Bitlis Eren Üniversitesi Fen Bilimleri Dergisi
BİTLİS EREN UNIVERSITY JOURNAL OF SCIENCE
ISSN: 2147-3129/e-ISSN: 2147-3188
VOLUME: 13 NO: 3 PAGE: 808-821 YEAR: 2024
DOI:10.17798/bitlisfen.1494562

An Innovative Approach for Mission Sharing and Route Planning of Swarm Unmanned Aerial Vehicles in Disaster Management

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Keywords: UAV, Mission Sharing, Route Planning, Disaster management, optimization, simulation.

Abstract
Fast and effective response in disaster situations is critical for the success of rescue operations. In this context, swarm Unmanned Aerial Vehicles (UAVs) play an important role in disaster response by rapidly scanning large areas and performing situation assessments. In this paper, we propose an innovative method for task allocation and route planning for swarm UAVs. By combining Genetic Algorithm (GA) and Ant Colony Optimization (ACO) techniques, this method aims to ensure the most efficient routing of UAVs. First, clusters are created using GA to determine the regions of the disaster area that need to be scanned. At this stage, factors such as the capacities of the UAVs, their flight times, and the breadth of their mission areas are taken into account. Each UAV is optimized to scan a specific area assigned to it. Once the clusters are formed, the routes of the UAVs within each cluster are determined by the Ant Colony Algorithm (ACA). The route planning is tested both on Google Maps and in a Gazebo simulation environment. Google Maps is used to evaluate the accuracy and feasibility of route planning based on real-world conditions, while the simulation environment provides the opportunity to test the behavior of the UAVs and the effectiveness of the routes in a virtual setting. With real-time data integration, the UAVs' route planning can be updated instantly and quickly adapted to emergency situations.

1. Introduction

In Fast response in disaster situations is critical to saving lives and mitigating damage. Making timely and well-informed decisions during natural disasters, fires, earthquakes, and other emergencies directly affects the success of rescue operations. After these disasters, terrestrial cellular networks are often disrupted due to damage to base station infrastructure [1-2]. In this context, swarm UAVs can quickly and efficiently scan large areas to assess the status of disaster zones and provide vital information to emergency responders [3]. Swarm UAVs are particularly effective in complex and large terrain areas, facilitating the work of search and rescue teams. By communicating with each other, swarm UAVs can work in a coordinated manner, enabling them to quickly scan extensive areas. Thanks to these features, the process of locating and rescuing missing people and those trapped in disaster areas is significantly accelerated [4].

The most significant limitations of UAVs are their low payload capacity, limited battery power, and short flight durations [5]. To overcome these challenges, the use of swarm UAVs is becoming increasingly common. Swarm UAVs distribute the area to be scanned and the tasks to be performed among individual UAVs according to the principle of task sharing for a specific purpose. This allows for the scanning of large disaster areas with multiple UAVs

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Received: 03.06.2024, Accepted: 08.07.2024

that have short flight durations. The initial response time is critical for search and rescue operations. Swarm UAVs play a crucial role in these operations, as they can quickly and effectively search large areas. With their high-resolution cameras and other sensors, they can provide detailed observations of the surroundings, offering a significant advantage in locating missing or distressed individuals. Additionally, by working in a swarm, they facilitate the coordination and direction of operations, thereby having the potential to guide rescue teams.

In this study, a new clustering approach is presented that divides the area to be scanned into clusters, allowing for the determination of the optimal path for each UAV to obtain disaster images in the fastest and most effective way after a disaster. To achieve this, a novel method is proposed to determine the optimal flight routes for UAVs to acquire images from the disaster area. The system is designed to enable UAVs to reach disaster areas from a specific starting point as quickly as possible, collect images, and return, first by using the proposed clustering method and then by planning the optimal route to be followed. The proposed method was tested in a simulation environment for different regions, varying numbers of UAVs, and different starting points. After the tests, the effectiveness of the proposed method was verified. The main contributions of the proposed approach are as follows:

• Introduction of a novel GA-based clustering approach for routing multiple UAVs,
• Enabling UAVs to collect data from different regions with minimal distance cost,
• Testing the method in both a two-dimensional environment on real maps and in the Gazebo simulation environment.

Especially the test performed in the Gazebo simulation environment has not been applied in the literature to the best of our knowledge. The studies in the literature mostly apply tests by applying two-dimensional or three-dimensional obstacles on a graph. This study allows for easy point determination and route planning with an interface to be written for a UAV with GPS.

2. Literature Review

Disaster management is a critical area that enables societies to recover quickly and effectively after natural or man-made disasters. Satellite imagery and unmanned aerial vehicles (UAVs) are used in disaster management and damage assessment. High-resolution satellite imaging systems have limitations such as image acquisition time, satellite connectivity, weather conditions, and delays in data delivery [6]. In contrast, UAVs are preferred in disaster management because they are fast, safe and flexible [7]. The video and still images captured by UAVs provide more detail than satellite images, making it easier to quickly identify and respond to damaged infrastructure [8-9]. In addition, the data collected enables emergency teams to make fast and effective decisions. UAVs can easily access areas that are difficult to reach with traditional methods. UAVs can be used for reconnaissance, detection, search and rescue support and coordination activities in disasters such as earthquakes and landslides, as well as for the detection and rescue of people under rubble [10]. UAVs have been used to provide communication and coordination by creating a communication infrastructure after disasters [11]. The advantages of UAVs such as rapid response, accessibility and cost-effectiveness make this technology an indispensable tool in disaster management, and the wider and more effective use of UAVs in disaster management will help minimize the negative effects of disasters by increasing social resilience. When UAVs are used in disaster situations, they are organized in multiples. A single UAV cannot complete complex missions on its own due to limitations such as flight time and computational capacity. Therefore, the swarm UAV system is used to accomplish a variety of challenging missions. Swarm UAVs have an important mission allocation problem that needs to be solved before they can accomplish the missions [12-13]. One of the most important issues for UAVs is route planning algorithms. An efficient route planning not only allows UAVs to perform their missions more efficiently and safely, but also saves energy and time. Optimal routes minimize unnecessary flights, shorten mission duration and extend battery life. The control and communication structure in swarm UAVs is used to improve route planning operations [14-15].

