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Autonomous Architecture for UAV-based Agricultural Survey

Sabyasachi Mondal* and Alex Williamson †
Cranfield University, Cranfield, MK43 0AL, United Kingdom

Zhengjia Xu‡
Cranfield University, Cranfield, MK43 0AL, United Kingdom

Antonios Tsourdos§
Cranfield University, Cranfield, MK43 0AL, United Kingdom

This paper presents the concept of autonomous architecture for UAVs to minimize human involvement for agricultural surveying. Agricultural surveying applications include monitoring crop health and collecting ground truth data for treatment and harvest planning. The proposed architecture can automate the entire surveying process and helps farmers to obtain specific and essential knowledge about the crop more quickly. This architecture helps to increase crop yields while reducing operating costs. The autonomy is achieved by integrating functional modules such as Mission Planning, image processing, task allocation, and communication. This work is focused on describing the mission planning and task allocation since image processing is not within the scope.

I. Introduction

Agricultural decision-makers require information that is specific to both crop type and characteristic. An example of this is to ascertain percentage crop canopy coverage, as this information can identify the crop's actual vs. planned growth profile, which can be used to assist both yield prediction and harvest date. Identification of unhealthy crop, weed, water stress, and soil moisture is additionally beneficial in establishing a complete overview of a crop's health. A lot of human effort is involved in collecting this information in a large field and farms. The use of unmanned aerial systems (UAS) and unmanned aerial vehicles have been introduced into agricultural workflows in recent years and are predominately for the collection of multi-spectral crop image data [1]. Data collected is post-processed typically to identify crop growth stage and characteristics, which in turn enable agronomists to make more informed treatment and harvesting decisions.

The existing architecture in agricultural surveying consists of a set of operations such as Aerial Survey, Data Acquisition, Data Analysis, Ground Truthing. UAVs of fixed-wing or Quad-copter types are used as a platform to fly sensors (e.g., [2], [3], [4], etc.) and imaging devices, such as Multi-spectral cameras and Infra-red sensors. UAV flights conducting aerial surveys (fig. 1) are typically autonomous in that the UAV flies a predetermined flight path (fig. 2) while automatically acquiring images using onboard sensors (data acquisition) to identify 1. water stress, 2. Crop disease, 3. soil moisture, and 4. weed. However, significant flight planning and sensor configuration are required by a Remote Pilot before each survey, with subsequent data extraction and export to an external processing engine, also being a manual process. Post-processing the images (data analysis) involves creating 'index' maps (e.g., Normalised Difference Vegetation Index (NDVI) fig. 3) based on an algorithmic calculation of colour reflectance of crop canopies. Interpretation of the map leads to the identification of the affected areas. After identification, farmers need to visit the affected areas (Ground Truthing) to diagnose the crop status in detail fully. Existing architecture has numerous issues which can be summarized as follows

- Pilots need to upload the survey plan before each survey. They need to extract the data and export to an external processing engine.
- Map creation takes approximately twenty-four hours. This results in the farmer waiting one day before knowing the location and scale of variation.

*Research Fellow, SATM,Aerospace Engineering, sabyasachi.mondal@cranfield.ac.uk
†Experimental Research Fellow, SATM,Aerospace Engineering, Alex.A.Williamson@cranfield.ac.uk
‡Ph. D., SATM,Aerospace Engineering, Zhengjia.Xu@cranfield.ac.uk
§Professor, SATM,Aerospace Engineering, a.tsourdos@cranfield.ac.uk

