

Target-Barrier Coverage Improvement in an Insecticidal Lamps Internet of UAVs

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Abstract—Insecticidal lamps Internet of things (ILs-IoTs) has attracted considerable attention for its applications in pest control to achieve green agriculture. However, ILs-IoTs cannot provide a perfect solution to the migratory pest outbreak if the ILs are fixed on the ground. In this paper, we embed ILs in unmanned aerial vehicles (UAVs) as the mobile nodes, which can be rapidly landed on the ground to kill agricultural pests, and the Internet of UAVs (IoUAV) is introduced to extend the application of ILs-IoTs. To take full advantage of the IL-IoUAVs, we formulate the problem of target-barrier coverage and investigate how to minimise the number of IL-UAVs in constructing the target-barrier coverage. The ϵ -target-barrier coverage is introduced utilizing the realistic probabilistic sensing model of IL-UAVs, based on which we study how to guarantee the ϵ -target-barrier coverage while minimizing the number of IL-UAVs needed. The problem is solved by an optimal algorithm to merge multiple target-barriers. Evaluation results show the efficiency of our designed algorithms for constructing ϵ -target-barrier coverage.

Index Terms—Internet of things (IoT), insecticidal lamp (IL), target-barrier coverage, probabilistic sensing model, unmanned aerial vehicle (UAV).

I. INTRODUCTION

It is critical to enhance crop productivity for the exponential growth of population in the world while shrinking agricultural

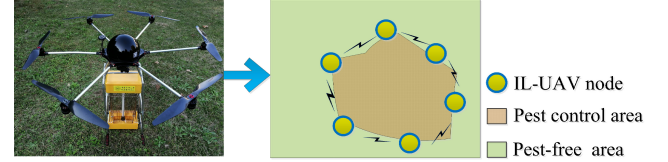


Fig. 1: Our designed IL-UAV node and the architecture of an IL-IoUAV.

lands and saving natural resources. As is well known, migratory pests cause serious crop damage and yield loss. Chemical pesticides have long been used to control pests, which emerge widespread disadvantages including environmental pollution, life-threatening, pesticide residues in food, and loss of natural antagonists to pests [1], [2]. As a fast-growing pest control technology, insecticidal lamps (ILs) have been widely applied in the Internet of things (IoT) to control agricultural pests. ILs-IoTs was introduced by [3] for the first time, where ILs are combined with wireless sensor networks (WSNs). This green technology has received increasing attention from both academia and industry since it is an effective measure to assist pest control.

However, the ILs-IoTs can handle the surrounding insects and monitor the insect population. However, changes in climate, interspecific competition, food quality, and other variables might precipitate the explosive growth of insects. In this case, the ILs-IoTs may not cope with the explosive growth of insect pests. In other words, ILs-IoTs cannot provide a perfect solution to the pest outbreak if the ILs are fixed on the ground [4]. Besides, insects are active at different times depending on the species [5]. Due to the limited battery, the ILs fixed on the ground cannot work all night.

As unmanned aerial vehicles (UAVs) have attractive advantages of easy deployment, flexible movement and line of sight (LoS) connections, they have been equipped with various sensors for a wide range of applications [6], [7]. In smart agriculture, UAVs are utilised to spread agricultural chemicals such as pesticides, fungicides, and fertilizer across farms [8], [9]. In particular, thanks to their adaptive mobilities, UAVs can be used to track migratory insects and rapidly landed on the ground to kill these agricultural pests. Inspired by this, we embed ILs in UAVs and construct the IL-Internet of UAVs (IoUAV), as shown in Fig. 1.

Since migratory insects with the phototactic feature are attracted by the ILs and collide with its metal mesh, the

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mesh releases high voltage pulse discharge. Then, the faster the discharge frequency of ILs, the higher insect density. The highest density locations are scheduled as the pest outbreak area. Before these ILs run out of batteries, IL-UAV nodes can be employed in response to an outbreak of agricultural pests. However, how to schedule IL-UAV nodes to perform the insecticidal mission is a challenging coverage problem, which can be classified into three types, i.e., area coverage [10], target coverage [11], and barrier coverage [12]. To prevent pests migrating from an area to the other, the IL-UAV nodes have to be rapidly landed on the ground to form a continuous circular barrier enclosed the pest control area. Compared with traditional coverage measurements, this application exhibits special features and requires different construction considerations. The deployment of an IL-IoUAV needs to form a closed barrier while keeping a certain distance between the barrier and the pest area centre. Then, the pest area center can be considered as a target, and the enclosed barrier is applied in the pest control using an IL-IoUAV, which refers to target-barrier coverage [13].