In the literature, some studies have been conducted for different purposes such as coordination of swarm UAVs for search and rescue activities, reaching the target as soon as possible, and target identification. Zahng et al. [16] proposed a mathematical optimization framework for communication of UAVs in post-disaster affected areas. Aydin and Altun [17] compared differential evolution and particle swarm optimization for route planning of UAVs in an environment with multiple obstacles. The comparison proved that differential evolution is more successful in terms of both the number of steps and the path traveled. Wang et al. [18] presented an approach combining linear programming and PDA for the multi-point vehicle routing problem for post-disaster relief delivery. The proposed approach is tested on standard benchmark datasets. Zahng et al. [19] proposed a modified differential evolution algorithm for disaster emergency routing. The proposed approach considers two parameters to be optimized. These are risk and vehicle angle. To solve the problem with a constrained optimization, a differential evolution algorithm based on exponential selection is proposed and the B-spline method is used for route generation. The proposed approach is tested in both two-dimensional and three-dimensional environments in the presence of obstacles. Wan et al. [20] proposed a multi-objective swarm intelligence algorithm for three-dimensional route planning. The method transforms the path planning task into a multi-objective optimization task with multiple constraints and simultaneously optimizes the objectives based on the total flight path length and terrain threat degree. Scherer et al. [21] proposed an architecture for building an autonomous system of small-scale UAVs for search and rescue missions. The proposed architecture allows the use of swarm UAVs with different autonomy levels. The proposed architecture supports the addition or removal of a new UAV at a scalable level. Silvagni et al. [22] designed an unmanned aerial vehicle with special capabilities for mountaineering activities. The proposed UAV is equipped with capabilities customized for mountain operations, such as flying at high altitude, flying in rainy and snowy weather conditions, and flying day and night. Arnold et al. [23] investigated the effect of UAV role on first response time by using multi-role swarm UAVs in a simulation environment for search and rescue operations. They were successful in finding more than 90% of the survivors in less than 40 minutes in their tests with 10 to 50 UAVs in the simulation. Karaköse [24] used GA to optimize the task allocation of UAVs. The number of UAVs to be assigned for each target point and the optimum path and number of UAVs were determined according to the obstacles on the route. Gladence et al. [25], organized a flood disaster in a simulation environment and detected people trapped in the flood. In the developed simulation, swarm UAVs were used and each UAV was given a route. The images collected by the UAVs were processed on the server and people trapped in the flood were detected in each region. Alawad et al. [26] proposed a swarm optimization algorithm based disaster and crisis management control system for disaster and crisis management in smart cities. The proposed swarm optimization method enables UAVs to find the optimal path and consume less energy. Bakirci and Ozer [27] used k-means clustering algorithm and hierarchical virtual communication ring strategy for subtasks such as task allocation of swarm UAVs, communication between UAVs, and determination of unsafe routes. They also developed recommendations for UAVs not to collide during take-off and not to communicate securely among themselves. Masroor et al. [28] proposed a linear optimization-based approach to reach more disaster victims with minimum UAVs in an emergency. The main objective is to enable users to communicate with the UAV. Wang et al.[29] modeled the 3D UAV deployment problem as a Markov process involving role assignment and role switching for each UAV. In this study, reward and cost functions are defined to minimize energy consumption. Ashraf et al. [30] presented an approach that optimizes the order of places to visit and the speed of the IHA to minimize the task time in IHAs. For this purpose, they treated the problem as a nonlinear integer problem and presented two algorithms that combine the optimal radius of trajectories and circular trajectories. Mahajan et al. [31] proposed a multi-objective Markov decision process based route management. The proposed approach utilizes Markov decision process and Q learning approach. For routing performance, they compared energy minimum remaining node ratio, delay and power to distance ratio. Li et al. [32] proposed an adaptive full coverage algorithm for data collection with UAVs in a disaster situation. The proposed approach provides an approach to optimize the path planning of UAVs in which optimal paths intersect less and routes are minimized. In the proposed approach, two different algorithms are developed for node distribution density and optimal path planning on the generated nodes. Wan et al. [33] proposed an attention-based deep reinforcement learning approach for the routing problem with multiple IHAs. Service time and route selection at each node are analyzed. For the collected potential disaster data, the interaction between UAV arrival time and service time is analyzed and an approach is developed to speed up the process.

Despite the growing body of research on the use of swarm UAVs for disaster management and search and rescue operations, several significant gaps persist in the literature. Firstly, most existing studies are heavily reliant on theoretical implementation and lack real-world implementation and validation. This discrepancy raises concerns about the practical applicability and robustness of the proposed methods under actual disaster conditions. In addition, most of the studies consist of placing obstacles and running algorithms in a two-dimensional environment. Simulation environments such as Gazebo give very accurate results in terms of modeling real life. There is no study in the literature on the use of swarm UAVs in such an environment in case of a disaster.

3. Proposed Approach for Route Planning

In the proposed study, a system has been designed to enable UAVs to reach disaster areas from a specific starting point as quickly as possible, collect images, and return. This system first distributes tasks using a proposed clustering method and then plans the optimal routes for the UAVs to follow. The system is coded in the Python programming language. In the designed system, calculations can be made using either the Cartesian or Geographical Coordinate System, and the results can be displayed and tested in a simulation environment. The general scheme of the system is shown in Figure 1.

