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UAV Search Path Planning For Livestock Monitoring

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Abstract—Unmanned Aerial Vehicles (UAVs) are being extensively deployed in numerous Livestock Management applications such as cattle disease diagnosis, counting and behavioral monitoring from videos and images captured by drones. The paper focuses on one increasingly important family of applications, UAV-assisted cattle monitoring applications where the objective is to remotely acquire some health state information from IoT nodes attached to the herding cattle. Such livestock data acquisition applications have many challenges. One of these challenges, which is the focus of this paper, is the problem that the target cattle position may not be known precisely, and might be defined with a large area. To address this issue, we design a formulation of this UAV-cattle search path problem as a mathematical optimization problem and show how it can be derived from other well-known formulation and related literature. A Mixed-Integer linear Programming (MILP) formulation is introduced to minimize the expected search time while covering all the search area to efficiently locate the animal. This formulation exploits a cattle position probability distribution map. The results show that the suggested approach yields excellent results using the existing MILP solvers.

Index Terms—Precision Agriculture, Livestock Management, UAV, Search Path Planning, Mixed-Integer Linear programming

I. INTRODUCTION

The Agriculture sector is one of the most prominent pillars of the world economy. Hence, applying the appropriate strategies for improving and increasing the sector productivity is crucial for the economy and for human life eventually [1]. However, researchers and domain's experts have been given a lot of scrutiny to the agriculture domain and invested lots of efforts to propose some sophisticated approaches and methodologies to ensure the field advancement; this is justified by the continuous evolution of concepts from traditional Agriculture 1.0 to Agriculture 4.0 [2] and the emergence of various concepts such as Smart Farming and Precision Agriculture (PA). Therefore, PA integrates Information and Communication Technologies to aid farmers make efficient decision in the exact time via real time data acquiring and processing [3]. The technologies implemented include remote sensing, data acquisition and analysis, wireless communication

protocol and last but not least smart flying machines as the UAV [4]. UAVs are aircraft systems that can function under the command of a human or be entirely autonomous [1], the exceptional capabilities of these devices such as fluent mobility, ease of deployment allow it to be relevant and widely implemented in PA [4] generally and in livestock management specifically. Livestock management requires the adoption of the appropriate methodologies to ensure the cattle welfare. Hence, some tasks such as cattle health and behavior surveillance in large pasture could be a tedious and time-consuming mission to be performed manually. To alleviate the manual effort and increase the accuracy, farmers begin to deploy the UAVs in livestock management. The fluent mobility of drones allows them to be able to efficiently execute various tasks related to the agriculture sector and in livestock management such as the remote data acquisition.

Autonomous UAV-assisted remote cattle data gathering is the kind of mission where the drone autonomously travel inside a limited area (pasture or ranch) for the purpose of remotely collecting some information from nodes attached to the livestock. However, one critical issue in such type of operations is the case when the position of the cattle is not perfectly known: traveling to the cattle exact position and data gathering mission becomes challenging as it requires some area exploration for livestock searching. Thus, this is the focus of the paper: assuming that only a very inaccurate general position of the cattle is predefined, e.g. a large area, we study the problem of efficiently finding the livestock in this area. In other words, we aim to identify the optimal search path that guarantees the animal finding with minimum search time given an imprecise information about the cattle position. The problem can be divided in two related parts. The first is formulating a mathematical model of the problem. The second is designing a strategy to explore systematically a large area where the cattle is expected to be located.

In effect, to the best of our knowledge, fastest drone path planning for cattle searching and monitoring problem have not been tackled in the literature even though researchers investigated similar problems: most notably the problem of

Search and Rescue (SAR) missions [5], that have been recently been studied even in UAV-assisted scenarios, that tackled the target search path planning in considering multiple scenarios, different search environments, different objectives and introduced various approaches and algorithms to solve it.

This paper investigates the search path planning optimisation in UAV-assisted data gathering for livestock monitoring. The major contributions of our study are:

- Identifying the tools, formulations, and potential solutions that can be applied from wide, remotely related research areas.
- Introducing a new mathematical formulation of UAV-assisted cattle search path planning problem.
- Designing a strategy to explore systematically the search area where the cattle is expected to be located.

