}, s_{i1}), (s_{i1}, s_{i2}), \ldots, (s_{iK}, s_{target}\}$$

where is the length of the corresponding path P_i. If the cost between two successive nodes S_{iK} and S_{iK+1} is represented as $f_i(s_{ik}, s_{ik+1})$ the total cost is then calculated as,

$$COST_j(\Gamma_{pi}(s_{start}, s_{target})) = \sum_{0\le k\le K} f_i(s_{ik}, s_{ik+1})$$

where $j_\in$ {*distance, time, fuel*}

Note that the above cost function uses only one of the three flight objectives. This single objective cost function can simply be converted into a weighted objective function similar to [20, 21]. The weighted objective function is presented as follows:

$$COST_{weighted}(\Gamma_{pi}(s_{start}, s_{target})) = \sum_{0\le k\le K} w_{dist} \times f_{dist}(s_{ik}, s_{ik+1}) + w_{time} \times f_{time}(s_{ik}, s_{ik+1}) + w_{fuel} \times f_{fuel}(s_{ik}, s_{ik+1})$$

Flight Distance: The distance cost function first calculates the grid distance on search space, then transforms that result into geographical distance.

$$f_{dist}(s_i, s_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2}$$

Flight Time: Our model calculates optimal paths for UAVs that leads to the target location in minimum time. Flight time is a function of distance, UAV motor speed and wind. The wind vector effects the flight time. The time cost is calculated with the following formula. The cost of each trajectory between node pairs is calculated based on the distance between nodes and the vector summation of UAV engine speed and wind speed.

$$f_{time}(s_i, s_j) = \frac{f_{dist}(s_i, s_j)}{|\vec{v}_c + \vec{v}_w|}$$

where $\vec{v}_c$ is UAV engine speed, and $\vec{v}_w$ is the wind speed.

It is assumed that the UAV flies at a constant engine speed. UAV relative-to-ground speed is calculated with vector summation of throttle and wind speed.

Fuel Consumption: Flight endurance depends on fuel consumption in UAVs. Although many factors affect fuel consumption, we include altitude (pressure), speed/acceleration, temperature, payload weight, climb/descend rate, engine specifications as parameters in our model[12]:

The UAV fuel consumption model is developed based on EngineSim, an analysis tool for aircraft engines developed by NASA[52]. Note that the overall conceptual model and the resulting simulation architecture is modular[29], therefore it is also possible to easily replace the fuel consumption model with another model. In the current model, the UAV climbs with maximum throttle, descends with minimum throttle and cruises with optimal throttle. For example, the UAV uses less fuel in high altitudes or low speeds. The formula for calculating the fuel consumption:

$$F_{fuel}(x_{alt} x_{spd} x_{temp} x_{payload} x_{rate}) = g(f_{alt}(x_{alt}), f_{spd}(x_{spd}), f_{temp}(x_{temp}), f_{payload}(x_{payload}), f_{rate}(x_{rate}))$$

where $f_{alt}(x_{alt})$ is the fuel consumption at altitude x, $f_{spd}(x_{spd})$ is the fuel consumption at speed x, $f_{temp}(x_{temp})$ is the fuel consumption at temperature x, $f_{payload}(x_{payload})$ is the fuel consumption at payload x, and $f_{rate}(x_{rate})$ is the fuel consumption at rate x.

The fuel cost between the successive nodes is calculated by,

$$f_{fuel}(s_i, s_j) = F_{fuel}(\overline{x}_{ij}) \times f_{time}(s_i, s_j)$$

where $\overline{x}$ is the parameter vector, $\overline{x}_{ij}$ is obtained using the altitude of s_i and s_j, the speed of UAV, the temperature of the environment, payload of the UAV, and climb/descend rate of the UAV, respectively.

3.4 Path Search

A* search algorithm is chosen for this study. A* provides simplicity and efficiency in implementation and is known to be suitable for path search when used iteratively in dynamic environments[60]. Note that there are newer search algorithms in the literature. However, most of them are derivations of A*. Since the goal in this research is to empirically compare a 3D and a 4D approach, not to develop a new algorithm, we chose A* search algorithm that provides the basis for most search algorithms used in UAV path planning. As a result, this comparison study is applicable to a wide range of other studies.