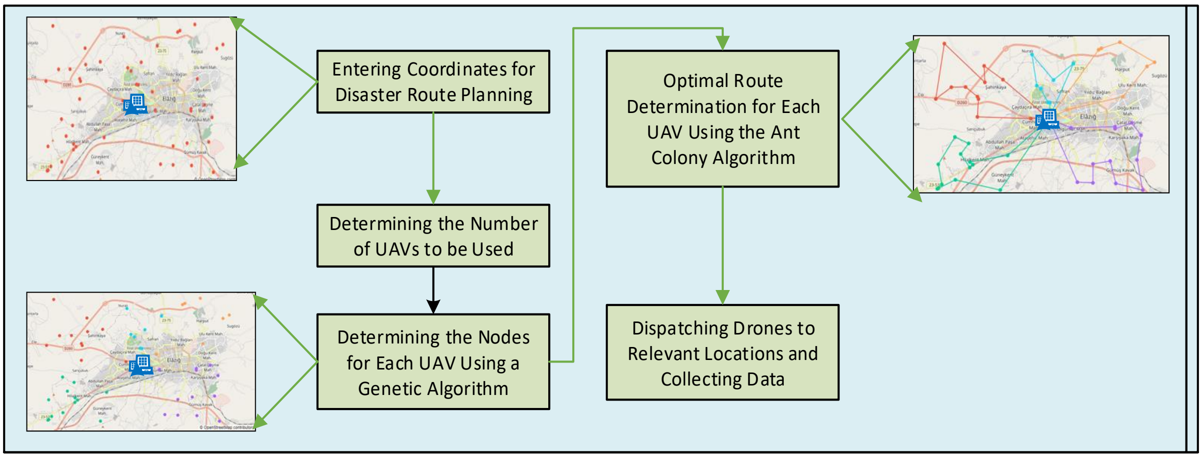


Figure 1. Workflow diagram of the system designed for route planning

In this study, a Genetic Algorithm (GA) is used to allocate the coordinates to be reached by a large number of UAVs departing from a selected starting point. The UAVs at the starting point are positioned to reach the coordinates closest to them. This 360-degree positioning ensures that the UAVs can fulfill their missions in the fastest and easiest way. As the number of UAVs and coordinates increases, this becomes a very long computation process, which is optimized using GA in this study. First, the coordinates to be accessed during the image collection process must be defined in the system. To exemplify this process, random coordinates are used in the study. Examples of 100 random coordinates for the Cartesian Coordinate Plane and 50 random coordinates for the map representation can be seen in Figure 2.

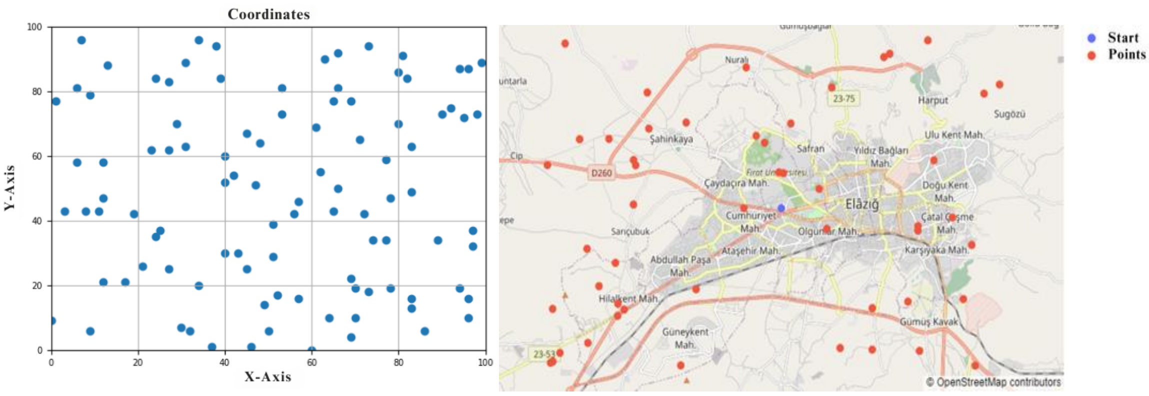


Figure 2. Cartesian Coordinate Plane and map representation of randomly determined points

In the study, the matplotlib library was used for visualizations on the cartesian coordinate plane, and the plotly library was used for map visualizations. The determined coordinates need to be allocated according to the number of available UAVs and a selected starting point for the UAVs to begin their movement. In this study, a clustering method is proposed to enable the system to perform this task allocation. Although this process can be done with known clustering methods, those methods are inefficient since the clustering process is independent of the starting point. In the proposed method, the coordinates are allocated so that the UAVs closest to the starting point are in the same cluster. The position of each UAV is determined by placing it at an optimal location on a circle with a small radius around the origin. GA is used to calculate the positions of the UAVs on the circle [34]. According to an angle value between 0 and 360 degrees determined for each UAV, its position on the circle is found using Equation 1. This process is performed with an objective function that minimizes the intra-cluster Euclidean distance using GA. Figure 3 shows the proposed GA clustering approach.

$$Location_X = \cos\left(\frac{2\times\pi\times açı}{360}\right), Location_Y = \sin\left(\frac{2\times\pi\times açı}{360}\right) \quad (1)$$

function clusters=Genetic_clustering(#uavs, x, y, points)
#uavs: Number of UAVs to be deployed
x: Point x where UAVs will start flying
y: Point y where UAVs will start flying
points: Points where UAVs will fly1. Chromosome coding
a. Create as multiple angle values as the number of UAVs for each chromosome on the circle as K=[a_1,a_2,…a_n].
b. Determine the UAV positions from the angles created according to Equation (1)
2. Create the initial population
3. **while**(number of iteration)
4. **for** each chromosome in population **do**
a. Determine the position of UAVs
b. Find the clusters of each of the locations to visit according to the closest UAV
c. Find the average distance to the center for each cluster and take the highest distance as the objective function
5. **endfor**
6. Crossover
7. Mutation
8. Rulet Selection based selection
9. **endwhile**