In the target-barrier coverage, two conflicting characteristics emerge concerning the combination of target coverage and barrier coverage. First, a distance constraint is used to characterise the pests' migration. If the deployed IL-UAVs cannot approach the enclosed region with the distance constraint, more IL-UAVs need to be scheduled around the pest control region to yield the distance constraint. From another perspective, to achieve more benefits from an IL-IoUAV, the number of IL-UAVs should be reduced for forming the target-barrier coverage. Driven by the above conflicting characteristics, the IL-UAVs are deployed evenly on a circle and the centre is located in the target with radius of the distance constraint. Based on this, the number of IL-UAVs and the total cost for many targets are minimised through deploying the IL-UAVs in optimal locations. Moreover, we consider the simultaneous control of many pest areas in a vast farmland through the target-barrier coverage, which refers to a deterministic deployment method of IL-UAVs for meeting the requirements of all targets.

Furthermore, new challenges are modelled by probabilistic sensing to applied to the target-barrier coverage in the IL-IoUAV. The traditional binary sensing model is superseded by the probabilistic sensing model, which depicts the decreasing ability with distance [14], [15]. The reason is that not all phototactic insects are attracted and killed by the IL-UAVs. Then, the probabilistic sensing model appropriates to investigate each IL-UAV's capability of killing pests. Thus, it is harder to specify the overlapping between the sensing ranges of individual IL-UAVs. Besides, the traditional converge definition, which ensures all parts of the surveillance region must be covered by the employed IL-UAVs' sensing. Then, it is not suitable to analyse the performance of coverage using the binary sensing model in the IL-IoUAVs, which should take the probabilistic nature of each IL-UAV. However, to the best of our knowledge, the deployment of IL-IoUAVs in the probabilistic sensing model to construct the target-barrier coverage has not yet been investigated.

To address the aforementioned challenges, this paper investigates the target-barrier coverage problem on the deployment

of IL-IoUAVs in the agricultural pest control. Our goal is to minimise the employed number of IL-UAVs using the probabilistic sensing model to construct the target-barrier coverage. In brief, the main contributions of this paper are summarized as follows:

- We combine the advantages of UAVs and ILs-IoTs to construct a new IL-IoUAVs framework in the practical applications of pest control for smart agriculture.
- We formulate the optimisation problem of the deployment as the minimisation of the number of IL-UAVs for constructing the ϵ -target-barrier coverage, which the first study of the probabilistic sensing model in the target-barrier coverage problem, to the best of our knowledge.
- We propose a deterministic deployment strategy to solve the optimisation problem for the deployment of IL-UAVs. After we make the analysis of the target-barrier circles and its properties, a merged algorithm is derived to construct the optimal ϵ -target-barrier coverage.

The rest of this paper is organized as follows. Section II reviews the state-of-the-art of the coverage problems. Section III presents the network model and defines the ϵ -target-barrier coverage. Section IV formulates the optimisation problem of the deployment of IL-UAVs and proposes the algorithm to solve the optimisation problem. Section V evaluates the proposed algorithms by simulations. Finally, we conclude this paper in Section VI.

II. RELATED WORKS

The coverage problems including three types: area coverage, target coverage, and barrier coverage, have attracted many researchers. Among them, the barrier coverage problem is the most similar one with our target-barrier coverage problem. In this section, we enclose previous works that are related with the barrier coverage problem of deployment and the studies on IoUAVs.