The remaining sections of the paper are structured as follow. Section II describes the UAV applications in PA and reviews some studies about search path planning. Sections III and IV present the system model and the linear program formulation. The results of the simulation experiment are given in Section V to verify the performance of the model. Section VI summarizes the paper.

II. RELATED WORK

A. UAVs Applications in Precision Agriculture

Any UAV system includes three major components, the drone which is the flying device, a ground control station which is a computer with a high computation capabilities then a flight control system for autonomous UAVs and an agent for remotely controlled UAVs. Thus, the exceptional features of these devices such as fluent mobility, ease of deployment and light weight allow it to be versatile, efficient and widely implemented in divergent domains and execute several operations. One of these domains is the precision agriculture.

However, drones technologies have been deployed in the two pillars of the agriculture domain: the vegetable farming [4] and the livestock management [6].

The major applications of UAVs for vegetable farming are presented in Figure 1:

Weed Mapping and Yield Estimation: Drones can be attached with different types of cameras (RGB, multi spectral and thermal cameras). The captured images from the overall crop field which can be leveraged to drive an accurate weed cover map outlining which locations chemicals are required. Hence, the map can be used as an input for the spraying system in the tractor and only the areas with weeds are sprayed. For instance, KerKerch et al., [7] present a Convolutional Neural Network (CNN) and color information based model to detect symptoms in the vine yards. In addition, having an insight about the crop production mass can help to decide when and where the harvest need to be started but yield estimation is a tedious, time consuming and expensive task. However, via UAV images and computer vision algorithm we could have an accurate estimation on the production quantity and quality.

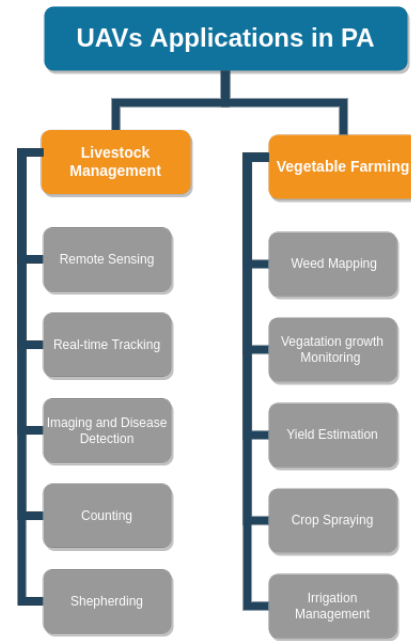


Fig. 1: UAV Applications in Precision Agriculture

Apolo et al., [8] propose a deep learning model in order to detect and count the number of apples in each individual tree. Also, it is possible to have measurement estimation like the plant height, width and chlorophyll percentage. Such measurements are significant for plant health, growth monitoring and disease detection [9]. Hence, remote sensing is the process of detecting some information remotely. The drone could gather data from IoT nodes such as air quality, soil quality, temperature, water quality and these information are relevant for farmer decision making distributed in the field [4].

UAVs are also efficient in livestock management applications as shown in Figure 1 :

- **Imaging and Video Taping:** the images and videos captured by the drone plus applying the appropriate computer vision algorithm present a significant source of information and support decision making:
 - Disease detection and estimating vital health parameters such as temperature from thermal scanners, weight, size, and visual ailments aid in the diagnosis and the treatment of ill animals in the right time before the occurrence of any complications.
 - Real-time Tracking: Tracking cattle behavior and activity is detrimental in livestock management that gives insights about cattle state (health, rumination, movement, etc). In [10], authors propose an approach for drone imaging processing to detect goats and predict the animal activity grazing or sleeping.
- **Counting:** In [11] authors introduced an approach for counting cattle in pasture via animal geolocations and a graph-based algorithm.
- **Data Harvesting:** or in another word remote sensing. Drones are equipped with an antenna to capture data

emitted from the RFID tags or electronic collar tags attached to cattle. Webb et al [12] describe a drone tethered to a repeater (RFID) to capture temperature data released from the RFID tags linked to the livestock.

