Path Planning for Unmanned Aerial Vehicles in Constrained Environments for Locust Elimination

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ABSTRACT

Present-day agricultural practices such as blanket spraying not only leads to excessive usage of pesticides, but also harms the overall crop yield. This paper introduces an algorithm to optimize the traversal of an Unmanned Aerial Vehicle (UAV) in constrained environments. The proposed system focuses on the agricultural application of targeted spraying for locust elimination. Given a satellite image of a farm, target zones that are prone to locust swarm formation are detected through calculation of the Normalized Difference Vegetation Index (NDVI). This is followed by determining the optimal path for traversal of a UAV through these target zones using the proposed algorithm in order to perform pesticide spraying in the most efficient manner possible. Unlike the classic travelling salesman problem involving point-to-point optimization, the proposed algorithm determines an optimal path for multiple regions, independent of its geometry. The savings obtained by employing the proposed method is directly proportional to the total non-infested area in an agricultural land compared to the conventional method. Finally, the paper explores the idea of implementing reinforcement learning to model complex environmental behaviour and make the path planning mechanism for UAVs agnostic to external environment changes. This system not only presents a solution to the enormous losses incurred due to locust attacks, but also an efficient way to automate agricultural practices across the globe in order to improve farmer ergonomics.

Keywords: Multispectral image, Normalized Difference Vegetation Index, optimization, path planning, reinforcement learning, targeted spraying, Unmanned Aerial Vehicle

1. INTRODUCTION

Over the last few years, the world has witnessed substantial change in the way robotics and automation has revolutionized various industrial sectors. Notwithstanding this technological revolution, farming practices in several regions of the world are extremely labour intensive, uneconomical and inefficient which result in enormous losses to farmers.

In the recent past, there has been an adoption of technologies in the agricultural domain which have laid major emphasis on automation of tasks to reduce the skilled labour requirement. Digital technologies have additionally paved the way to help farmers to improve crop yield through smarter implements and solutions. However, real-time use of intelligent systems has been a major challenge due to the diverse applications and conditions that exist in this domain. One of the prevalent precision agriculture techniques, is the operation of blanket spraying performed by agricultural drones. This operation not only utilizes a significant amount of time, but also results in excessive wastage of fuel and pesticides. It also damages the good crops which is detrimental to the overall crop yield. Addressing these issues through the introduction of resource optimization, involving solutions such as intelligent navigation algorithms, can prove to be extremely beneficial in transforming present day agricultural practices.

This paper aims to devise an efficient and resource optimized solution to alleviate the problems caused by locust swarms in agriculture. The detrimental effects that locust swarms pose to agricultural practices is a major area that has been addressed in recent years. Locust swarms can destroy fields within a matter of weeks and based on the trends presented by the FAO[1], losses to agriculture from locusts could cross \$5 billion on 25% infestation solely in Southwest Asia[2]. One of the methods to eliminate locusts is through aerial spraying of pesticides. Devising a path optimization algorithm to perform targeted spraying can prove to be extremely essential to mitigate the aforementioned shortcomings in the most efficient manner possible. Furthermore, this technology for targeted spraying can be extended to a multitude of use-cases within and outside the agricultural domain. Targeted spraying of herbicides and pesticides falls under the scope of agricultural applications. Other areas that can benefit from this technology include door-to-door delivery systems, delivery of medicinal packages or rescue missions in calamity-affected areas.

Section 2 provides insight into the related work that inspires the research theme of this paper. Section 3 provides details pertaining to the proposed implementation methodology and the simulation observations through *ArduPilot Mission Planner*. The work presented in the paper is summarized in section 4 along with the future scope for this technology.

2. RELATED WORK

Desert locusts have the ability to rapidly increase their population when ecological conditions such as vegetation blooms or rainfall corroborate locusts' reproductive cycle[3]. The life cycle of the desert locust involves several stages[4]. It begins with the egg laying and hatching phase. The new born might remain in this phase, mounting up to five or six times as they grow in size[5]. During the adult phase, their wings enable them to colonize new areas[6].