Figure 3. Determining the clusters to be flown for each UAV with the genetic algorithm

As a result, the optimal clustering positions for the UAVs are calculated, as shown in Figure 3. In the circle formed by centering on the initial position of the UAVs, they are placed at positions determined by angle values between 0 and 360 degrees. The UAV positions are derived from these angle values. Clusters are then formed based on the proximity of the UAVs to the points they will fly to. The average distance of the points to the cluster centers is calculated, and the cluster center with the highest average distance is minimized. The algorithm prevents UAVs from hovering at the same points by ensuring the formation of disjoint clusters. The UAVs are placed at the starting point designated for image collection. They must reach the targeted coordinates to collect the images and return. With appropriate route calculation, it is important for the UAVs to accomplish this task in the shortest distance possible, in terms of time and fuel savings. In this study, the Route Determination Algorithm (RDA) was used for route calculation. For each UAV, the shortest route that allows them to reach their designated coordinates from the starting point and return is calculated using RDA [35]. The initial pheromone values (τ_ij,), attractiveness (η), number of ants (n), importance of the pheromone trail (α), importance of attractiveness (β), and pheromone evaporation rate (ρ) are determined for each UAV for route planning. As a first step, the probabilistic path selection from point i to point j is calculated as follows.

$$P_{ij}(t) = \frac{|\tau_{ij}(t)|^{\alpha}|\eta_{ij}|^{\beta}}{\sum_{k\epsilon N_i}|\tau_{ik}(t)|^{\alpha}|\eta_{ik}|^{\beta}} \quad (2)$$

In Equation (2), $P_{ij}(t)$ represents the probability that an ant moves from point i to point j. In equation (2), $\tau_{ij}(t)$ is the pheromone density between point i and j, and η_{ij} is the attractiveness between point i and j. Ni in the equation represents the set of points that can be traveled to. At the end of each tour, the pheromone trails on the paths that the ants have traveled are updated. The pheromone update is done according to equation (3).

$$\tau_{ij}(t+1) = (1-\rho).\tau_{ij}(t) + \Delta\tau_{ij}(t) \quad (3)$$

In the equation, the pheromone value is multiplied by (1-ρ) for the evaporation of the existing pheromone trail. In this equation, ρ is chosen between 0 and 1. The $\Delta\tau_{ij}(t)$ in the equation is used for the ants to leave a new pheromone trail. The new pheromone trail left by the ants depends on the length of the path taken by the ant. This is usually expressed as in equation (4).

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t) \tag{4}$$

In route planning with ACO, possible routes are selected using pheromone trails and attractiveness. The ants then complete their routes according to the determined probabilities. After the tours are completed, the pheromone trails are updated, and the process is repeated for a given number of iterations until the best solution is found. The proposed approach was also tested in a simulation environment using multiple UAVs. For this purpose, ROS software and the Gazebo simulation environment were used. ROS, which stands for Robot Operating System, is a software framework based on FreeBSD, an open-source operating system by Berkeley Software Distribution [36]. It is not a traditional operating system but a meta-operating system that provides services expected from an operating system, including hardware abstraction, low-level device control, implementation of commonly used functions, message passing between processes, and package management [37]. ROS promotes flexibility and modularity in a system, represented as nodes in a network, allowing robot components to communicate through an anonymous and asynchronous publish/subscribe mechanism [38]. The simulation environment used is Gazebo, a 3D dynamic simulator capable of accurately and efficiently simulating robot populations in complex indoor and outdoor environments. Unlike game engines, Gazebo offers physics simulation with a high degree of accuracy, along with a range of sensors and interfaces for both users and programs [39]. Gazebo is built on two different executable file structures: gzserver and gzclient. The gzserver executable runs the physics update loop and generates sensor data, while the gzclient executable provides the user interface. Typical uses of Gazebo include testing robotics algorithms, designing robots, and implementing realistic scenarios [40]. An experimental study was conducted on the deployment of multiple UAVs to capture simultaneous images from multiple points in a real-world setting. The study was carried out using Gazebo, a 3D simulation program. Within the scope of the study, a 20,000 m² experimental area consisting of 50 target points was designed in the Gazebo simulation environment. The geometric objects representing the target points were modeled as square prisms with a side length of 1 meter. A 3D view of the simulation environment is shown in Figure 4.

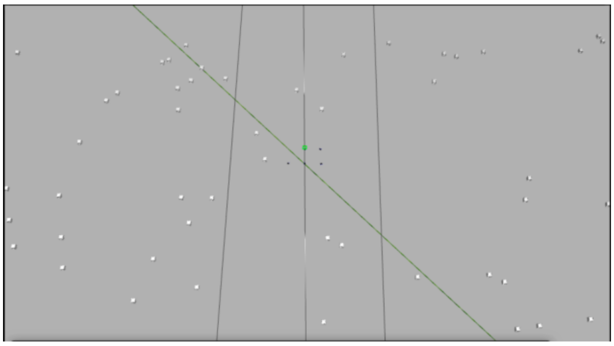


Figure 4. Representation of points in Gazebo Simulation environment

Four UAVs controlled by Ardupilot flight controllers were added to the 3D working environment. The UAV model with Ardupilot flight controller is given in Figure 5.