- **Herding:** is the process of rounding up livestock, preventing them from splitting up and straying (wandering). It can be conducted for a wide variety of situations, such as routine health controls and livestock treatments, marking, shearing, lamb marking, selling, feeding and transporting or leading them to a new area. Li et al., [13] present an approach that aims to navigate a network of barker drones to gather a herd of livestock by adopting boids model to imitate the animal behavior.

Besides the herding applications, in most of literature related to UAVs livestock management the drone is remotely piloted. However, this study tackles the search path planning of UAV-assisted cattle application.

B. UAVs Path Planning for UAV Cattle Search (UCS)

As mentioned, the UCS problem is related to research areas with a large literature ranging from Search-And-Rescue (SAR) to several variants of the Traveling Salesman Problem (TSP). One starting point is the area of SAR, which has important applications, and a long history: the example is to visually locate (and rescue) a target from plane, for instance a maritime vessel in distress. It is historically linked to the optimal search theory [14]. Optimal Search Path Planning (OSP) is the process of computing the sequence of decisions that a searcher should take in order to locate the target optimally. One version of the problem can be formulated as follow: given a large area to explore, given a probability of containment indicating the probability that the object is around a given point, and given a probability of detection at one point that increases with the amount of time spent exploring that point, we want to find the path that maximizes the probability of detection of the searched object. Trummel et al., [15] proved that the OSP problem is NP-complete.

In practice, a SAR solution has to perform a sweep of an area, and is related to the Coverage Path Planning (CPP) where the agent has to cover the hole search area optimally in order to detect the target [16], also found in other applications such as robots in patrolling missions or mines detection.

CPP itself is one variant of the well-known Traveling Salesman Problem (TSP). The CPP literature consists of a significant number of research works that investigate the optimization of the robot and UAV coverage path planning problem and implement various methodologies to resolve it such as the classical methods (Spanning Tree coverage) or heuristic-based methods as (Greedy Search, Bio-inspired Algorithms) [17].

All variants of TSP problems formalize a mathematical optimization problem. Many of them, including the original TSP problem (with for instance the Miller–Tucker–Zemlin formulation [18]) can be recast with mathematical modeling approaches such as Linear Programming (LP), a core discipline in the optimization field. It offers a potent technique

to model numerous real-world problems wherein a linear function is either maximized or minimized and constrained in different several manners [19]. Due to the progress of LP solver since last decades it becomes more pertinent to adapt MILP for problem solving [20].

When looking at problems close to UCS Problem: Berger et al. [21] propose a MIP formulation to find an optimal solution for single agent search and rescue operation. The objective is the maximise the sum of probability of success in detecting the target given numerous constraints and use the CPLEX solver to test the applicability of the formulation. Pedersen et al., [5] propose both a linear program formulation and a heuristic based approach that scales better for a related problem: automating the UAV searching process using a scored map as a model of the area of interest (AOI) and that the approach is able to determine the optimal trajectory for the purpose of covering the whole search area and they prove that the proposed approach outperforms the traditional heuristics such as the Greedy method. In the case of the UCS problem, one important issue, is that the objective function itself depends on the time at which each point is visited, hence it is actually a *time-dependent* problem. On this topic Barrera et al., [22] investigate a variant of TSP problem which is STSP-TP which stands for selective TSP with time dependant profit. In other context, this problem could be called Orienteering Problem (OP) where the purpose is that the traveler chooses the path that maximises the profit (city-reward) without the obligation of visiting all the cities. In the last study authors provide a mathematical modeling as a piecewise-linear profit function in two different scenario either multiple visit of the same city is allowed or denied. The mathematical formulation presented in the last paper has an objective to maximise the profit which depends on the time and the proposed approach is the basis of our mathematical formulation.

III. SYSTEM MODEL

A. Overview

We assume one UAV aiming to collect information from one cattle herd. All animals are located exactly in the same location, in the minimum possible time.