Fig. 1 Drone survey of agricultural field

Fig. 2 Predefined survey plan

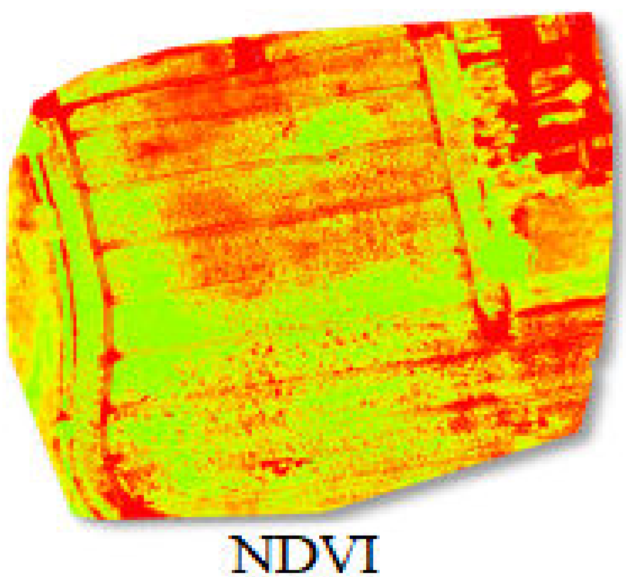

Fig. 3 NDVI map of a field

- Ground Truth data can only be collected once the index map has identified the locations. Therefore data collection cannot begin until at least one day from the initial survey, which could be significant if the crop is experiencing a rapidly increasing threat or change (e.g., pest damage).
- Collecting Ground Truth data requires additional journeys back to the field. This takes additional time and increases the cost to farmers. Collecting Ground Truth data is a completely manual process, and relies on the individual doing Ground Truthing to make a diagnosis, and therefore to have specific crop knowledge.

Ideally, farmers need the locations of affected areas while the survey is going on such that they don't have to wait for a day. Moreover, if high definition images of those affected areas are available, the farmers don't need those additional journeys for ground-truthing. These facilities need more UAVs, which in turn need more pilots and results in an increase in operation cost. However, these facilities can be obtained without human involvement by designing an autonomous architecture which can deal with the issues stated above. Therefore autonomy is the key to save time and overall costs.

The statement for the autonomy problem is given in the following section.

II. Problem Statement

The requirement for implementing autonomy in agriculture is given as follows

A) Autonomously upload the survey plan to a UAV as soon as it is powered on and start executing the plan.

B) Autonomously identify and communicate locations of significant index-based crop variation (affected areas) from a UAV. Thereby providing locations of such variation twenty-four hours earlier than conventional post processing methods. While post-processed maps can still be created as normal, it is understood that farmers require targeted information so they can act fast.

C) Autonomously divide the locations among the UAVs and upload those locations to UAVs such that they can visit those affected areas.

D) Autonomously collect and communicate further ‘Ground Truth’ information (high-resolution images of the affected areas) from a scalable number of UAVs. Thereby removing the need for additional and subsequent ‘manual’ visit to the field.

Autonomous architecture can provide live location information together with high definition imagery of areas of interest. Being able to provide live location information requires identification of affected areas by onboard learning based image processing. Learning based image processing is becoming popular for object identification. Researchers have used Machine Learning algorithms in agriculture to identify weed, disease, water stress, and other abnormalities. In [5] and [6] weed detection is done by Naive Bayes and Discriminant analysis algorithms, respectively. Vegetation Segmentation in [7] is done by the Naive Bayes algorithm. In [8] k-Nearest Neighbour algorithm is used for disease detection in leaves. Yield prediction using k-Means clustering is presented in [9]. In [10], estimation of Water Stress is done by using the Gaussian Mixture Model. More references can be found in [11]. In addition to machine learning, Deep learning algorithms (Convolutional Neural Network (CNN)) are increasingly incorporated, and have been used for image processing in many research works [12, 13] etc. More references can be found in [14].

In addition to the identification of affected areas, autonomous visits to those locations are necessary to capture local high-quality imagery data. Autonomous visit of UAVs to the affected areas require task allocation and mission planning. Task allocation is common in robotic applications. A range of different kinds of algorithms have been established and documented. An examples is Consensus-Based Auction Algorithm (CBAA) [15] .Another kind of algorithm exists which is designed using Game theory [16]. Some of the Bio-Inspired algorithms are also used to solve task allocation problems. Genetic Algorithm is a bio-inspired algorithm which is used for task allocation [17, 18]. Other bio-inspired algorithms such as Particle Swarm Optimization (PSO) [19, 20] and Ant Colony Optimization (ACO) [21, 22] have been used for task allocation.

A. Contribution

The significant contribution of this work is to implement autonomy in agricultural surveying processes. Autonomous task allocation and path planning remove the need for manual ground truthing. Moreover, all of these processes can be monitored in a mobile or tablet with the help of an android application which helps the pilot and farmers to get the knowledge of the affected location quickly. Use of this architecture is not limited to agriculture. People can use this architecture and the app to automate various applications (e.g., search and rescue operation).