In the A* algorithm, the cost function $f(x)$ is calculated by;

$$f(x) = g(x) + h(x)$$

where $g(x)$ is the actual traverse cost from start to current node and $h(x)$ is the estimated heuristic cost from the current node to the target. Therefore, $f(x)$ is the estimated cost of the cheapest solution through x. If $h(x)$ is an admissible heuristic, A* is optimal and complete. An admissible heuristic never overestimates the cost to reach the goal. If the heuristic is not admissible, A* finds suboptimal solutions. Another requirement to ensure optimality of A* is consistency. A heuristic is consistent if, for every node n and every successor n' of n, the estimated cost of reaching the goal from n' is not greater than the step cost of getting to n' plus the estimated cost of reaching the goal from n'.

For the distance objective, the heuristic function is the straight-line distance (h_{SLD}) from start to target location. For the time objective, the heuristic function is the shortest flight time, (h_{SFT}), which is based on wind direction and UAV course:

$$(h_{SFT}) = \frac{(h_{SLD})}{v_{UAV} + v_w \times e}$$

where v_{UAV} is UAV speed, v_w is wind speed and e is the side effect. Side effect is calculated based on the angle between wind direction and UAV course. It gets values between –1 and +1. While the wind blows opposite to the UAV course, side effect has minimum values. On the other hand, if the wind blows from the same direction, it gets maximum values.

For the fuel consumption objective, we calculate the heuristic based on the highest altitude that a UAV can fly in similar environments. Fuel consumption reduces in high altitudes. Fuel consumption (h_{MPC}) is calculated with the formula.

$$(h_{MPC}) = (h_{SFT}) \times f_{fuel}(x)$$

where $f_{fuel}(x)$ is fuel consumption at maximum altitude.

4. SIMULATION MODEL AND EXPERIMENTATION

4.1 Overview

In building the simulation model, two software packages are used: Simkit[58-59] and OpenMap[8]. The Simkit package is a discrete event simulation (DES) code library written in Java[59]. Although it is a generic simulation package, it performs well in modelling defense systems[9]. The OpenMap package is a Geographical Information System (GIS) also written in Java. In the study, these environments are used together with a similar approach presented by Mack[10].

4.2 Inputs

Simulation inputs and parameters (modeled after existing medium altitude high endurance UAVs) are given in Table 2. In the simulation scenarios, the obstacles are positioned in such a way that they intersect with obvious optimal paths such as straight lines or diagonal lines. Thus, we intentionally increase the complexity of the scenarios and better test our model. In addition, the size of the man-made structures is defined as large obstacles to increase the environmental complexity, thus testing the model robustness.

4.3 Experiments and Results

The computer used for simulations is an IBM compatible PC with an Intel i5 2.93 GHz processor and 3 GByte RAM. The dimension of the world space is 60 nm x 60 nm x 31000 ft x 10 t grid. The grid is sampled with nodes having a dimension of 2 nm x 2 nm x 1000 ft. The UAV calculates its path considering the nodes in the world space. However, each node represents a real geographical location in terms of latitude, longitude, and altitude. A screenshot of a simulation run is presented in Fig. 3. In the figure, the optimal path from the starting point in the south to the end point in the north is drawn with a dotted line. Circular and rectangular shapes in the figure represent the obstacles. In this scenario, the target is moving with a constant speed.