More precisely, given a wireless IoT node(s) that integrates *temperature, heart rate, respiration rate sensors and a RFID tag* attached to neck-mounted collars for the objective of recording health state parameters of the livestock, the UAV aims to remotely gather the data stored in the node(s). Once the UAV comes close enough to the cattle, it is able to establish a communication link with the IoT node and receive all the animal information recorded by the wireless node.

Prior to that, the required operation consists of an automated drone searching for this one herding cattle inside a large area where it is known to be, denoted *area of interest* (AOI). This is done by exploiting a probabilistic location map model, assumed to be known. The search problem here, the *UAV Cattle Search* (UCS) can be classified as a one sided-search problem with stationary target. The UCS objective is to perform an

efficient search, that is to find the target with the minimum expected time.

B. Area of Interest Partitioning

Our system model follows assumptions commonly found in SAR problems. Following these traditions, we assume that the entire search environment has been divided into a virtual regular grid, where each cell of the area designed to match the drone footprint. More precisely when the drone is standing at the center of the cell, it is assumed to perfectly detect any cattle standing in the cell.¹ Again, as in SAR formulations, since the target (cattle) locations are imperfectly known, we model the search environment by a probability distribution map that indicates the *probability of containment* (PoC), e.g. the probability that the target is inside a given cell. To limit the scope of this study, we consider a static map with only one cattle location (e.g. all are exactly on the same place, due to herding behavior). Also, we assume that the area where the cattle is located is perfectly known, i.e., the sum of PoC is equal to one. Therefore, the target can always be found at worst after visiting all cells. Figure 2 illustrates these assumptions.



Fig. 2: System Model

C. UAV Modeling

The mission begins by positioning an autonomous drone on a starting point s typically a refuel station that does not belong to the AOI. From s , the UAV has to decide an ordered sequence of cells to be visited. After the drone has covered a sufficient area, located the cattle, and collected monitoring data, it needs to reach a depot e which is also out of AOI. The trajectory from s and to e is not considered in the computation in the path cost function.² From s , the drone visits the first cell

¹Note that more sophisticated decompositions are possible and had been proposed; the *area of interest* (AOI) partitioning is the process of splitting the search area into sub-areas for the purpose of coverage simplification and that is a primary and initial phase in SAR and CPP problems. There exists numerous cellular decomposition techniques. The decomposition methods most frequently applied in CPP problems that involve drones are exact and approximate spatial decomposition.

²because it is not the main difficulty of the problem, but simple changes to our formulation would allow it

of the AOI and spends a duration τ_h ; during this duration, the UAV hovers inside the cell trying to determine if the cattle is located in the visited cell or not, via detected signals that would be emitted by the cattle IoT node. If not, it continues to visit the next planned cell until it finds the cattle after which it stops searching and reaches the depot e .

In this context, we propose an approach that optimizes the UAV search path by computing an estimation of search time and the estimation is based on the probability distribution map, and then minimizing it.

IV. MIXED-INTEGER LINEAR PROGRAMMING FORMULATION

The UCS problem is formulated mathematically with the goal of optimizing the cattle search path while exploring the sub-areas in AOI given a livestock distribution map and the necessary duration for visiting each cell. The problem formulated as an optimization problem where the objective function represents the expected search time. A solution of this problem is a path that visits all cells: ideally, the cattle will be found in the first visited cells, but the search time is stochastic, and in the worst case, all the cells have to be visited (if the cattle happens to be in the last visited cell).