Traditionally, locust control strategies assumed that only when swarms migrate from outbreak areas and breed in neighbouring regions, an outbreak occurs. Locust control can be achieved by focusing on smaller, more accessible areas and providing the necessary preventive, monitoring and treatment equipment[7]. Extrapolating this idea, locusts' control can be achieved by spraying pesticides on the locusts in their egg laying/post egg laying phase, which are generally concentrated in small, accessible regions. This allows for effective locust control, mitigating the risk of outbreaks. NDVI is highly useful in detecting features of the visible area which are extremely beneficial for decision making[8]. NDVI may be used in disaster management solutions as well as devising new methods in prevention of plague outbreaks and disasters[9]. In this paper, NDVI is used as a parameter to replicate the presence of potential locust hotspots.

The latest technology makes use of blanket spraying or humans manually spraying pesticides over farmlands. The WHO (World Health Organization) estimated over 1 million pesticide cases from which 100,000 deaths each year were due to the pesticides sprayed by human beings[10]. Making the use of Unmanned Aerial Vehicles (UAV) has multifold benefits. Pesticides can be accurately dispensed in only the affected areas that can be detected using vegetation index parameters like NDVI. UAVs are also used in non-destructive data collection rapidly and efficiently. UAVs are intelligent robots, capable of analyzing air quality and soil components[11]. UAVs have the ability to collect and transmit data to servers in real time. Although as the number of subsystems increase, the endurance or mission flight time of UAVs reduces. Short battery life is a problem that can be resolved by path planning algorithms that minimize the total trip-length cost[12].

3. IMPLEMENTATION METHODOLOGY AND RESULTS

This section gives detailed information on the proposed approach for identification of locust hotspots and determination of the optimal trajectory to be traversed by a UAV for performing targeted spraying. Fig. 1 shows a high-level representation of the system architecture.

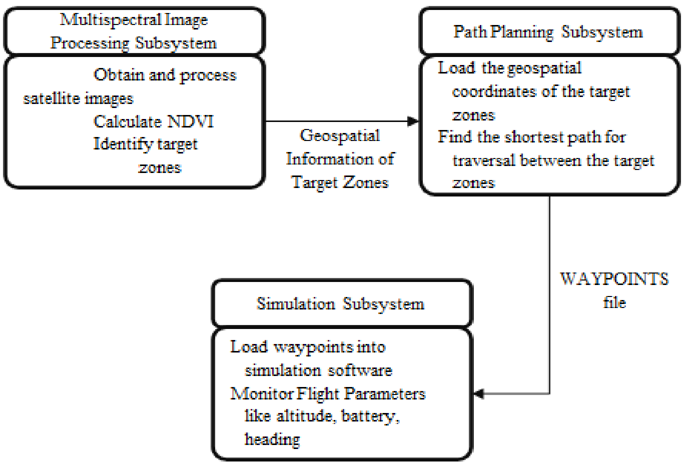

Fig. 1 System Architecture

3.1 Acquiring Multispectral Images

Using Google Earth Engine, the Landsat Image Collection is selected to acquire multispectral images. For superior accuracy, the image with the least cloud cover was selected. Geospatial information such as latitude and longitude, and NDVI (crop health parameter) of the selected region were extracted. For this paper, a region in central Maharashtra, India was selected as the region of interest.

3.2 Generating NDVI Map

Normalized Difference Vegetation Index (NDVI) is an indicator used in the agricultural domain to monitor crop health using spectral characteristics. In this work, NDVI is used as a parameter to detect potential locust hotspots. The regions of the image where the NDVI value lies within a threshold is considered to be a locust hotspot. Using the Near Infrared (NIR) and red bands of a multispectral image, the NDVI associated with every coordinate in the obtained image is calculated as depicted in (1):

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{1}$$

The problem of detecting locusts is extensively under research and there is no standardized method presently.