For the experiments, various scenarios containing different numbers of static and dynamic obstacles, target types, and grid dimensions are created. There are 24 world configurations and 3 flight objectives for each world configuration. A total of 72 scenarios are described in Table 3. Using a uniform distribution, the obstacles are randomly positioned in the map. In the simulations, the operational environment is categorised into three types in terms of static, dynamic, and highly dynamic. As the number of dynamic obstacles increases, the environment becomes more dynamic. When the number of dynamic objects reaches to 8, the 3D model fails in finding a solution. That is why we categorised these environments as highly dynamic. In the simulations, the UAV starts at a point located in the south of the map and moves to the ending point located in the north of the map. For each scenario, performance data is collected. The simulation performance data consist of grid generation time, path cost, and search time for different flight objectives. To compare the simulation performances of 3D and 4D simulations, the same world configurations with the same simulation parameters are used. The simulation results are presented in Table 3. In the table, when the search algorithm could not find a path, we mark the scenario as 'Path Not Found (PNF)'. The observations from the experiments are outlined as follows:

- The 4D search algorithm is superior in finding lower cost paths compared to 3D search algorithm since the 4D search algorithm looks ahead in time and tries to find optimal solutions based on the movements of the

Table 2. Simulation inputs

UAV model parameters			
Total weight	2.500 lb	Payload weight	500 lb
Endurance	24 h	Max/cruise speed	120 kts, 60 kts
Max flight altitude	30.000 ft	Tactical range	200 nm
Cruise fuel consumption	29,16 lb/h	Ascend fuel consumption	48,52 lb/h
		Descend fuel consumption	14,58 lb/h
Turn radius	1 nm	Ascend/descend rate	1000ft/min
Operational environment model parameters			
Field size	60 nm x 60 nm x 31000 ft x 10 hop	Wind direction	000° / 090°
Cloud origin location	Top of the target	Wind speed	0 kts / 20 kts
Region number	125 (5 x 5 x 5)	Temperature	70 °F
High resolution successor length	1-2	Goal location altitude	21000 ft
Low resolution successor length	Variable 1-5	Start location altitude	13000 ft
Rules	Cruise Level, AGL	Safe limits	1000 ft above AGL

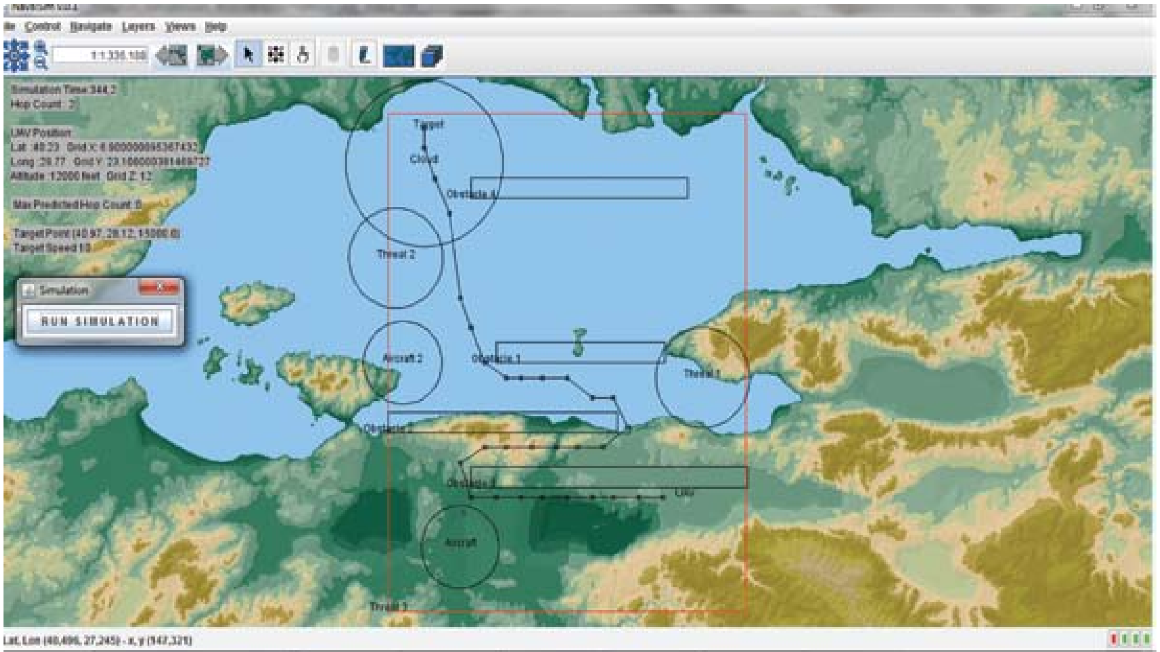


Figure 3. Screenshot of a simulation run.

dynamic entities.