Using graph terminology, we will refer to *cells* as *nodes* and the following notation is used in the mathematical formulation:

- V is the set of nodes (indices of cells) in the search environment: $V = \{1, \dots, n\}$
- s, e are the searcher starting and ending locations that does not belong to the search map, i.e. $s = 0, e = n + 1$. We denote $V^+ = V \cup \{s, e\}$
- p_i is the probability of cattle containment in node i
- x_{ij} is the decision variable equal to 1 if the drone visits the node j immediately after the node i
- t_i is equal to the arrival time to the node i
- τ_{ij} is equal to the travel time from the node i to the node j (the distance from i to j divided by the UAV speed)
- τ_h is equal to the hovering time in the visited node

To the best of our knowledge this exact formula of objective function for UCS has never been proposed in the literature and it is inspired by the linear program proposed by Berrena et al., [22]. Mainly, the expected search time can be written as:

$$E(\text{time of discovery}) = \sum_i \Pr(\text{cattle in cell } i) \times (\text{time of visit of cell } i)$$

and depends on the trajectory. Thus, the objective is to minimise the expected search time is linear in the times t_i , and the constraints can be linearized as well. This yields a Mixed Integer Programming (MILP) formulation of the UAV Cattle Search problem, as a path planning, is the following:

$$\text{Minimize } \sum_{i \in V} p_i t_i \quad (1)$$

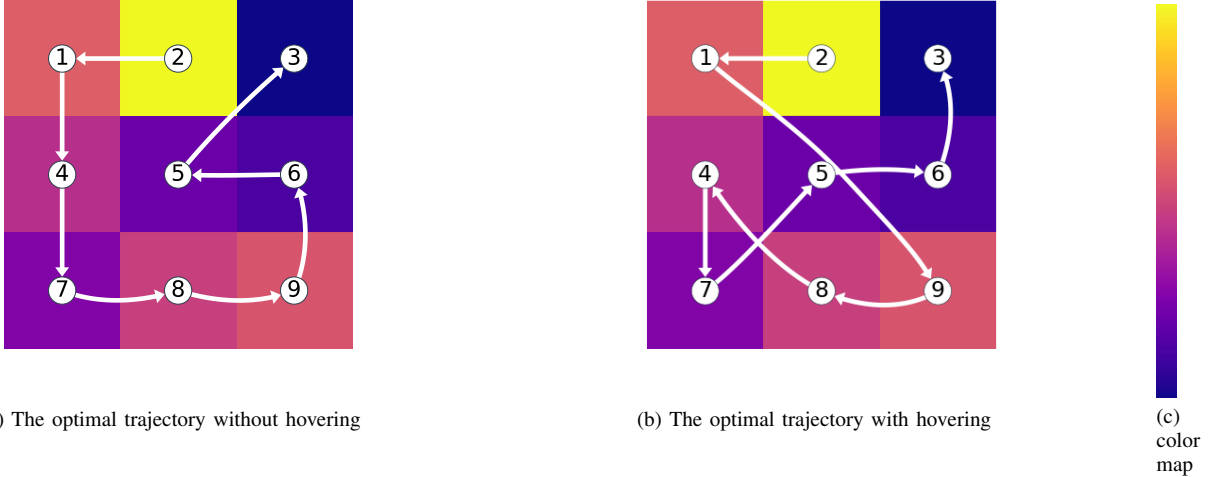


Fig. 3: UAV optimal trajectory

Subject to:

$$\sum_{j \in V, j \neq i} x_{ij} = \sum_{j \in V, j \neq i} x_{ji} = 1, \quad \forall i \in V \quad (2)$$

$$\sum_{j \in V} x_{js} = 0 \quad (3)$$

$$\sum_{j \in V} x_{sj} = 1 \quad (4)$$

$$\sum_{j \in V} x_{ej} = 0 \quad (5)$$

$$\sum_{j \in V} x_{je} = 1 \quad (6)$$

$$t_j \geq t_i + \tau_{ij} + \tau_h + M(1 - x_{ij}) \quad \forall i, j \in (V^+)^2 \text{ and } i \neq j \quad (7)$$

$$t_i \geq 0 \quad \forall i \in V^+ \quad (8)$$

$$x_{ij} \in \{0, 1\} \quad (9)$$

The objective function (1) is the mathematical formulation of the total expected search time which represents the stochastic path cost that needs to be minimised. The constraint (2) is the flow constraint to ensure that for each node in the search area there is one incoming and one outgoing edge. The constraints from (3) to (6) are for modeling the start point and the end point which indicate that only one outgoing edge from the starting point s and no incoming edge, and only one incoming edge the end point e with no outgoing edge. Constraints (7) and (8) imposes the bound on the travel time which means that the arriving time must be greater than the departure time t_i plus the travel duration τ_{ij} and hovering (scanning) duration and M is a large number that ensures the validity of the formulation. Finally constraint (9) defines the domains of the variables. This linear formulation of constraints is derived from [22], that essentially repeats the MTZ formulation [18].

