COVERAGE CONTROL WITH MULTIPLE GROUND ROBOTS FOR PRECISION AGRICULTURE

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The concept of precision agriculture (PA), as a farming management strategy, has received considerable attention in the last few years [1]. PA is a data-driven strategy for collecting, processing and better management of farm data with the aim of improving the understanding and management of soil and landscape resources in order to estimate and manage the health of crops in a farm. Consequently, it can improve crop productivity (yield) and farm profit that lead to higher environmental quality. Moreover, it assists farmers to make appropriate decisions, as well as automating some basic farming tasks [1], [2].

A key component of precision agriculture is data collection. This article presents a system composed of a team of unmanned ground vehicles (UGVs) that cooperate in order to address this requirement. Ground robots are capable of traveling long distances, carrying large loads, and measuring soil data. On the other hand, the use of multi-robot systems has several advantages in comparison with a single robot system, e.g., in reducing mission time, limiting human exposure to agriculture chemicals, and introducing fault tolerance by assigning another robot to cover the region initially assigned to a faulty robot. Although such a collaboration can be used for site-specific management of crops and developing treatment plans [3], very limited work exists on the collaboration between robots for agricultural use. In [4], the main goal is to design, develop and test a fleet of heterogeneous ground and aerial vehicles to cover various agricultural situations including effective weed and pest control, increasing crop quality and improving the health and safety of production operators. The authors in [5] examine the use of autonomous robotic platforms for experimental testing in agricultural fields. The authors in [6] present an augmented Voronoi partitioning and path planning approach for non-uniform sensor data collection in precision agriculture using unmanned aerial systems (UASs) and then generate focused trajectories about areas of interest, namely stressed areas. In [2], a system consisting of small, low cost UASs and UGVs working together is built for data collection and precision agriculture. The work in [7] has proposed the use of a team of UASs and UGVs for environmental monitoring in greenhouses especially in the presence of obstacles in the greenhouse.

In this article, a new scenario for the collaboration between a team of UGVs, equipped with multi-spectral and hyper-spectral cameras, for precision agriculture with no human intervention is considered to ensure that important areas in the field can be precisely inspected and monitored. This problem can be generally considered as a sensor coverage problem and is formulated as a locational optimization problem. The mobile sensor coverage problem was first formulated as a locational optimization problem in [8] and a distributed control and coordination framework for optimal coverage of mobile sensors was developed. It is worth mentioning that most of the existing literature on multi-robot deployment and coverage control are formulated for (spatially) continuous, convex environments. However, there exist many practical applications that have a discrete nature, such as in assembly, construction, transportation and resource allocation, among many others. Hence, it is necessary to develop a discrete formulation of coverage algorithms for these applications. Very recently, in [9], [10], distributed algorithms for coverage control of an environment represented as a graph with teams of robots were developed.

On the other hand, in many practical applications, the duration of the coverage task exceeds an agent's maximum energy level. Consequently, to ensure a safe and long-term operation, it is required to propose control schemes that can account for each agent's energy level. However, there exists only a very limited work that explicitly addresses energy-aware control. For example, in [11], an energy-aware coverage control with docking for robotic teams is proposed. In [12], a multi-robot path planning and optimal deployment strategy for a team of micro air vehicles with limited energy reserves and finite recharge times is proposed.

Based on the related literature review, we present an energy-aware coverage control strategy that integrates the two goals of coverage task and using a docking station to recharge. A specific scenario is examined to convert the field into a weighted directed graph. Then, by solving a locational optimization problem, motivated by the recent work of [9] and [10], the UGVs are deployed in the field in such a way as to maximize monitoring and coverage of the areas of interest. In the proposed approach, if an agent reaches a low energy reserve, it leaves the team's coverage formation and will be driven to the closest available base station for recharging. In this case, its teammates appropriately adjust their coverage to support its responsibilities.

The remainder of this paper is organized as follows. Our problem is defined and explained in Section II. In Section III, the process of modeling the field as a graph and also the energy-aware coverage control strategy for deployment of robots are presented. The simulation results are presented in Section IV followed by the conclusion and future work in Section V.