III. Autonomous Architecture

Design of Autonomous architecture for agriculture comprises of the integration of functional modules such as image processing, task allocation, and communication. The battery life of UAVs are in flight is short, $10-30$ minutes typically, and so the design of the architecture has to consider this limitation. Airborne UAV must comply with country regulations, and in the UK remain with $500m$ and Line of Sight (LOS) of the Remote Pilot. As fields are often larger than $500m$ and UAV increasingly small, so this reduces survey efficiency as optimum longer length flight paths have to be modified to stay within $500m$, or the Remote Pilot and ground station to be mobile. This restriction also has to be included in the architecture design.

In this work, autonomous architecture for agriculture is designed in a Centralized fashion. The details of the architecture are given as follows.

A. Centralized Architecture

A centralized Architecture consists of the main processing unit (PC or laptop). A pictorial representation of the autonomous architecture is shown in fig. 4. The UAV which flies at $120m$ (approx $400ft.$) is named as 'Survey UAV'. The Survey UAV is equipped with a processing unit (Raspberry-pi), a communication module (Xbee), and imagery unit (Multispectral camera). The autonomy can be achieved by following few steps as follows:

- 1. Captures images using Multi-Spectral camera
- 2. Extract locations of relevant images using raspberry pi
- 3. Reference locations are sent to ground station using Xbee
- 4. Task allocation in ground station and obtain the waypoints for each Monitoring UAVs are created
- 5. Ground station sends the waypoints to each monitoring UAVs through SMS using SIM800C GSM module
- 6. The SMS are received in an android app and creates a flight plan through this waypoints and upload to the corresponding UAVs

The pictorial representation of these steps and their sequence (steps 1 to 6) is shown in fig. 4.

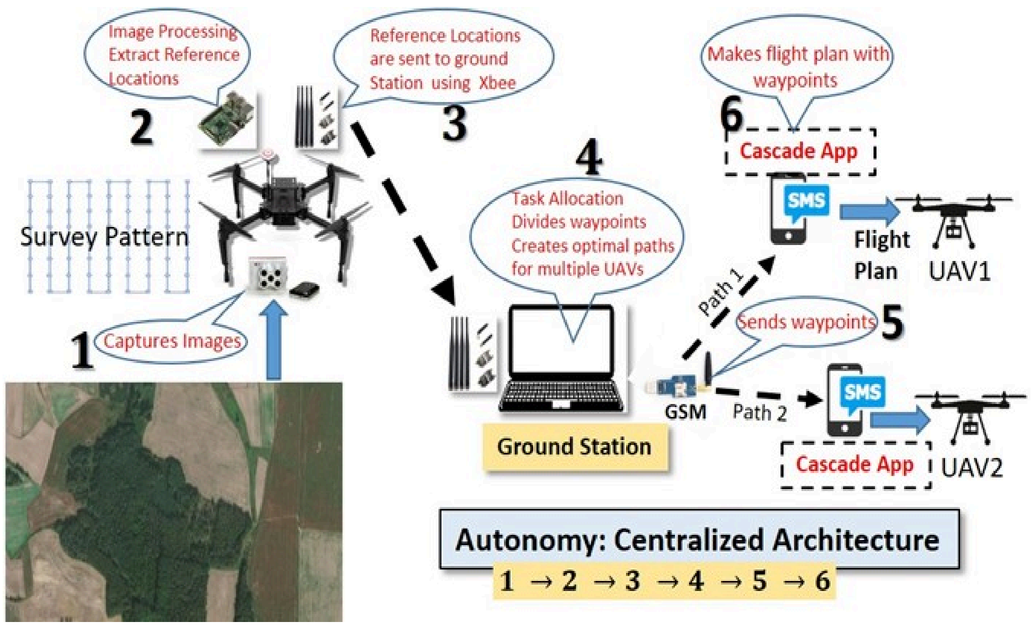

Fig. 4 Autonomous Architecture : Centralized

These steps are described in the following subsections.

*1. **Image Capture***

The Survey UAV flies in a predefined autonomous survey pattern (fig. 4) and captures images using the Rededge-MX multi-spectral camera. The camera captures five images in different wavelengths. An example of the images is shown in fig. 5.