The barrier coverage problem was first investigated in [16], which put forward the concepts of strong barrier coverage, weak barrier coverage, and K -barrier coverage. The purpose of barrier coverage is to construct a narrow and long barrier belt area of the employed sensors to detect intruders passing through the barrier area. In [17], the barrier coverage problem was extended to a concept of two-dimensional barrier coverage problem, where the barrier was regarded as a belt-shaped area instead of a single line. Later on, the barrier problems with various types of sensors have been addressed, e.g., with radar sensors, camera sensors, and heterogeneous sensors. In [18] and [19], the deployment of bistatic radar sensors was investigated in the barrier coverage problem. In [20] and [21], the full-view barrier coverage problem and the local full-view barrier coverage problem were discussed, respectively, in camera sensor networks. To make the best of the detection ability of heterogeneous sensors, a method was proposed in [22] to efficiently form barrier coverage.

Based on the traditional barrier coverage, several barrier coverage models have been proposed to cater for practical applications. In a large collection of works [23], [24], the construction of K -barrier coverage has been studied to enhance the detection capability of the IoTs. To exploit the

collaboration and information fusion between neighbouring sensors, a barrier information coverage was defined in [25] to reduce the number of active sensors needed for covering a barrier and hence prolong the network lifetime. Moreover, a widely adopted confident information coverage was exploited in [26] to provide the coverage service for ocean border environmental surveillance. Then, a novel coverage model called target-barrier coverage was introduced in [13], which considers the target-barrier as an enclosed barrier embracing the protected target area. The aforementioned works focused on the how to construct barriers in a distributed way while minimizing the number of sensors required in each barrier for satisfying predetermined thresholds.

However, most of these works adopted the classical boolean sensing model. Although this model helped with researchers' better understanding of the barrier coverage problem, it is a rough approximation to the real sensing. To investigate how many sensors are capable of providing an acceptable breach detection probability, a probabilistic detection model was proposed in [27] with a false alarm rate. Further, the barrier coverage problem using the probabilistic sensing model was investigated in [25], under the assumption that intruders have been crossing the barrier area along a straight line. Based on [25], the probabilistic sensing model was used in [28] to theoretically analyse the detection probability of arbitrary path for intruders crossing the barrier formed by sensors, where the maximum speed of possible intruders was taken into consideration since the sensor networks were designed for various intruders in various scenarios. In [29], the genetic algorithm was developed to solve the problem of combining point coverage and barrier coverage, with the probabilistic sensing model. With the aid of probabilistic sensing model, an optimal control-based solution was proposed in [30] to solve the sensors' deterministic deployment problem, where the proposed optimal control framework provided a theoretical basis for the resultant solution.

Concerning the applications of IoUAVs, they have been adopted in a wide range of agricultural aviation operations, including precision seeding, vegetation testing, and pesticide spraying [31]–[33]. However, the mobility and the constraints such as short battery lifetime, limited communications, and delay result in complicated problems of coverage in IoUAVs. Considering the anisotropy of monitoring angle, a monitoring model was established in [34], where the monitoring quality was anisotropic along with the monitoring angle and varying with the monitoring distance. Based on the actual trajectories of UAVs and the real-time control decisions, a coverage map can be constructed [35]. To achieve better IoUAVs, the problems on how to deploy UAV base stations have been investigated for maximising the coverage and reducing the interference [36], [37].

The combination of UAVs and IoTs has been promoted the development of precision agriculture, especially in the applications of aerial crop monitoring and smart spraying tasks [38]. Furthermore, based on the integration of wireless radio-frequency modules into existing ILs, the concept of IoT-based solar insecticidal lamps (ILs-IoTs) is introduced. In the existing works [4], [39], [40], the authors proposed

some methods to deploy the ILs-IoTs node on the ground. It is pointed out that these ILs-IoTs cannot provide a perfect solution to migratory pests with time-varying locations since all ILs-IoTs nodes are fixed on the ground. The flexibility of UAVs may provide a better solution for pest control. Thus, we introduce the IL-IoUAVs to take full advantage of both UAVs and ILs-IoTs.

To the best of our knowledge, [41] is the first work that the IL-UAV was put forward for emergency applications after theft and destruction of IL node, e.g., tracking, patrol inspection, and so on. However, the IL-UAV is only the auxiliary equipment of IL fixed on the ground, and the authors do not discuss how to deploy IL-UAV nodes to form an IL-IoUAVs. In this paper, for the purpose of agricultural pest control, the probabilistic sensing model is exploited to construct the target-barrier coverage in an energy-efficient way. For the practical implementation of IL-IoUAVs, we first propose the definition of ϵ -target-barrier coverage, utilizing the probabilistic sensing model for the target-barrier coverage model. Then, we propose a deterministic deployment method to construct the ϵ -target-barrier coverage.