Notation: We use $G(V, E, C)$ to denote a weighted directed graph, consisting of the node set $V=\{1, 2,\dots,m\}$, the directed edge set $E\subseteq V\times V$, and the specific costs (weights) C. By considering a group of n robots r_i, $i\in\{1, \dots, n\}$, $p_i\in V$ is assumed to be the vertex location of the ith robot. Moreover, $N_G(x)$ represents the set of robots (y) that robot x can sense and is designated as the nearest neighboring set of the robot x, i.e., $N_G(x)=\{y\in V|\overrightarrow{xy}\in E\}$. Let also $\varphi: V\rightarrow\mathbb{R}^+$ be a distribution density function that represents a measure of information or probability that some event takes place over a field Q. The distance $d(x,y)$ is a function that denotes the cost of the shortest path between nodes x and y. The distance $d(x,y)=\infty$ when there is no path from x to y in the graph.

PROBLEM STATEMENT

Our main objective in this work is to propose a framework for monitoring and inspecting important areas in an agricultural field Q using autonomous vehicles. These regions of interest can be considered, e.g., as plants with biotic or abiotic stresses or with particular interesting phenotypic traits such as flowering in the crop field. Hence, we consider a team of UGVs with limited onboard power, equipped with multi-spectral and hyper-spectral cameras, and propose an appropriate methodology to achieve the above objective.

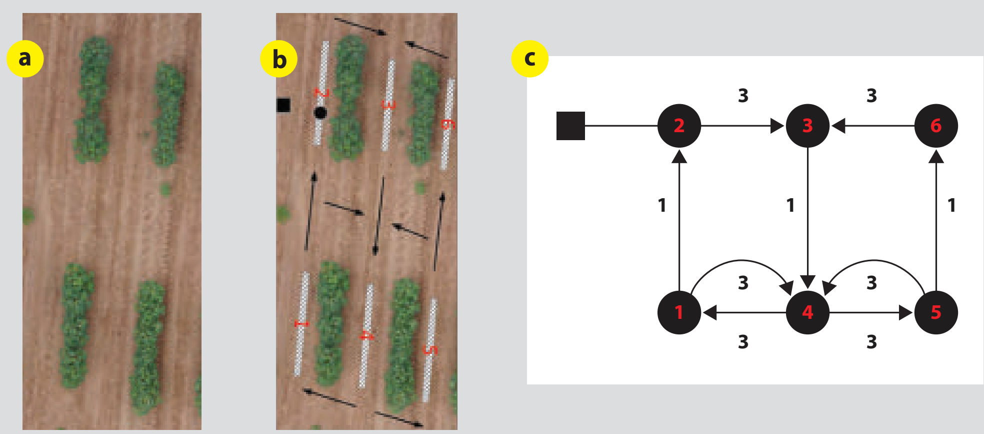

FIGURE 1 The map of the agricultural field: (a) without the detailed information; (b) with required information for modeling the graph; (c) the corresponding graph of the map.

Problem Definition: Distribute the team of n UGVs with limited onboard power and without the use of any type of metric information in a partially known field in such a way that events of interest over the field can be precisely monitored.

Since it is assumed that the robots have limited onboard power, while each robot's energy approaches a minimum level during a coverage mission, we would like it to exit the field Q and return to one of the existing base (charging) stations. At the base station, its batteries can autonomously dock to a charger [11]. To achieve this goal, q base stations with positions $x_{B_i}\in\mathbb{R}^2$, $i\in\{1,\dots,q\}$ for recharging the robots are considered. It is assumed that r_i is capable of measuring its time-dependent voltage reserve, denoted as $\gamma_i(t)$. Furthermore, Γ_i is defined as the desired voltage level that each robot should maintain before transitioning to one of the base stations. Additionally, with

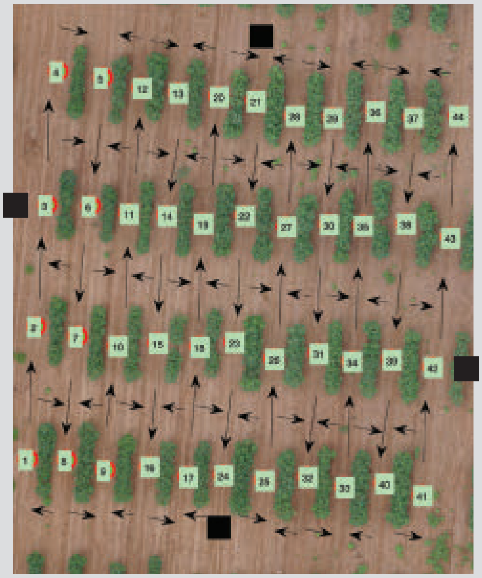

FIGURE 2 **The map of agricultural field: Image is captured by a UAS and the map is constructed using MATLAB. The black arrows indicate the allowed motion in each region and constrain the direction of movements of the robots. Numbers indicate the nodes of the corresponding graph.**