*2. **Location extraction***

The multi-spectral images contains the location information (lat-lon). Images with relevant information are identified in real-time using onboard learning based image processing algorithm. We have set up an experiment to identify the numbers in an indoor lab. The KNN based image processing algorithm is implemented on the raspberry pi. The algorithm detects the numbers in the captured image as shown in fig. 7. The same technique can be applied in agriculture to identify the defects in crops. An example of identified locations in a field look like as shown in fig. 6.

*3. **Sending locations to ground station***

The locations (lat-lon) of the detected images are transmitted to the ground station using Xbee module mounted on-board.

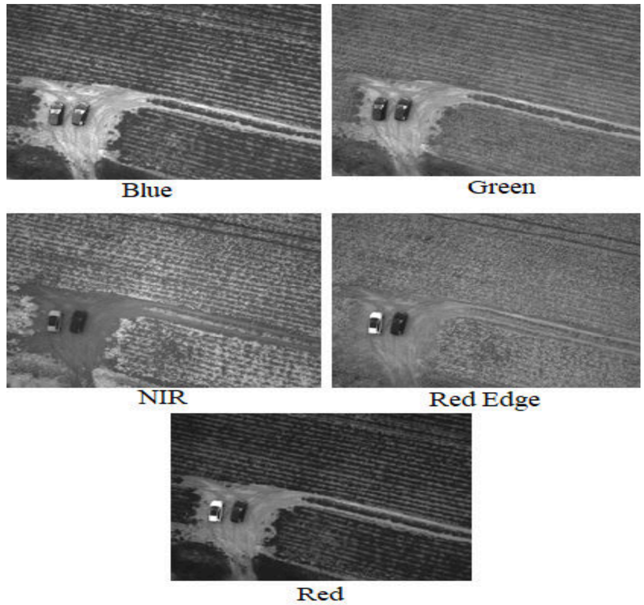

Fig. 5 Image captured by MS camera

4. Task allocation in ground station

All the locations communicated during the survey are received at the ground station following transmission. These locations (e.g., fig. 6) are used to perform the task allocation. The task allocation algorithm divides these locations to find an optimal path (sequence of waypoints) for each of the monitoring UAVs.

Task allocation is an essential part of autonomy. The task in the context of agriculture is to visit the affected areas and capture images of crops closely. The objective of this operation is to assign 'Monitoring UAVs' to visit those locations. The task allocation algorithm divides the tasks among the monitoring UAVs and finds an optimal path for them, considering their location. The high-quality images of the affected area help the farmers to visualize the crop without visiting those areas, and hence Ground Truth remotely.

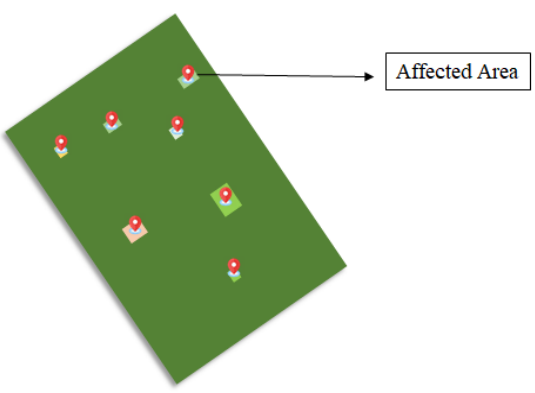

Fig. 6 Example of Affected areas identified by the on-board image processing algorithm

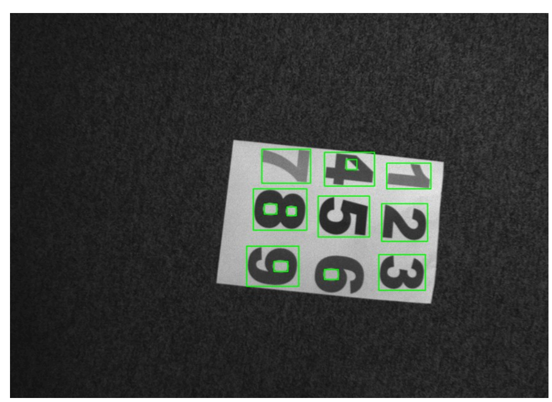

Fig. 7 Example of on-board image processing algorithm using KNN.

Task allocation in agriculture is very similar to the Vehicle Routing Problem (VRP) or Multiple Travelling Salesman Problem (mTSP). TSP is a well-studied problem, and there are a variety of solution methods. One of the popular methods is the Genetic Algorithm (GA), which is a bio-inspired algorithm. This class of algorithms has the power of finding solutions that are sub-optimal but consume less time and are computationally less extensive. One example of task allocation using GA is presented in the simulation section.