- If the scenario only consists of static obstacles, then both 3D and 4D search algorithms performs the same. Since static objects do not move, looking ahead in time does not change the results.
- The most striking observation is that when the operational environment becomes highly dynamic (number of obstacles is 16), the search in 3D cannot find a path while the search in 4D is successful in finding least-cost paths maintaining satisfactory performances.
- Naturally, the time required to generate the grid and conduct the search is higher in 4D grids.
- The grid generation time is affected mainly by the number and size of the obstacles.
- The search time increases when the locations of the obstacles are in the UAV flight path.
- The grid search time increases as the number of obstacles increases. Because the algorithm requires more time to expand nodes to find a least-cost path. The world becomes more complex as the number of obstacles increases.
- In contrast, as the number of obstacles increases, the grid generation time decreases since the search space gets smaller.
- The search time is longer in the scenarios having a fuel consumption objective. As expressed earlier, we used EngineSim, an analysis tool for aircraft engines developed by NASA. In the EngineSim, the fuel consumption computations take time because many parameters are used in the calculations.
- The path costs vary depending on the locations and mobility of the obstacles. If the obstacles are in the way of UAV naturally, the UAV has to move around them. As the number of obstacles increases, there is a higher possibility that more obstacles are located in the UAV path.
- When the objective in the scenario is consuming minimum fuel (fuel consumption), then the UAV climbs to higher altitudes as soon as possible. Since the engine module of our UAV model is adapted from EngineSim, the UAV acts realistically just as an aircraft would do. When the UAV reaches the target position, depending on the tasked mission it descends to the optimal altitude for the mission.

When the UAV environment is complex and dynamic, meaning that the number of obstacles is high, the number of possible paths to target location is limited. Even for certain scenarios, there may not be a path to the target location depending on the locations of obstacles at a specific time instance. In the experiments, the search algorithm utilising a 3D grid is incapable of finding paths for the particular scenarios 17, 19, 21 and 23. In these scenarios, existing locations of obstacles block any path to the target. Therefore, the results become PNF. However, the 4D search algorithm utilising 4D world space representation can find paths in the same scenarios, since the algorithm investigates future locations of obstacles. As the mobile objects move, new paths emerge. Investigating future locations of obstacles enlarges the search space containing these emerged paths. This enlarged search may find paths that are not found with a 3D grid representation. Figure 4 shows the simulation run for scenario 24. This scenario represents an example case in which the 3D search algorithm cannot provide a solution and the 4D search algorithm is successful in finding legitimate least cost paths for all objectives. Based on the results of the experiments, in terms of path costs in all three objectives, we conclude that the 4D search algorithm performs better in dynamic and complex environments than the 3D search algorithm performs.