each base station, a unique access point $x_{E_i} \in V$ is considered. As agents are leaving charging stations, they travel from x_{B_i} to x_{E_i} and enter Q from this position, at which point their coverage control takes over.

METHODOLOGY

In this section, the field is first represented as a topological map so that the group of robots can use it to navigate. Then, by solving a locational optimization problem, the UGVs are deployed in the field in such a way as to maximize monitoring and coverage of the areas of interest.

A. Modeling Field as a Graph

The field is converted into a weighted directed graph $G(V,E,C)$. To obtain the graph, we define nodes as parts of the environment. The considered scenario is based on the methodology first proposed in [10]. To obtain an insight into the underlying process, let us consider a map of agricultural field, as shown in **Figure 1a**. The required information to model the presented field in **Figure 1a** as a graph is shown in **Figure 1b**. Each of the regions next to the plant rows, represented as a hachured rectangular, is considered to be a cell and is associated with a node in V. The black arrows indicate the allowed motion in each region and constrain the direction of movement of the robots. If a robot can move from one node to another, we assume that these nodes are neighbors and add a corresponding edge to E. Given the graph G, a cost (weight) between two neighbor nodes $c(x, y) \in C$, $x, y \in V$ means that, to go from node x to y, a robot must execute a command $I(x,y)$ (such as Go-Straight, Turn-Right or Turn-Left) that will result in a cost $c(x,y)$. In this particular example, for going from one node to another node, one of the following two commands should be executed by the robots, namely: **Command 1**: Go-Straight, and **Command 2**: Turn-Right (-Left), Go-Straight, Turn-Right (- Left). It is assumed that the cost values (weights) *one* and *three* result from Commands 1 and 2, respectively. Moreover, the black square and circle denote, respectively, the docking station and access point for recharging the robots. Based on the above description, the weighted directed graph corresponding to **Figure 1b** is shown in **Figure 1c**.

B. Deployment Strategy

In this section, a distributed strategy is proposed for deploying the robots in the agricultural field modeled with a graph G and with a density function defined over it. To achieve this goal, motivated by [9], [10], the problem of optimally deploying the team of robots on a graph is treated as a locational optimization problem. In this methodology, the graph is first partitioned into n Voronoi regions g_i

$$g_i = \{x \in V \mid d(p_i,x) \leq d(p_j,x), \forall i \neq j\}. \tag{1}$$

If $d(p_i,x) = d(p_j,x)$, then the node x is assigned to the robot with smaller index number. Note that the ith robot is in charge of monitoring all the events that occur at the graph nodes in region g_i. Then, the general deployment problem is reformulated as the one of minimizing the following cost function:

$$H(p,G) = \sum_{i=1}^{n} \sum_{q \in g_i} d(p_i,q)\varphi(q) \tag{2}$$

The density function $\varphi(q)$ in (2) is defined over the graph G to indicate the nodes that have higher priority to be serviced. In order to define $\varphi(q)$, by considering a continuous density function over the original field, a large number is assigned to the node corresponding to the center of the