3.3 Identifying Regions of Interest

As per the FAO[1], locust hotspots are most likely to be found at the coordinates where the NDVI value is below 0.14. Following the thresholding standards, a binary image is created to represent the potential locus hotspots. Additionally, morphological operations are performed on the image to remove noise. Using Otsu's thresholding, the centroid of each region is identified and the regions are numbered and stored. Fig. 2 shows the detected locust hotspots.

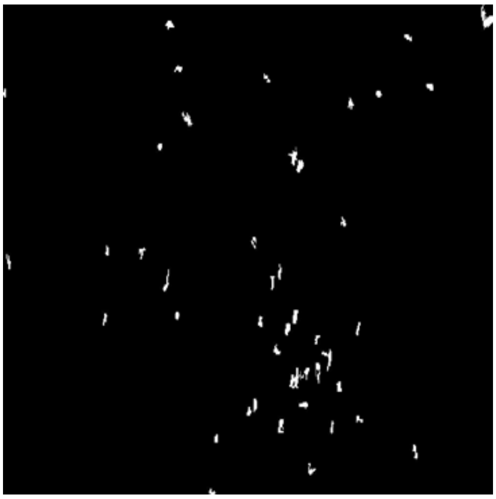

Fig. 2 Locust Hotspots

3.4 Region Sampling

This sub-section details the operations performed to sample the detected hotspots, create potential waypoints for traversal and store their positional information.

3.4.1 Region Splitting

The UAV can only spray pesticides over a certain region while being stationary at any given point of time due to its physical constraints, i.e., the swath of the drone. Each region is split into the largest possible grids keeping in mind this constraint. Larger the grid size, fewer waypoints for the UAV to follow. Each region is split into grids based on the geometry of the hotspot. Centers of all the grid boxes are used as waypoints for the UAV.

This implies, if the UAV was to visit and spray pesticides over all the centers thus created, the entire region would be covered, not leaving out any locust-infected hotspot. Irregular region shapes are discretized making the system computationally efficient. This operation is similar to signal sampling. An example is shown in Fig. 3.

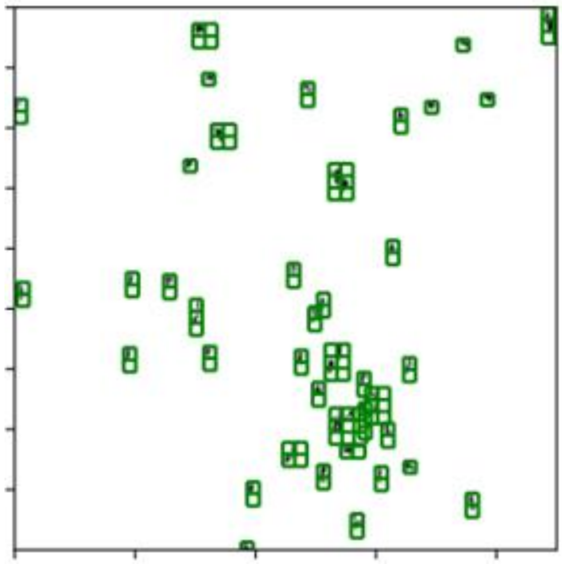

Fig. 3 Sampled Regions

3.4.2 Storing Region Center Information

Each center within a particular region has the following attributes associated with it:

a) Region Number
b) X index – the X coordinate of the center w.r.t the region
c) Y index – the Y coordinate of the center w.r.t the region
d) X global – the X coordinate of the center w.r.t the entire image
e) Y global – the X coordinate of the center w.r.t the entire image
f) Locust Check Index – an integer (0, 1 or 2) to store information of locusts in that region
g) Region Type – a string that stores if the center is in a vertically or horizontally oriented region
h) Corner Type – a string that stores if the center is a corner point or not.