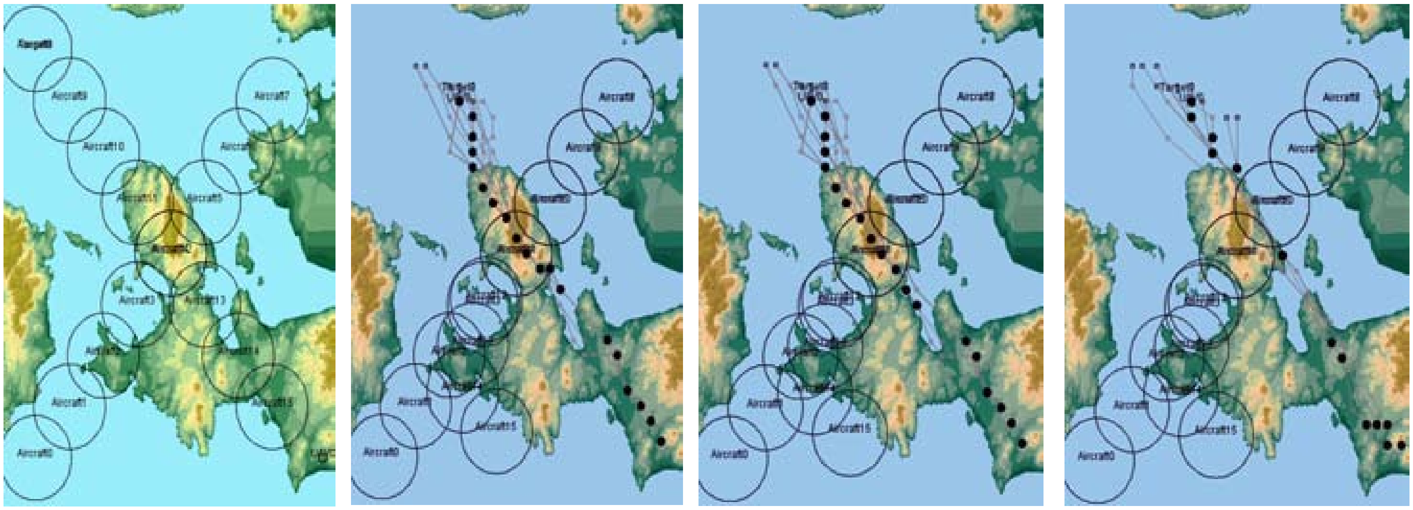
In Fig. 4(a), Scenario 24 starts up with 16 mobile objects (aircrafts) and the UAV calculates the path to the mobile target location. In Fig. 4 (b), the objective of the cost function is distance and the UAV calculates the shortest path to the mobile

Table 3. Simulation results (M: Mobile, S: Stationary)

Simulation inputs							Performance data					
Scenario specifications							Objective 1 distance		Objective 2 time		Objective 3 fuel consp	
Scenario	Number of static obstacles	Number of dynamic obstacles	Target type	Grid dimension	Operational environment type	Grid generation time (sec)	Search time (sec)	Path cost (node length)	Search time (sec)	Path cost (hours)	Search time (sec)	Path cost (lb)
1	0	0	S	3D	Static	1.6	0.1	34.02	0.3	0.95	0.3	24.82
2				4D	Static	2.6	0.1	34.02	0.3	0.95	0.3	24.82
3	0	0	M	3D	Static	1.6	0.1	31.54	0.2	0.87	0.4	23.74
4				4D	Static	2.6	0.1	31.54	0.2	0.87	0.4	23.74
5	4	0	S	3D	Static	1.2	0.4	36.38	1.2	0.99	1.7	29.06
6				4D	Static	1.4	0.4	36.31	2.6	0.99	2.0	29.06
7	4	0	M	3D	Static	1.2	0.4	35.26	1.3	0.97	1.6	27.73
8				4D	Static	2.1	0.4	35.14	3.6	0.97	2.3	27.23
9	0	4	S	3D	Dynamic	1.3	0.1	35.91	0.4	0.99	0.9	28.31
10				4D	Dynamic	2.1	2.1	34.04	14	0.97	5.0	27.76
11	0	4	M	3D	Dynamic	1.3	0.2	40.60	2.1	1.12	2.8	23.62
12				4D	Dynamic	2.1	1.4	29.19	5.1	0.80	4.7	19.95
13	4	4	S	3D	Dynamic	1.0	0.3	36.41	1.8	1.1	2.1	29.44
14				4D	Dynamic	1.8	5.1	28.90	3.5	1.0	5.3	28.90
15	4	4	M	3D	Dynamic	1.0	0.3	41.17	1.5	1.13	4.3	31.67
16				4D	Dynamic	1.9	3.1	33.09	12	0.91	15	21.91
17	8	8	S	3D	Highly Dynamic	PNF	PNF	PNF	PNF	PNF	PNF	PNF
18				4D	Highly Dynamic	2	1	35.96	1	0.90	22	23.14
19	8	8	M	3D	Highly Dynamic	PNF	PNF	PNF	PNF	PNF	PNF	PNF
20				4D	Highly Dynamic	2	1	30.82	1	0.76	28	18.70
21	0	16	S	3D	Highly Dynamic	PNF	PNF	PNF	PNF	PNF	PNF	PNF
22				4D	Highly Dynamic	2	1	36.69	1	0.91	12	25.04
23	0	16	M	3D	Highly Dynamic	PNF	PNF	PNF	PNF	PNF	PNF	PNF
24				4D	Highly Dynamic	2	1	34.84	1	0.79	22	23.17

target location. In Fig. 4 (c), the objective of the cost function is time and the UAV calculates the path with the shortest time to arrive at mobile target location. In Fig. 4 (d), the objective of the cost function is fuel consumption and the UAV calculates the path to the mobile target location while minimizing fuel consumption.