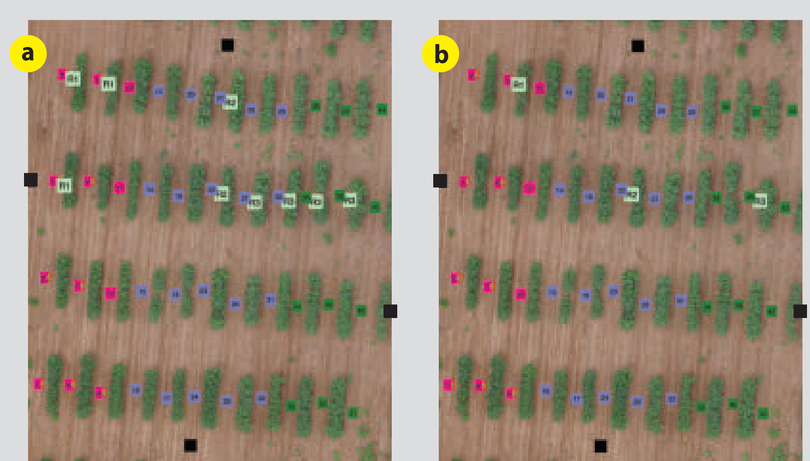

FIGURE 3 **The results corresponding to the first region of interest, (a) Voronoi regions and the traversed trajectory by robots, (b) the final deployment of robots.**

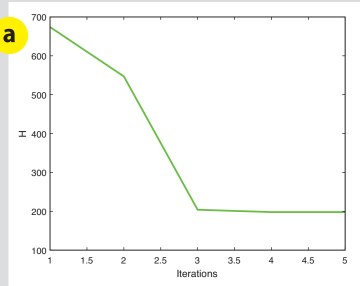

FIGURE 4 *(Above)* Coverage cost for the first region of interest.

FIGURE 5 *(Right)* The results corresponding to the second region of interest.

density function, and then lower numbers are assigned to the nodes that are far from this node.

Assumption: All the robots have access to the graph G and full knowledge of the density function $\varphi: V \rightarrow \mathbb{R}^+$.

The main idea behind our solution method is to generate successive iterations in which the robots are relocated to different nodes in such a way that H decreases until reaching convergence. In fact, these iterations consist of choosing a special node inside the robot subgraph and then moving the robot to this node. Our solution is presented in the form of a distributed control given in Algorithm 1. In this algorithm, we have extended the deployment strategy proposed in [9] to an energy-aware control policy with a fail-safe switching mechanism that permits an agent to drop out of the formation when it determines it can no longer support the coverage task without jeopardizing itself. In addition, Algorithm 2, motivated by [10], is proposed for finding the special nodes inside each robot subgraph.

To summarize, our proposed methodology is applied by implementing the following three steps.

1) After receiving the important regions, they are listed from smaller to larger index number.
2) For each region of interest, a density function is defined over G that indicates the node that has priority to be serviced.
3) Algorithm 1 is implemented for each of the important regions and the process is continued until all regions are effectively covered.

SIMULATION RESULTS

In this section, different aspects and capabilities of our methodology are demonstrated using a case study for the agricultural field shown in **Figure 2**. As shown in **Figure 2**, in our case study, the field is modeled as a directed graph G with 44 nodes. The four black squares in **Figure 2** are the docking stations for recharging the UGVs. Three robots with the initial positions 3, 21 and 27 are considered. Moreover, three nodes 5, 26, 37 are selected as the regions of interest that need more investigation. Based on our approach proposed in Section III, node 5 is first defined as the center of the density function, and so the robots are expected to autonomously relocate such that the whole field is optimally covered, while simultaneously this node is precisely monitored. After some iterations and the change in size of various Voronoi regions contributing to minimize the cost function, the robots converge to their final positions. The results are shown in **Figure 3**. It is worth mentioning that different Voronoi regions are indicated by different colors in this figure. As observed from **Figure 3**, robot 1 moves toward node 5 to monitor it more precisely. The positions of other robots are also changed so that they can effectively cover the whole field. Furthermore, the cost H decreases over time as shown in **Figure 4**.

Next, node 26 is considered as the (second) region of interest. It is also assumed that robot 3 is reaching to its predefined voltage reserve. The final deployment of the robots is demonstrated in **Figure 5**. As observed from **Figure 5**, robot 3 moves to its access point while other robots appropriately adjust their positions for field coverage. Moreover, node 26 is precisely monitored by robot 2.

Finally, node 37 is considered as the (third) region of interest. It is also assumed that robot 3 is now fully charged and returns to the mission from its access point. The final deployment of the robots is demonstrated in **Figure 6**. As observed

TABLE I: ALGORITHM 1: IMPLEMENTATION OF THE DISTRIBUTED CONTROLLER.