V. EXPERIMENTAL RESULTS

Computational resolution of examples of the linear program was carried out to asset the efficiency of the proposed approach for a wide range of instances. The program is implemented on machine with Intel (R) Xeon (R) 2.93GHz CPU, RAM 8 GB with 4 cores, using a mathematical optimization software Gurobi 9.5 and Python 3.9. Mainly, a 3x3 probabilistic map is fitted to the model and as shown in Fig.3.(a) the node 2 has the highest PoC followed by (1 and 9 with same PoC) then (4 and 8) then by (5 and 7) then node 6 finally node 3 with lowest probability. The MILP program was able to compute the optimal search path in two scenario. In the first scenario the hovering time is equal to zero. Here the UAV optimal path begins by node 2. Then it selects the node that requires the smallest time to travel and has high PoC which is the node 1. The program runs for 40 seconds to compute the optimal path.

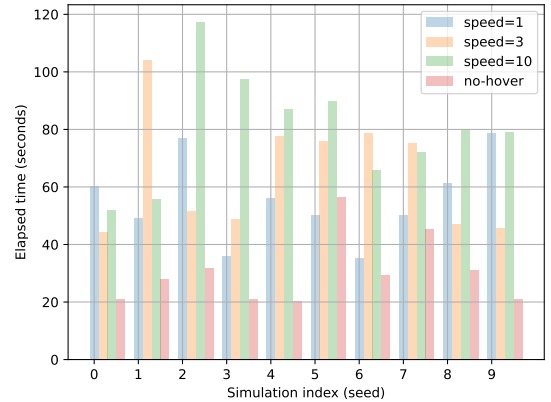


Fig. 4: System running time with different seeds

Hence, in the second scenario the drone had to hover in the cells for a period of time. Fig.3.(b) shows the optimal trajectory for the second scenario. In this case the path is the sequence of nodes ordered according to PoC. Here the UAV visits the next possible node with the highest probability no matter the travel time because of the extra time added once it visit an intermediary node with lowest PoC. To ensure the validity of the model we simulate multiple instances. However, we kept the map size the same but with uniform probability map, different seed and different hovering time, etc. Fig.4 illustrates that the average running time is 49 seconds when the drone speed is 1 ms^{-1} . Also this Figure shows that the drone speed and the computation time are proportional and the optimal trajectory is computed faster in the case where the hovering time is null.

VI. CONCLUSION AND PERSPECTIVES

UAV-assisted livestock monitoring is one of the most pertinent applications that ensure a better livestock management and monitoring. In the context of our research work, we want to remotely gather some health state information from IoT nodes mounted on the cattle neck. We investigate one of the challenges that could face the deployment of autonomous drones for cattle monitoring, which is the case where there is no accurate information about the cattle location. For this reason the UAVs have to search the livestock in large ranch. We denote this problem as UAV Cattle Search. To tackle the UCS issue we formulated a mathematical optimization problem, precisely a Mixed Integer Linear Programming formulation. The objective is to minimize the expected search time while covering the whole AOI in order to find the cattle by exploiting a cattle probability distribution map. The formulation of linear program was derived from literature related to Search and Rescue, Coverage Path planning and Travel salesman problem. Using mathematical optimisation software Gurobi, we were able to carry out the optimal solution while considering few assumptions such as the probability map that models the containment of only one static cattle. To the best of our knowledge the approach we propose have never been presented in the literature so comparing the performance of the solution computed by our linear program with other approaches turns to be impractical since there is no similarities between the approaches. Hence, for future directions we can assume that the search area includes multiple mobile cattle then we investigate the appropriate approach that efficiently solves the issue.

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