To show the extendibility of the model, we modified the model for multi-objective planning by implementing the weighted cost formula presented previously. Objective weights are determined as 0.4 for distance objective, 0.4 for time and 0.2 for fuel consumption. These weights may be different for different missions. Therefore, the weights are adjustable. The currents weights are determined based on our interview with a domain expert, an experienced UAV pilot. Naturally, the costs



(a) (b) (c) (d)

Figure 4. Scenario 24 screenshots: (a) Scenario 24 at startup, (b) Objective: distance, (c) Objective: time, and (d) Objective: fuel.

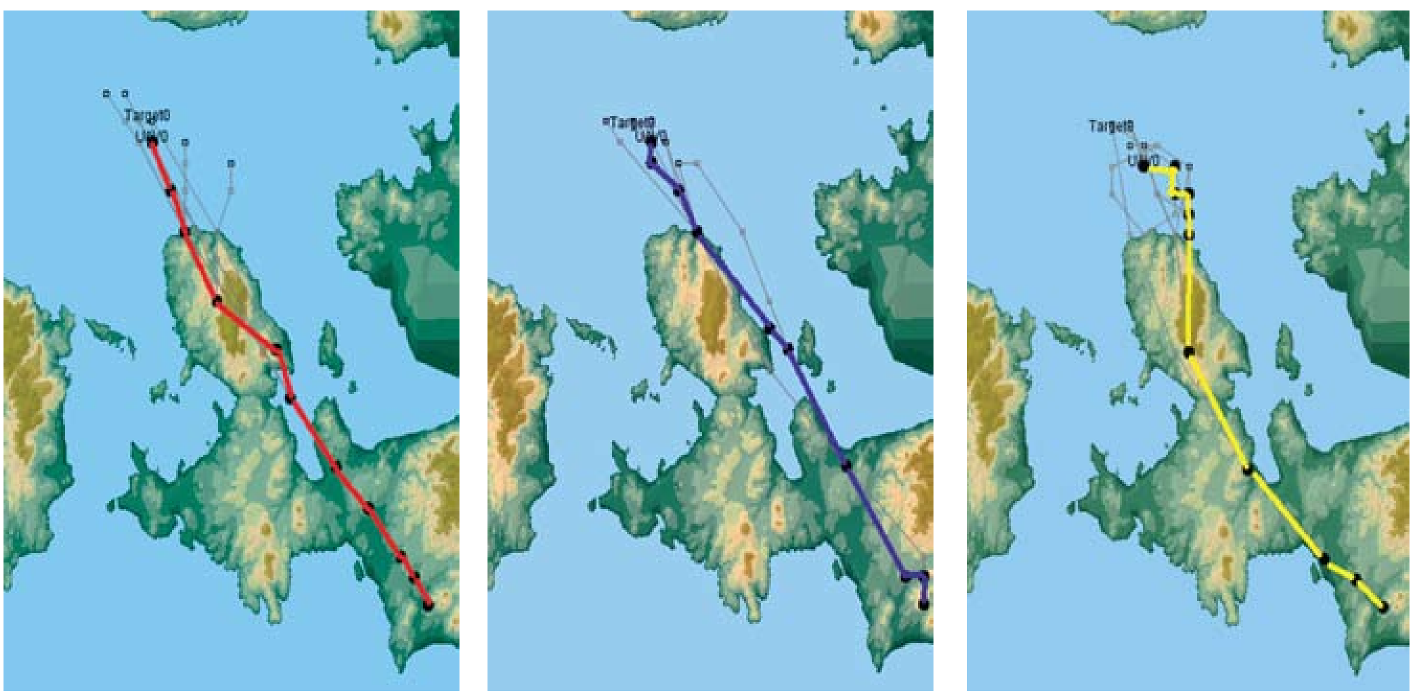
are normalised. As observed in Fig. 5, the solution may be different depending on the path planning objective.