These 8 features are extracted from all centers and stored in a list in the following format. Each center point represents all the characteristics of the grid it covers. The path planning algorithm uses information from this list to decide the order of every waypoint.

Locust Check: this is done by checking if there is any pixel with intensity 1 in the swath*swath area associated with the center. If there is no pixel with intensity 1, it implies that the sub-region does not contain any locust infestation. The following values indicate the type of center and presence of locusts in the associated sub-region:

a) 0 – center with locust
b) 1 – corner without locust
c) 2 – center without locust (need to skip this waypoint)

Next, the order of regions and the respective sub-paths within a region are decided.

3.5 Generating Optimal Path

This sub-section provides details about the steps followed to generate the optimal path for traversal of a UAV.

3.5.1 Deciding Region Order

Keeping a fixed start point, the first step towards optimizing the path is deciding the order in which the drone has to visit all the regions. This is akin to the Travelling Salesman Problem[13]. Using the MATLAB Optimisation Toolbox[14], an algorithm was devised to return the order of regions that would cover minimum distance.

The most optimized tour covering all the regions in the right order is found. The program goes through several iterations before forming the shortest path. Fig. 4 shows all the points and the path connecting the centroids of every detected region.

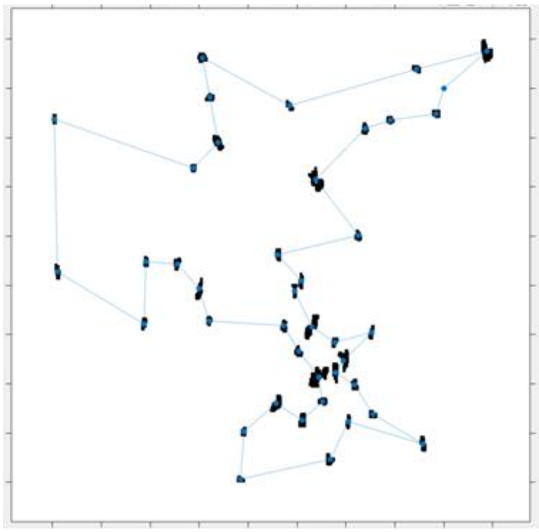

Fig. 4 Determining Order of Regions

3.5.2 Deciding Path Within a Region

Once the regions have been sampled and the order of the regions to be visited has been decided, all the hotspot centres within a particular region need to be covered optimally. A few examples of the regions are shown in Fig. 5.

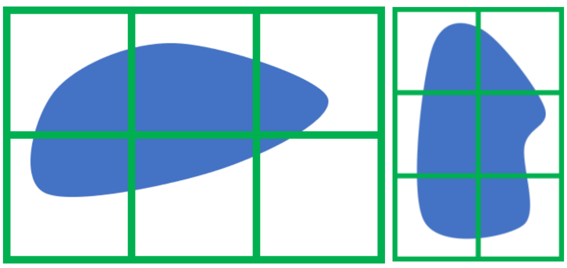

Fig. 5 Examples of Sampled Hotspot Regions

3.5.2.1 Deciding Entry Point

Each region has a maximum of 4 corner points that act as entry points for the UAV in that particular region. Consider 2 regions N_i and N_{i+1}. Assume the drone has covered all the points in region N_i and is now moving towards N_{i+1}. The algorithm computes the distance of all the 4 corner points of region N_{i+1} from the current point and chooses the minimum distance corner as the next waypoint. Once the entry point has been fixed, the sub-path within the region has to be decided.

3.5.2.2 Types of Sub-paths

Within a region, the drone has 2 options. Either start moving vertically or horizontally. Depending on the entry point (top left, top right, bottom left, bottom right) each sub-path has 4 options. Since there are 2 configurations of the regions (horizontal and vertical) in all there are 8 possible sub-paths. Fig. 6 shows some examples of the sub-paths for a vertically oriented region. The sub-path within regions is decided by the location of the next region and the minimum distance from its corners.