III. SYSTEM MODEL

In this section, we describe the system model, which consists of the sensing model and the target-barrier coverage model.

The main notations summarize in Table I.

TABLE I: Summary of Key Notations

Notation	Meaning
\mathcal{T}	A set of targets
t_k	The k th target
m	The number of targets
\mathcal{S}	A set of IL-UAVs
s_i	The i th IL-UAV
n	The number of IL-UAVs
$d_{t_k t_l}$	The distance between targets t_k and t_l
$d_{s_i s_j}$	The distance between IL-UAVs s_i and s_j
$d_{s_i t_l}$	The distance between IL-UAV s_i and target t_l
δ	The distance constraint of target-barrier coverage
$p(\xi)$	The detection probability of escape path ξ
ϵ	The predetermined threshold of target-barrier coverage
\mathcal{B}	A set of ϵ -target-barriers
b_v	The v th target-barrier in \mathcal{B}
u	The number of target-barriers in \mathcal{B}
$c(t)$	The target-barrier circle of t
$\mathcal{L}(b_v)$	The perimeter of b_v
$\mathcal{S}(\mathcal{B})$	A set of IL-UAVs used to construct \mathcal{B}
$ \mathcal{S}(\mathcal{B}) $	The number of IL-UAVs in $\mathcal{S}(\mathcal{B})$
$\mathcal{S}(b_v)$	A set of IL-UAVs in ϵ -target-barrier b_v
$ \mathcal{S}(b_v) $	The number of IL-UAVs in $\mathcal{S}(b_v)$
$\mathcal{T}(b_v)$	A set of targets monitored by ϵ -target-barrier b_v
$ \mathcal{T}(b_v) $	The number of targets in $\mathcal{T}(b_v)$

A. Probabilistic sensing model

Most existing works [4], [39], [40] adopted the boolean sensing model of a circular region for sensors, where a sensor can detect any event occurring at any point within its sensing region at probability 1 but it cannot detect anything outside the region. However, the boolean sensing model is an ideal model for the insecticidal lamp. The probabilistic sensing model is

appropriate for the deployment of IL-UAVs in the application of agricultural pest control.

As an important technology of physical prevention and control, insecticidal lamps (ILs) attract pests by the phototaxis of insects. The phototaxis of pests drives them to fly to the launched lamp of an IL, which is equipped with a set of the high-voltage power grid to kill pests. On the one hand, we cannot ensure all phototactic insects are attracted by the IL-UAVs since the phototaxis of insects cannot guarantee that all insects reach the launched lamp of the IL. Insects are affected by their habits, size, wind direction, crop height, and other environmental factors during flight. The farther the distance between insect pests and the IL, the lower the probability of insect pests successfully flying to the launched lamp of the IL. On the other hand, even if pests successfully get to the launched lamp of the IL, it cannot be guaranteed that all insects are killed by the IL. The reason is that the success rate is affected by the size of the insect, the angle of flight, the ability to withstand electric shocks, and other factors. Thus, not all the attracted insects will be killed by the IL-UAVs. Based on the above analysis, the pest control ability of the IL can be approximate as a probabilistic sensing model.

Besides, It has been demonstrated that the probabilistic model is more accurate to depict the IL-UAVs in terms of killing agricultural pests [42], [43]. In this work, we adopt the Elfes sensing model [44] to describe the probabilistic characteristics of IL-UAVs. According to this sensing model, the probability that pest e is killed by IL-UAV s_i , is given by

$$p_{s_i e} = \begin{cases} 1, & d_{s_i e} \leq \tau_1 \\ e^{-\lambda \alpha}, & \tau_1 < d_{s_i e} \leq \tau_2 \\ 0, & d_{s_i e} > \tau_2 \end{cases} \quad (1)$$

where $d_{s_i e}$ is the distance between pest e and IL-UAV s_i , and τ_1 and τ_2 are the starting of uncertainty and the maximum sensing range of the IL-UAV, respectively. Besides, λ is adjusted according to the physical properties of the IL-UAV, and $\alpha = d_{s_i e} - \tau_1$. Note that, the probabilistic sensing model turns into the boolean sensing model when $\tau_1 = \tau_2$.