5. Sending the waypoints to CASCADE Application

The paths or sequence of waypoints are sent to the CASCADE application which is installed in a phone attached to each monitoring UAV. The sequence of waypoints are sent as SMS through the GSM module SIM800C.

6. App creates flight plan and uploads to UAV

The SMS is received in mobile which is attached to each UAV. An example of received SMS is shown in fig. 8. In

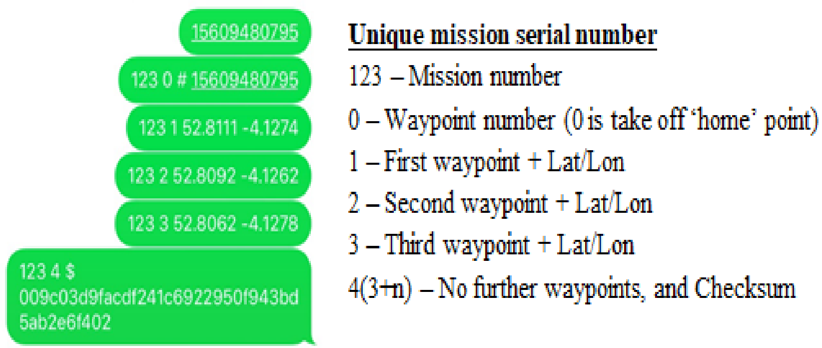

Fig. 8 An example of SMS received from ground station.

this figure, three waypoints are received in the SMS. Each SMS has a mission number and a checksum. The details about the SMS and CASACDE app is published in [23]. Some pictures of the app are given in fig. 9 and 10.

Fig. 9 App in the mobile

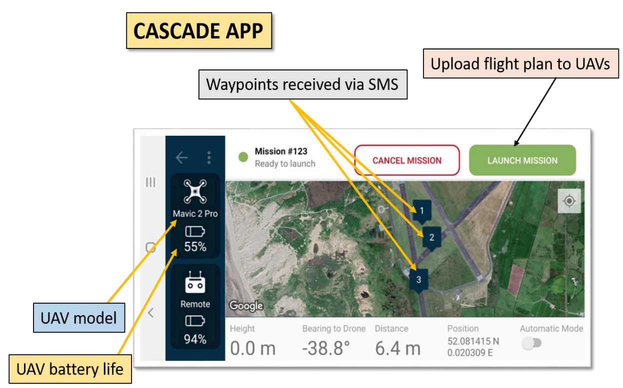

Fig. 10 Mission launching view of app

IV. Simulation

A simulation study is performed to verify the autonomous reception of GPS location and task allocation algorithm. In this study, DJI M100 is selected as Survey UAV. Raspberry-pi, RedEdge Multispectral camera, and Xbee module are mounted on it (figs. 11 and 12).

The UAV is taken to a field near Cranfield Airport and is flown in a random path. During this flight, RedEdge camera captures images with a predefined frame rate. These images are stored in the SD card of RedEdge. It can be noted that the RedEdge camera has a GPS unit, and the metadata of each image contains GPS location information. Few images are selected randomly from the SD card, and the locations are extracted in Raspberry-pi (by a Python script). An Xbee module sends these locations to the ground station. These locations are received as a .txt file at the ground station using a separate Xbee module. Then the locations are extracted from the file because the file contains garbage values along with the locations. These locations are used to run the task allocation algorithm, which gives separate paths for each Monitoring UAVs.

Fig. 11 DJI M100 with Raspberry-pi

Fig. 12 DJI M100 with RedEdge and Xbee

Six locations and two Monitoring UAVs are considered in this simulation study. The received data from the Survey UAV is shown in fig. 13. It also shows the autonomous data reception and task allocation.