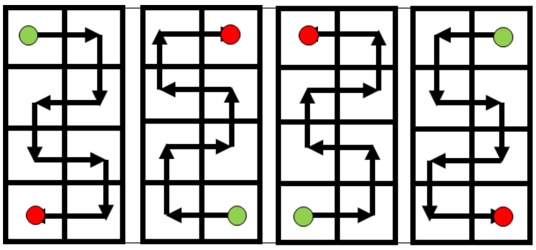

Fig. 6 Examples of sub-paths in vertical orientation

3.5.2.3 Next Region Entry

Since the entry point of the drone is fixed in a particular region N_i, the sub-path within that region has to be such that the distance from the next region is to be minimized. This is computed as follows:

i. Take the vertical sub-path
   a. Get the exit point
   b. Compute next region's (N_{i+1}) entry point according to the minimum distance
   c. Store total distance travelled as *verticalDist*
ii. Take horizontal sub-path
   a. Get the exit point
   b. Compute next region's (N_{i+1}) entry point according to the minimum distance
   c. Store total distance travelled as *horizontalDist*
iii. Compare *verticalDist* and *horizontalDist*.
iv. Choose the path with the least distance.

Once the path has been chosen with the minimum distance, the points that have been traversed are stored in a list. This covers all the centers in a particular region.

3.5.2.4 Eliminating Unwanted Points

It is possible that a particular center does not have any locust infestation in a small section of a particular hotspot. Fig. 7 demonstrates an example. Clearly, if the UAV visited every single point in the region, it would waste time and fuel by visiting regions that don't have locust infestation (points marked in red). Therefore, while writing the waypoints into the trajectory, the points that are marked in red are skipped and the UAV does not visit these points. Every point in the sub-path is checked and if the *Locust Check* parameter is 2, that point is discarded from the sub-path. The final path for this region looks as shown in Fig. 8.

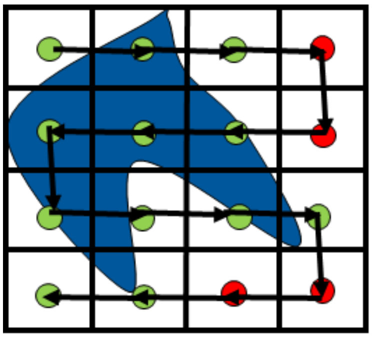

Fig. 7 Identifying unwanted points

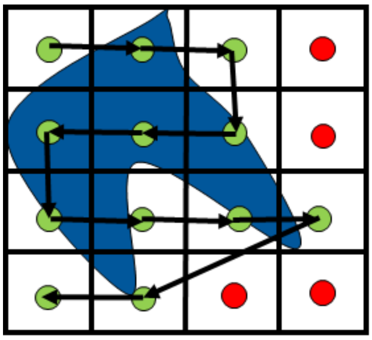

Fig. 8 Final sub-path within a region

This process is followed for all the hotspot regions and their respective sub-paths until the last region is covered and the drone returns to the start point. These waypoints of the trajectory of the UAV are stored.

The resultant path obtained by the algorithm after iterating through all the regions is shown in Fig. 9.