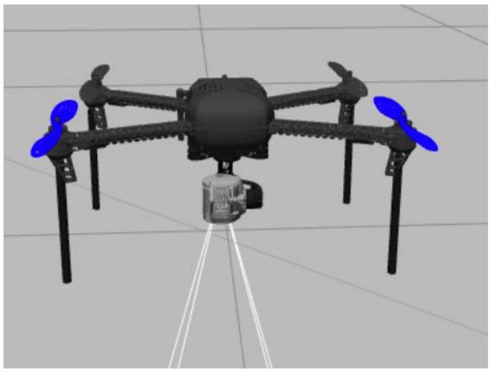


Figure 5. Gazebo UAV

MAVProxy ground station software was used to control the UAVs. A ground station software was run for each UAV and a connection was established with the UAVs. Instant command sending and data retrieval operations were performed with UAVKit, a Python library that enables application development for UAVs connected in a 3D simulation environment.

4. Application Results

The implementation of the proposed approach consists of three stages. In the first stage, cluster points are determined using a Genetic Algorithm (GA) for the given coordinates. In addition to GA, the K-means clustering algorithm was also used to determine the cluster centers. According to the number of UAVs and the starting point where the UAVs will take off, GA determines the points each UAV will fly to. The parameters of the GA are provided in Table 1.

Table 1. The parameters of genetic algorithm

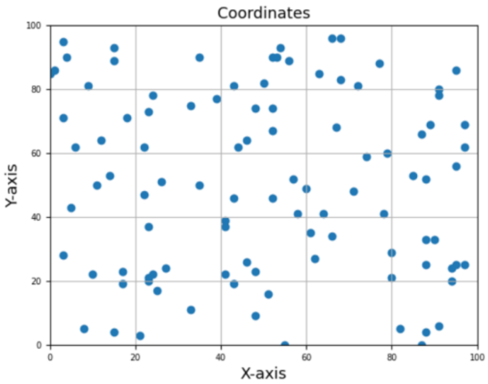
Parameter	Value
Number of iteration	500
Population size	100
Mutation rate	0.01
Crossover rate	0.7

In this study, we also compare the proposed method with one of the known clustering methods, K-Means. Figure 5 shows examples of clustering with both algorithms. In the study, for each UAV, the shortest path will be taken between the points determined by ACO, starting from the starting point, traveling through all the points in the relevant cluster with the shortest path and returning back to the starting point. Table 2 shows the ACO parameters.

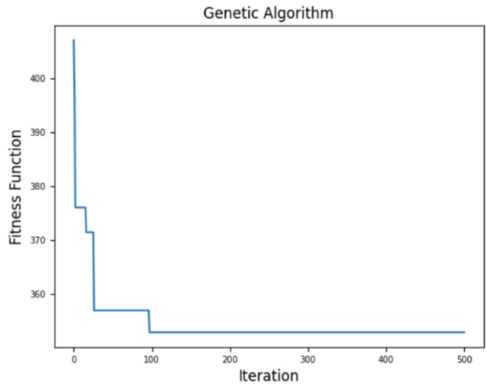
Table 2. The parameters of ACO

Parameter	Value
Number of ants for each coordinate	4
Size of colony	100
Pheromone amount	1
Evaporation rate (ρ)	0.1
Relative importance of pheromone (α)	1
The importance of attractiveness (β)	5

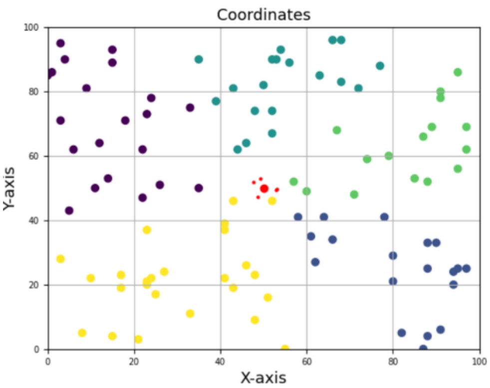
The UAVs, which are placed at the starting point determined to collect the images, need to reach the targeted coordinates in sequence, take the images and return back. With an appropriate route calculation, it is important for the UAVs to perform this process on the coordinates from the shortest distance in terms of time and battery savings. In this study, ACO was used for route calculation. For each UAV, the shortest route that allows them to reach their own coordinates starting from the starting point and return to the starting point was calculated with ACO. Figure 6 shows the clusters generated by GA and K-means and the routes generated by ACO for 5 UAVs in two-dimensional space.



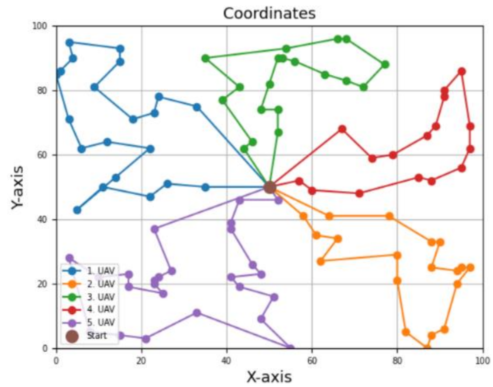
(a) Points generated in the coordinate system



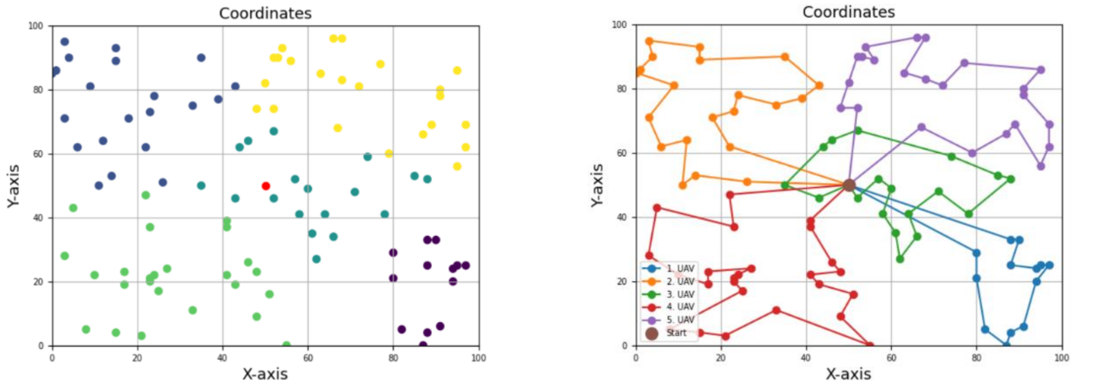
(b) Genetic algorithm objective function change