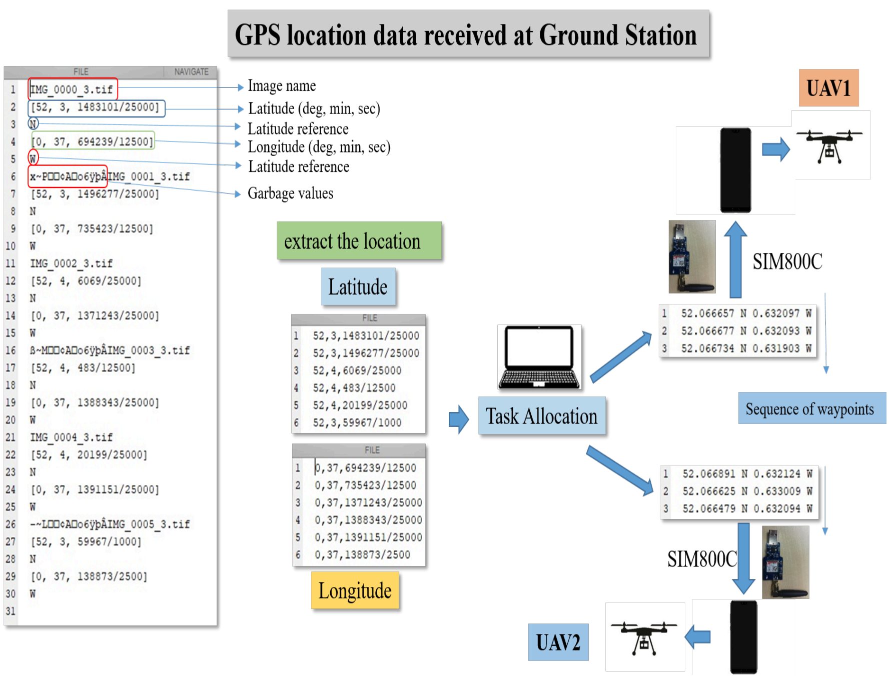

Fig. 13 Flow diagram: Receipt of locations and sending the optimal paths to the UAVs

The task allocation is done using Genetic Algorithm (GA) which produces two paths for two Monitoring UAVs as shown in fig. 14.

V. Conclusion

All of the steps 1 to 6 are tested successfully and they work in the synchronization. It has been observed the operations like image processing on raspberry pi, sending locations of affected areas from on Raspberry-pi, receipt of those locations at the ground station, execution task allocation algorithm, sending SMS, Receipt of SMS in the mobile app are executed autonomously. This architecture is useful to implement autonomy in various missions like search and

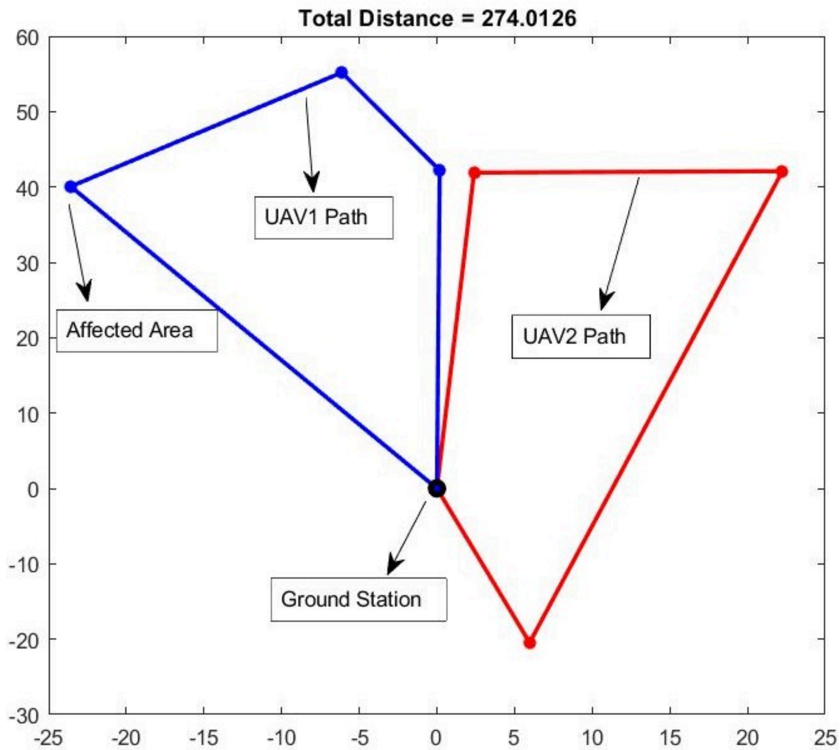

Fig. 14 Optimal Path for Monitoring UAVs using GA

rescue, surveillance etc.

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Mondal, Sabyasachi

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