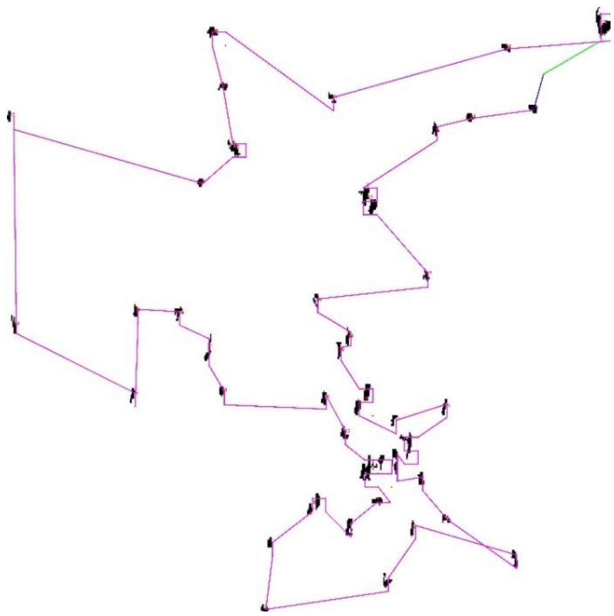

Fig. 9 Resultant Path

3.6 Generating Final Waypoints

Once the trajectory of the drone has been determined, it is stored as a waypoints file. This work uses *ArduPilot Mission Planner* as the simulation software to visualize the path devised by the proposed algorithm with precise real-world coordinates. The geospatial coordinates corresponding to each waypoint are retrieved from the obtained multispectral image and integrated with the proposed algorithm.

The file consists of information such as the type of waypoint (take-off, hover and land), latitude, longitude and altitude information corresponding to each waypoint. Fig. 10 represents a path devised by the proposed algorithm on *ArduPilot*

Mission Planner. It can be vividly noted that the algorithm is not restricted by the geometry of the target areas or the overall span of the entire operation, and can cover large areas at a single stretch with equal efficiency.

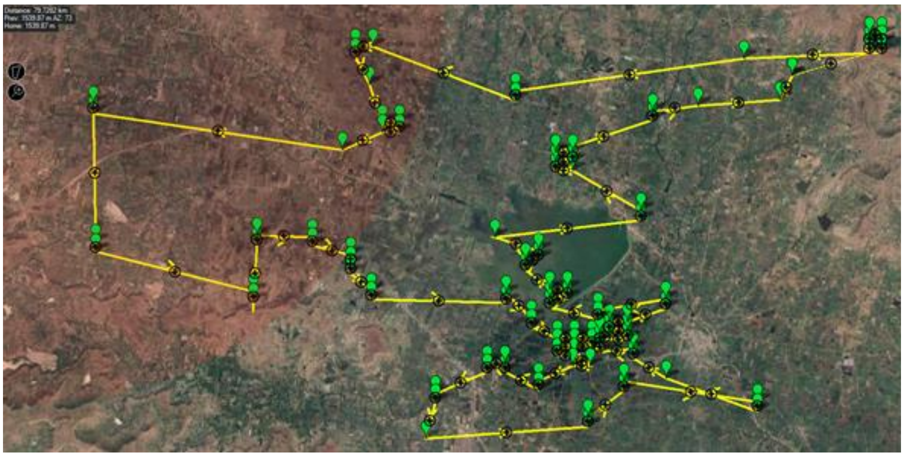

Fig. 10 Simulation on ArduPilot Mission Planner

3.7 Exploring Reinforcement Learning

To delve deeper into the future scope of further improving the path determination process, the paper explored the possibility of developing a reinforcement learning agent that can learn to take actions optimally in a particular environment. In this case, the agent will parallel the tasks to be performed by the drone in a real-world scenario. A custom simulation space was created to train the agent to learn to reach a target while also avoiding an obstacle. Here, the agent, the obstacle and the target are *1x1* blocks in an *n x n* grid as the environment.

To train the agent, certain penalties are set to craft the reward function effectively. During an iteration there are penalties for every step the agent takes without reaching the target and for hitting the obstacle. There is a reward when the agent reaches the target. The goal of the agent in this process is to maximize the reward obtained. The agent's movement is confined to 1 unit diagonally in a single step in a training episode. Fig. 11 depicts training of an agent (*blue*) to reach the target (*green*) while avoiding an obstacle (*red*).

The motivation is to expand this idea and train an agent to traverse multiple hotspots optimally in the presence of more obstacles, which is a desirable way forward in the mission to create next-gen path planning systems.