(c) Clusters generated by genetic algorithm



(d) Routes generated for genetic clusters



(e) Clusters generated with K-means **(f)** Routes generated for K-means clusters

Figure 6. Clusters created in two-dimensional space and route planning

In Figure 6, the starting point of the UAVs in the coordinate system is given as coordinate (50,50). With GA, the initial angles of the UAVs on the unit circle were found as [90, 163, 217, 318, 343]. These points are shown in Figure 6(c). It is seen that the routes of the UAVs in the clusters created with k-means intersect more than the clusters created with genetics. We also compared the distances traveled by the UAVs for each case. The comparison result is given in Figure 7.

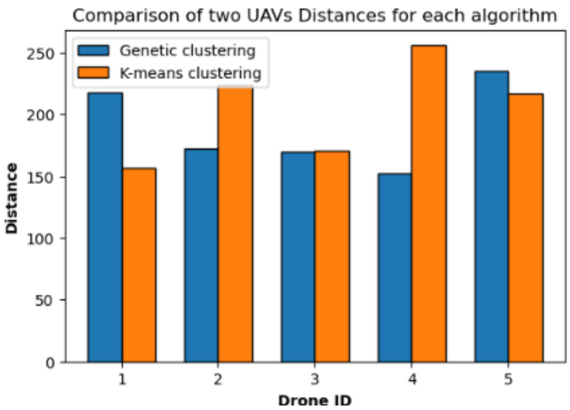
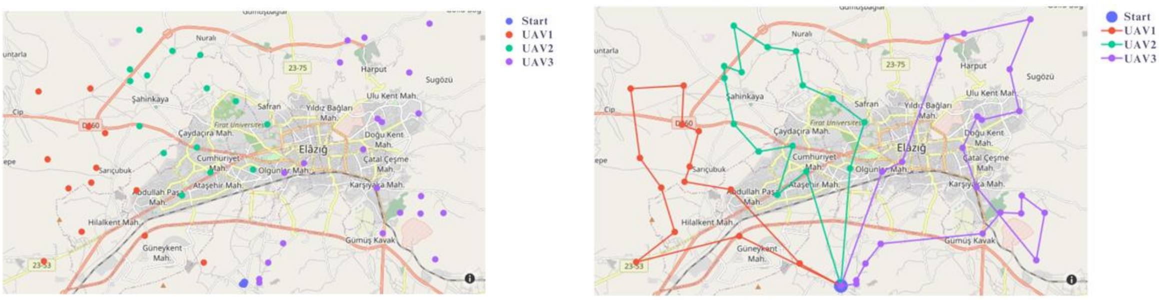


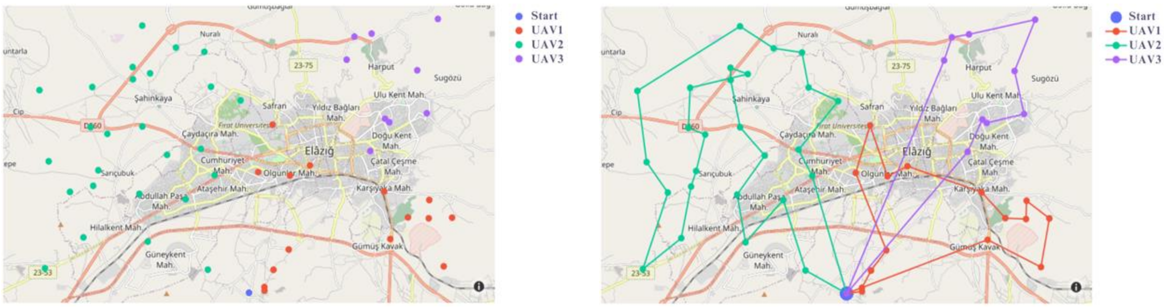
Figure 7. Total route length in each clustering for five UAVs

Figure 7 shows that the genetic clustering model finds shorter routes for many UAVs and shortens the total flight time. In addition, the total distance traveled is 945 units in genetic clustering and 1023 units in k-means clustering. Another advantage of genetic clustering is that UAVs are less likely to collide with each other. Because the routes do not intersect. In the second scenario, 3 UAVs were used on a map. The application results are shown in Figure 8.

(a) Points generated on the map **(b)** Genetic algorithm objective function change



(c) Clusters generated by genetic algorithm **(d)** Routes generated for genetic clusters



(e) Clusters generated by K-means **(f)** Routed generated for K-means clusters

Figure 8. Clusters and route planning in two-dimensional space

In Figure 8, when the clusters created with GA and k-means are considered, it is seen that the routes overlap with each other in the clusters created with k-means. On the other hand, the routes generated with GA appear more disjoint. In addition, the total path taken with the proposed clustering method for the three UAVs is 1.04 units, while the path taken with k-means is calculated as 1.13 units. The proposed approach was also tested in the Gazebo simulation environment for 5 UAVs. Five UAVs with Ardupilot flight controllers were added to the simulation environment via ROS software and are shown in Figure 9.