Require: Check
1. Check the voltage reserve, γ_i, of each robot.
2. **if** $\gamma_i < \Gamma_i$ **then**
3. $x^*_{Ei} \leftarrow$ Find the closest docking station for recharging.
4. State $\leftarrow$ Recharging
5. **else**
6. State $\leftarrow$ Compute
7. **end if**

Require: Compute
8. Recieve locational information of neighbor robots.
9. Compute the Voronoi subgraph of each robot.
10. $p^*_i \leftarrow$ Find next best point using Algorithm 2.
11. **if** $p^*_i \neq p_i$ **then**
12. State $\leftarrow$ Moving
13. **end if**

Require: Moving
14. Move to p^*_i.
15. **if** $p^*_i = p_i$ **then**
16. State $\leftarrow$ Check
17. **end if**

Require: Recharging
18. Move to x^*_{Ei}
19. **if** $p_i = x^*_{Ei}$ **then**
20. State $\leftarrow$ Compute
21. **end if**

TABLE II: ALGORITHM 2: FINDING THE NEXT BEST POINT.

1. $\mathcal{H}_i \leftarrow$ Compute the cost function of the current position of robot r_i, namely, $\sum_{q \in g_i} d(p_i, q)\phi(q)$.
2. **for** $a \in \mathcal{N}_g(p_i)$ **do**
3. $\mathcal{H}_a \leftarrow$ Compute the cost value for all the neighbor nodes of p_i, namely, $\sum_{q \in g_i} d(a, q)\phi(q)$.
4. $p^{min}_i \leftarrow$ Find the minimum cost $\mathcal{H}_k$ among the neighbor graph nodes, namely, $\text{argmin}_{k \in \{\mathcal{N}_g(p_i)\}} \mathcal{H}_k$.
5. **if** $\mathcal{H}_k < \mathcal{H}_i$ **Then**
6. $p^*_i \leftarrow p^{min}_i$
7. **else**
8. $p^*_i \leftarrow p_i$

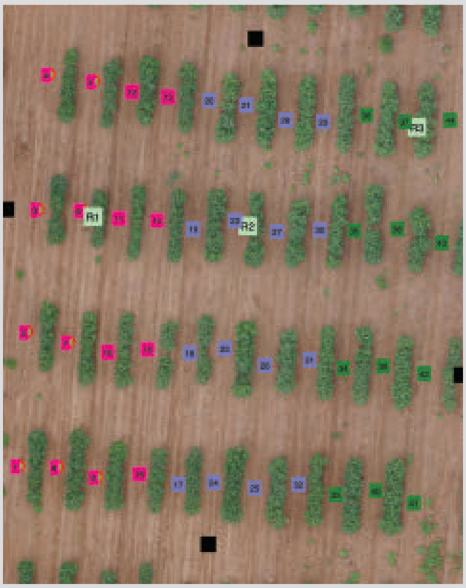

FIGURE 6 The results corresponding to the third region of interest.

from **Figure 6**, the robots converge to their final positions such that node 37 is precisely monitored by robot 3.

CONCLUSION

In this work, collaborative coverage and monitoring of an agricultural field using a group of UGVs was studied. To this end, the field was first represented by a weighted directed graph. The important areas on the field were detected and identified on the graph using a distributed density function. Next, this information was sent as input to a distributed energy-aware deployment strategy. Based on the proposed strategy, the robots were optimally deployed in such a way that coverage of the whole field and monitoring of the areas of interest were maximized so that UGVs could acquire more measurements of those areas. Furthermore, the robots continuously checked their level of energy; when a robot approached its threshold value, the team would cooperatively adjust the coverage formation to allow the robot to visit the closest base station to recharge before rejoining the coverage mission. The experimental validation of the proposed methodology is ongoing research. ■

ABOUT THE AUTHORS

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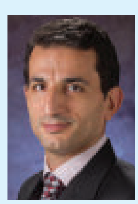

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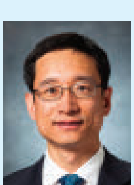

Dr. Changying Li is a Professor in the College of Engineering and the Founding Director of the Phenomics and Plant Robotics Center at the University of Georgia. The long-term goal of Dr. Li's research program is to develop sensing and robotics technologies for high-throughput plant phenotyping, precision agriculture, and postharvest biology. Dr. Li's research efforts have resulted in more than 100 peer-reviewed journal articles and conference proceedings. His work has been recognized by several major awards in his professional societies.

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