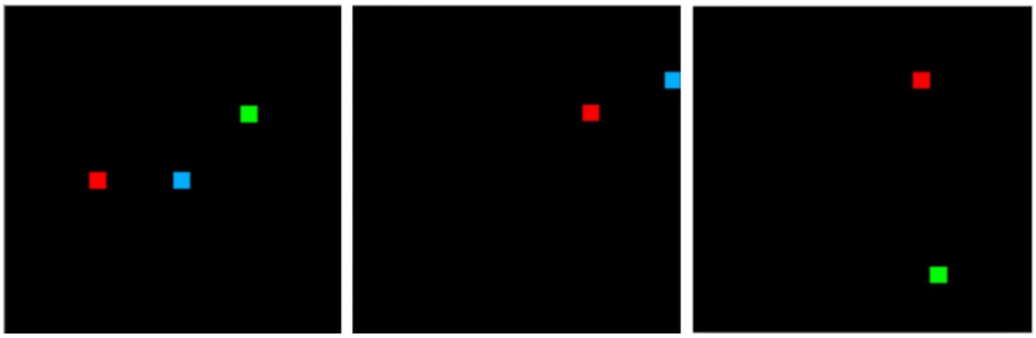

Fig. 11 Training a Reinforcement Learning Agent in a Custom Environment (left);
Agent reached the target (middle); Agent hits the obstacle (right)

4. CONCLUSION AND FUTURE SCOPE

This paper proposes a technique for resource optimization through targeted spraying in precision farming. The paper also showcases the potential of using state-of-the-art artificial intelligence techniques such as reinforcement learning in conjunction with the existing technologies to revolutionize agricultural practices globally. The proposed system can devise optimal paths for a UAV to efficiently traverse along locust formation hotspots and perform targeted spraying. Development of intelligent agents using reinforcement learning that incorporate obstacle avoidance can be a key extension to the proposed solution in addressing real-world scenarios with complex environmental conditions. Other research prospects include the scope to account for system parameters such as fuel and payload, external factors such as wind and a real-time adaptable drone swath based on the target area geometry.

A long-term goal of this work is to create an Internet of Things (IoT) ecosystem connecting the farmer to a coterie of robots meant to perform precision farming activities on farmland. This includes crop harvesting, de-weeding and targeted spraying. An IoT solution that makes the use of a mobile app as an interface between the server, drone and the user is visualized in Fig. 12. This can allow farmers to monitor their fields remotely. This work advocates the use of ideas on these lines to form an infrangible part of future precision farming technologies.

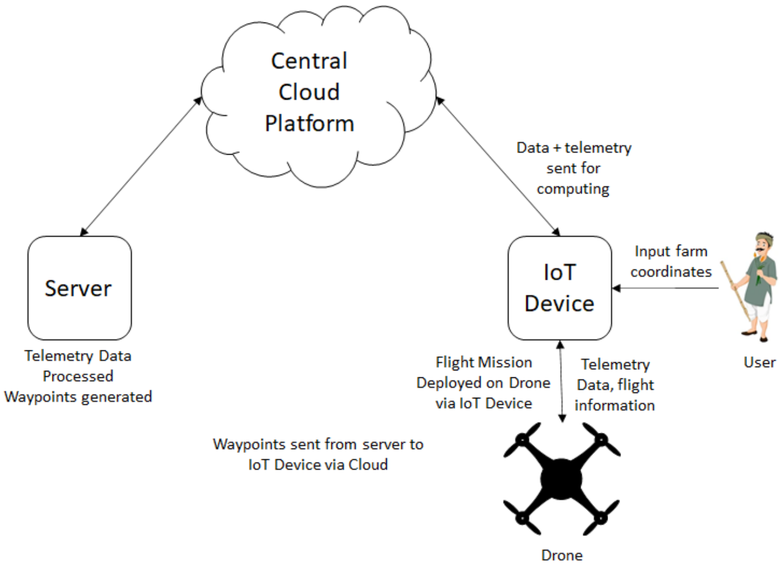

Fig. 12 Envisaged IoT Ecosystem

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