Further, the model in (1) can be approximated for $\tau_1 = 0$ as

$$p_{s_i e} = \begin{cases} e^{-\lambda \alpha}, & 0 \leq d_{s_i e} < \tau_2; \\ 0, & d_{s_i e} \geq \tau_2. \end{cases} \quad (2)$$

Certainly, pest e is not always killed by IL-UAV s_i when $d_{s_i e} < \tau_2$. The probability that pest e is not killed by IL-UAV s_i can be defined as the miss probability.

$$\tilde{p}_{s_i e} = 1 - p_{s_i e} \quad (3)$$

It is obvious that the total miss probability of pest e in IL-IoUAVs is

$$\tilde{p}_e = \prod_{s_i \in S} (1 - p_{s_i e}) \quad (4)$$

where S denotes all IL-UAVs landed on the ground to kill pests in the farmland.

Then, the probability of pest e killed by all IL-UAVs is

$$p_e = 1 - \tilde{p}_e = 1 - \prod_{s_i \in S} (1 - p_{s_i e}) \quad (5)$$

B. Target-barrier coverage model

Based on the probabilistic sensing model, we introduce some definitions for our target-barrier network model.

In the pest area, there are m targets to be monitored continuously and the target set is denoted by $\mathcal{T} = \{t_1, t_2, \dots, t_m\}$. All targets in \mathcal{T} are static in a known position. The m targets are distributed in random in a given region, and all targets know their locations. Furthermore, these m targets are random distribution in the farmland. The distance between two targets t_k and t_l is denoted by $d_{t_k t_l}$, $k, l = 1, 2, \dots, m$.

Definition 1: Target-barrier coverage. A continuous circular bound formed around a target is a target-barrier [13]. A δ distance constrained in the target-barrier by the application requirements, where δ denotes the minimum distance from the target to each IL-UAV.

Definition 2: Escape path. A curve in the target-barrier coverage is referred to as an escape path if it crosses the completed barrier coverage.

As illustrated in Fig. 2, as for the escape path ξ , which detection probability is $p(\xi)$, i.e., $p(\xi)$ denotes the probability that a migratory pest fleeing along the escape path ξ is detected by at least one IL-UAV. It is guaranteed that the pest can be detected if the binary sensing model is used for IL-UAVs in the target-barrier coverage networks. In this case, the detection probability of the pest, $p(\xi) = 1, \forall \xi$. However, as the barrier coverage has various breadths, the barrier is represented by several discrete points in certain parts, where the pest can escape from IL-UAVs if it flies fast to cross the fragile barrier. In this case, the detection probability of the pest may be equal to 0, i.e., $p(\xi) = 0, \exists \xi$. Thus, to improve the detection probability of agricultural pests passing through the barrier coverage, this paper studies how to achieve the target-barrier coverage when the detection probability higher than a predetermined threshold using the probabilistic sensing model.

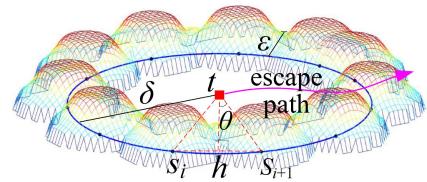


Fig. 2: An example of the ϵ -target-barrier coverage.

Definition 3: ϵ -target-barrier coverage. In an ϵ -target-barrier coverage, the detection probability of the pest escaping across any part of the barrier coverage is higher than the predetermined threshold $\epsilon \in (0, 1)$, i.e., $p(\xi) \geq \epsilon, \forall \xi$.

An ϵ -target-barrier coverage model is illustrated in Fig. 2, with a distance constraint δ , where the ϵ -target-barrier coverage is constructed by 11 IL-UAVs using the probabilistic sensing model. And ϵ is the minimum detection probability for the pest crossing the barrier area.