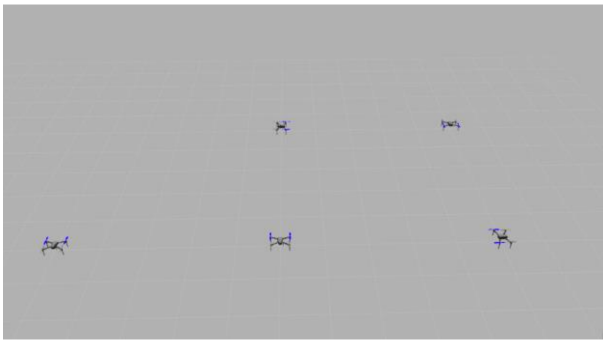


Figure 9. Multiple UAVs in Gazebo environment

MAVProxy ground station software was used to control the UAVs. A ground station software was run for each UAV and a connection was established with the UAVs. Instant command sending and data retrieval operations were performed with DroneKit, a Python library that allows application development for UAVs connected in a 3D simulation environment. In order to scan the field in the shortest time with the number of available UAVs, which is the aim of the study, clusters were created as many as the number of UAVs to be activated with the proposed clustering method. The clusters are shown in Figure 10.

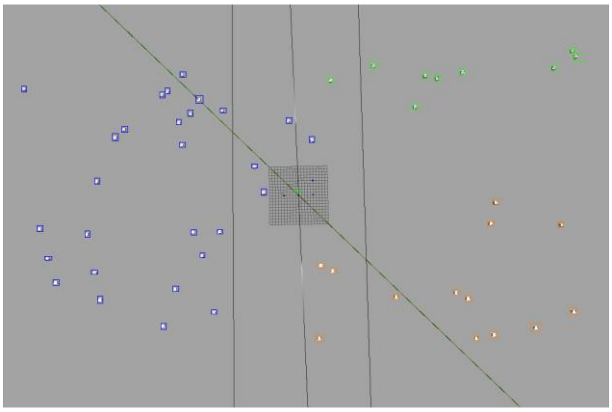


Figure 10. Coordinates clustered with the proposed method

Those marked with blue boxes represent the first cluster, i.e. the coordinates to be reached by UAV 1, those marked with orange boxes represent the second cluster, i.e. the coordinates to be reached by UAV 2, and those marked with green boxes represent the third cluster, i.e. the coordinates to be reached by

UAV 3. In order to control the points within the determined clusters by the UAVs in the fastest and shortest way, the route generated by the ACO was used. The front side of the UAV points to the +x axis and the right side points to the +y direction. Since it is different from the classical coordinate system, there is a difference in location information. The cluster created in the Gazebo simulation environment and the route structure within the cluster are given in Figure 11.

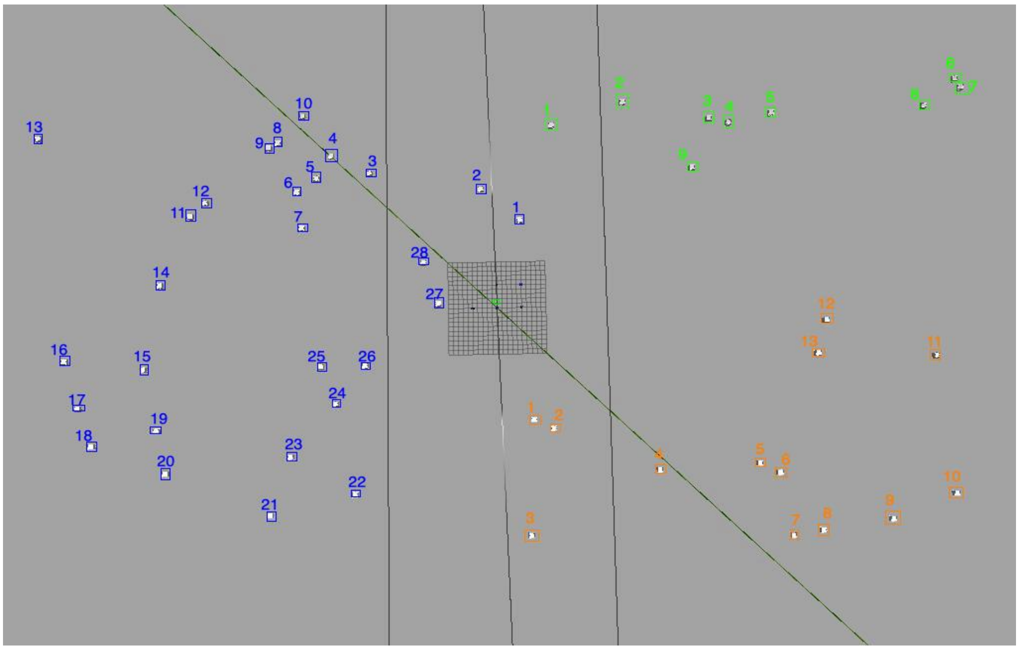


Figure 11. Routes generated for clusters in the simulation environment

The routes created cannot be uploaded to the UAVs at once. Therefore, the coordinate information will be sent to the UAV as a message and the DroneKit library is used to query whether the UAV has reached the target or not. In order to manage multiple UAVs at the same time in this way, multi-threading method was used. A thread was created for each UAV, location information was queried instantly for each UAV, and if the UAV reached the desired target, new location information was sent and the mission was tried to be performed. Thus, multiple UAVs were managed with a single software. The image of the UAV's progress to the target in the Gazebo environment is given in Figure 12.