As a result, it is shown that the path planning approach developed in this study provides a successful approach to online and offline UAV path planning to meet various and multiple objectives. The approach produces optimal, resolution-complete, and smooth paths in complex dynamic environments. In addition, variable length adjacency successors ensure smoother paths. The grid dimension, number of obstacles, and wind vector are the main factors on path optimality and process time. However, the search time increases in complex environments as the search algorithm expands more nodes to find least cost paths.

The simulation results show important shortcomings of 3D approaches. When the UAV operates in a complex dynamic environment consisting of different types of obstacles having different behaviors, the need for a 4D search approach becomes inevitable.

5. CONCLUSION

In this study, we empirically compare the 3D and 4D path planning for UAVs in complex dynamic environments. We aimed at achieving higher levels of realism by including an extensive set of criteria. The criteria include flight dynamics, geographical structures, buildings and architectures, danger zones, mobile objects, mobile threats, mobile targets, above



(a) (b) (c)

Figure 5. The difference in paths between single and multi-objective planning in same scenario: (a) Single objective: distance/time, (b) Single objective: fuel, and (c) Multi-objective.

ground level rule, cruise level rule, wind, air classes, and cloud. Some of the criteria (such as wind and air classes) are only investigated in some studies while some (cruise level rule and cloud) only exist in one or two studies. Furthermore, the current operational efficiency issues discussed in UAV Roadmaps[61-65] are also considered. The developed path planning approach is capable of finding solutions with respect to multiple objectives including distance, time, and fuel consumption. The research approach and resulting conceptual model is validated by conducting interviews with an experienced military MALE UAV pilot and mission planner.

The main contribution of this study is the empirical data supporting the superiority of 4D path planning over 3D path planning in UAV research. The superiority becomes obvious when the UAV environment is complex and dynamic. Because a 3D approach may not be able to find solutions as the UAV mission environment gets complex and highly dynamic. This is shown by running simulations with various scenarios. In the simulations, when the number of obstacles reaches to a certain number, the 3D approach is unable to find a solution. Furthermore, even when the 3D path planning finds solutions for different objectives, the 4D path planning performs better with higher performance.

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CONTRIBUTORS

Mr Halil Cicibas received his Master in C4I Systems from Institute of Naval Sciences and Engineering, in 2011. Currently, he is working as an Information Systems Manager at the Turkish Naval Forces Headquarters and pursuing his PhD at the Middle East Technical University. His research interests include: C4I systems, information systems, modelling and simulation of unmanned systems path planning.
In the current study, he constructed the conceptual model and simulation architecture. He wrote the software for the simulations and conducted the experiments.

Dr Kadir Alpaslan Demir, received MS (Computer Science) and MS (Software Engineering) during 2003 - 2005, and PhD (Software Engineering), in 2008. Currently, working as an Assistant Program Manager at Turkish Naval Research Center Command. His research interests include: Project management, software engineering, information systems, project management measurement and metrics development, UAV systems simulation, systems and software modelling, process improvement, R&D and innovation management.
In the current study, he set the scope and outline of the research. He helped to build the conceptual model and modular simulation architecture. He guided the study on 3D and 4D comparison experimentation.

Dr Nafiz Arica received both MSc and PhD in Computer Engineering from Middle East Technical University (METU), in 1995 and 1998, respectively. He is now working as an Associate Professor at the Department of Computer Engineering and Director of Graduate School of Applied and Natural Sciences, Bahcesehir University. His current research interests include: Object detection, recognition and tracking, path planning for unmanned vehicles and facial expression analysis.
In the current study, he set the direction of the research. He guided the algorithm development for the autonomous path planning algorithm. He outlined the experimental design, oversaw the experiments, and validated the experimental results.