The target-barrier set is denoted by $\mathcal{B} = \{b_1, b_2, \dots, b_u\}$, which means that u ϵ -target-barriers will be constructed to monitor or protect the target set \mathcal{T} in the farmland. Note that

the maximum number of target-barriers is that of targets. $\mathcal{S}(b_v)$ and $|\mathcal{S}(b_v)|$ denote the set of IL-UAVs landed on the ground and employed to construct the ϵ -target-barrier b_v and the number of IL-UAVs in $\mathcal{S}(b_v)$, respectively. Moreover, assume $|\mathcal{T}(b_v)|$ as the number of targets in $\mathcal{T}(b_v)$, and $\mathcal{T}(b_v)$ is the set of targets in b_v . Let $\mathcal{S}(\mathcal{B})$ represent the set of IL-UAVs employed to achieve the ϵ -target-barriers for \mathcal{T} , and $|\mathcal{S}(\mathcal{B})|$ is the number of IL-UAVs.

To monitor all targets in \mathcal{T} , we adopt a deterministic method to deploy a set $\mathcal{N} = \{s_1, s_2, \dots, s_n\}$ of IL-UAVs for forming a ϵ -target-barrier coverage. The distance between IL-UAVs s_i and s_j is denoted by $d_{s_i s_j}$, and the distance between IL-UAV s_i and target t_l is denoted by $d_{s_i t_l}$. The location of each IL-UAV is known through the localisation mechanisms. Wireless communications within the IL-IoUAVs comply with the ZigBee protocol.

IV. OPTIMAL DEPLOYMENT OF IL-UAVS

The optimal deployment problem is first formulated to construct an ϵ -target-barrier coverage IL-IoUAV, based on which the ϵ -target-barrier coverage is theoretically analysed, and then an algorithm is introduced to release the optimal deployment problem.

A. Problem formulation

In this work, our problem is how to minimise the number of IL-UAVs landed on the ground and employed to form an ϵ -target-barrier coverage. The optimal deployment problem is therefore formulated as

$$\text{P1: } \min |\mathcal{S}(\mathcal{B})| \quad (6)$$

subject to

$$d_{s_i t_l} \geq \delta, \forall s_i \in \mathcal{S}(b_v), t_l \in \mathcal{T}(b_v), b_v \in \mathcal{B}; \quad (7)$$

$$p(\xi) \geq \epsilon, \forall \xi, 0 < \epsilon \leq 1; \quad (8)$$

$$\sum_{v=1}^u |\mathcal{T}(b_v)| = m, \forall b_v \in \mathcal{B}. \quad (9)$$

The constraint (7) imposes that the minimum distance between each target and its ϵ -target-barrier constructed is greater than δ . The constraint (8) indicates that the detection probability of the pest flying along any escape path is higher than ϵ . The constraint (9) denotes that the constructed target-barriers monitor all targets in \mathcal{T} .

Intuitively, to minimise the number of IL-UAVs employed to construct the ϵ -target-barrier coverage, we have to land IL-UAVs on the ground evenly around the enclosed target with the distance constraint. However, it is hard to enumerate the detection probabilities over all escape paths of a pest in the farmland. To deal with this dilemma and take advantage of the probabilistic sensing model, we utilise the detection probabilities between two IL-UAVs to indicate the monitoring situation of the target-barrier coverage since all IL-UAVs are evenly distributed around the enclosed target.

Lemma 1. The point with the minimum detection probability is located at the midpoint between two IL-UAVs.

Proof. To prove this geometry property, let $d_{s_i s_j}$ represent the distance between the IL-UAVs s_i and s_j , and set d_x as the

distance between a point x in the target-barrier coverage and the IL-UAV s_i . Then, the distance between the point x and the IL-UAV s_j is $d_{s_i s_j} - d_x$. Thus, the detection probability at the point x is:

$$\begin{aligned} p_x &= 1 - (1 - p_{s_i x})(1 - p_{s_j x}) \\ &= 1 - (1 - e^{-\lambda(d_x - \tau_1)})(1 - e^{-\lambda(d_{s_i s_j} - d_x - \tau_1)}) \end{aligned} \quad (10)$$

Note that we only consider the exponential part of the probabilistic sensing model, i.e., in the condition that $d_{s_i s_j} \leq 2\tau_2$, since it does not make sense to analyse the detection probability for the target-barrier coverage if IL-UAVs do not have sensing capability.