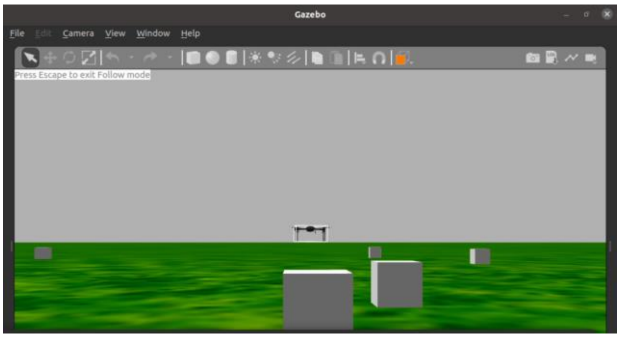


Figure 12. UAV's progress to the target in a gazebo environment

Table 3 shows the distances covered by each method for scenarios with different number of points, number of UAVs and starting points.

Table 3. Routed coordinates for UAVs

Example scenario	Number of points	Number of UAVs	Starting point	Total distance traveled with K-Means Clustering	Total distance traveled with the proposed clustering method
1	100	5	(50, 50)	970.39	955.96
2	100	3	(50, 0)	1000.97	947.40
3	100	4	(0, 50)	1068.11	1018.43
4	50	5	(39.1890, 38.6728)	1.27	1.14
5	50	3	(39.1890, 38.6228)	1.13	1.05
6	50	4	(39.2690, 38.6728)	1.42	1.25

According to the results obtained, the proposed coordinate sharing method for UAVs sent from a starting point to reach the assigned coordinates works more efficiently than clustering methods such as K-Means, which only performs a standard grouping in terms of distance similarity. Subsequently, successful results were obtained in the routing process performed with RDA for each UAV to reach their assigned coordinates from the shortest distance. This method is expected to be used to perform operations such as taking images and transferring cargo in order to quickly determine the situation during and after the disaster until detailed mapping with satellite images or aerial vehicles.

In the literature, different approaches have been used for task allocation and route planning of swarm UAVs. Some studies aim to reach the target with the shortest path in an environment with obstacles. For this purpose, route planning of a single UAV was mostly performed. In studies conducted with swarm UAVs, on the other hand, multiple UAVs were used for shortest route planning. The routes to be traveled by each UAV were determined by clustering approach. Table 4 shows the comparison between the methods in the literature and the proposed approach.

Table 4. Comparison of the proposed method with other studies

Reference	The method	Simulation tool	Results
[7]	Clustering with k-means and distributed route planning	Display on a map	- Decentralized control - Low real-time applicability
[19]	Exponential rank differential evolution algorithm	Representation in two and three dimensional space	- Route planning in the presence of obstacles - Single destination
[20]	Route planning with multi-objective swarm optimization	Representation in two and three dimensional space	- Route planning for a single destination - Avoiding obstacles
[28]	Integer linear optimization	Representation in two dimensional space	- UAV positioning in a distributed environment - Protection of inter-UAV communication
[32]	Adaptive full coverage and intelligent route planning	Representation in two dimensional space	- Preventing intersection of routes - Quality of service and establishment of minimum routes
[33]	Deep Q learning based route planning	Representation in two dimensional space	- Minimum service time - Attention-based deep reinforcement approach - Mathematical modeling
This study	Multiple route planning with genetic algorithm based clustering and ant colony algorithm	Two-dimensional environment, map and representation in Gazebo simulation environment	- Route planning of multiple UAVs with minimum distance - Preventing crossing of routes - Suitable for real life application

Considering the results in Table 4, it is evident that many methods only use two-dimensional graphical representations. Although some studies have applied three-dimensional environments, the main focus has been on guiding to a target in an obstacle-rich environment [19-20]. In multi-route planning with swarm UAVs, only study [32] proposed a method to prevent route intersections. Due to the complexity of the mathematical structures of some models, there is a need to adjust specific parameters [28, 33]. This study offers two main contributions compared to the existing literature. The first contribution is the creation of non-intersecting routes for UAVs using a genetic algorithm, resulting in a low intersection rate. The second contribution is the demonstration of the algorithm in three different platforms: a two-dimensional space, on a map, and in the Gazebo simulation environment. The Gazebo environment models UAVs in a way that accurately reflects real-world scenarios, providing a reliable simulation of actual field conditions.

5. Conclusions

This study proposes an innovative method combining Genetic Algorithm and Ant Colony Optimization techniques for task allocation and route planning of swarm UAVs in disaster situations. Firstly, k-means and GA based clustering techniques are used to determine the mission regions of UAVs. Genetic-based clustering creates more discrete and clear clusters, thus avoiding overlaps between the mission areas of UAVs. This allows for a more efficient and faster scanning of disaster areas. In addition, operational efficiency is increased by ensuring that the routes of the UAVs do not intersect. Route planning using Ant Colony Optimization helped to minimize the total path distance of the UAVs. Thus, energy consumption is reduced and the UAVs can operate for longer periods of time. The proposed approach was tested both on a two-dimensional coordinate system and on Google Maps and Gazebo simulation environment. In particular, the tests in the Gazebo simulation environment demonstrated the applicability and effectiveness of the method in real-world conditions. Similar simulation environment tests have not been conducted before, which emphasizes the novelty of this study in the literature. With real-time data integration, the route planning of UAVs can be updated instantaneously and quickly adapted to emergency situations. This contribution is a great advantage when time is of the essence in disaster response. As a result, the proposed method successfully solves the problem of task sharing and route planning of swarm UAVs in disaster situations and improves operational efficiency. The results of the study provide an important contribution to the optimization of UAV use in future disaster response operations.

Acknowledgement
This study was supported by the Scientific and Technological Research Council of Turkey (TUBITAK) under Project No. 123E669.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Author Contribution Statement

Conceptualization: IA, ÇK, GA
Methodology: ÇK, GA, IA
Manuscript writing reviewing editing: IA, ÇK, MUS
Supervision: IA

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