To achieve the extremum value of the detection probability at point x , p_x , we acquire the first-order and the second-order derivatives of (10) with respect to d_x as

$$p'_x(d_x) = \lambda(e^{\lambda(d_x - \tau_1)} - e^{\lambda(-d_x + d_{s_i s_j} - \tau_1)})e^{-\lambda(d_{s_i s_j} - 2\tau_1) + 1} \quad (11)$$

and

$$p''_x(d_x) = \lambda^2(e^{\lambda(d_x - \tau_1)} + e^{\lambda(-d_x + d_{s_i s_j} - \tau_1)})e^{-\lambda(d_{s_i s_j} - 2\tau_1) + 1}, \quad (12)$$

respectively.

Obviously, $p'_x(d_x)$ is a monotonic increasing function since $p''_x(d_x) > 0$. Therefore, p_x is a convex function of d_x as it is a continuous function on the interval $d_x \in [0, d_{s_i s_j}]$. Thus, p_x achieves its extremum value, i.e., the minimum detection probability, in the condition that $p'_x(d_x) = 0$, where $d_x = d_{s_i s_j}/2$.

Thus, the proof is concluded. \square

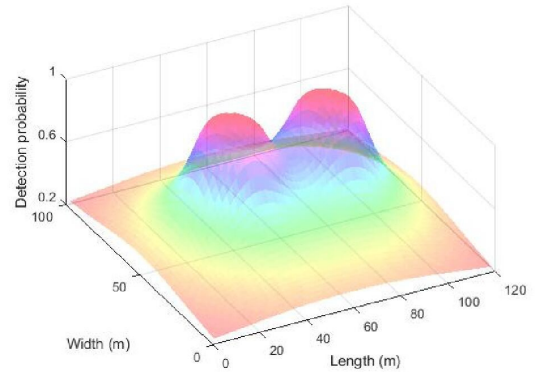


Fig. 3: Illustration of the minimum detection probability at the midpoint between two IL-UAVs.

Since all IL-UAVs have to land on the ground to perform the prevention and control of migratory insects, the altitude of IL-UAVs equal to 0 and we simplify the problems. Fig. 3 depicts two IL-UAVs, which locate in the points (40, 50) and (80, 50), respectively. The midpoint between these two IL-UAVs, (60, 50), is of the minimum detection probability. In other words, the point of the minimum detection probability has the same distance from each IL-UAV. As our aimed detection

probability is higher than ϵ , the distance from the midpoint to each IL-UAV should be shorter than

$$d_\epsilon = \tau_1 + \sqrt[\beta]{-\frac{\ln(1 - \sqrt{1 - \epsilon})}{\lambda}}. \quad (13)$$

Then, the problem P1 can be simplified to the optimisation as

$$\text{P2: } \min |\mathcal{S}(\mathcal{B})| \quad (14)$$

subject to (7), (9), and

$$d_\epsilon \leq d_{s_i s_{i+1}} \leq 2d_\epsilon, s_{|\mathcal{S}(b_v)|} = s_1; \forall s_i \in S(b_v), b_v \in \mathcal{B}. \quad (15)$$

The constraint (15) represents that the distance between two adjacent IL-UAVs constructing each target-barrier should be shorter than $2d_\epsilon$ to guarantee the detection probability of the pest. Besides, the distance between two adjacent IL-UAVs is greater than or equal to d_ϵ , which can be defined as the safe distance to avoid the collision of the adjacent IL-UAVs.

B. Discussions

Since targets are randomly distributed in the farmland, it is hard to solve the problem P2 directly. To minimise the number of required IL-UAVs, we will make full use of the sensing probability for each IL-UAV to meet the tight constraint (15). Then, for the optimisation problem to be bounded, the minimisation of the number of required IL-UAVs is converted into the construction of the target-barriers accompanying the shortest perimeter.

How to construct the target-barrier coverage for one target using the minimum number of employed IL-UAVs is first discussed.

Definition 4 (Target-barrier circle): A target-barrier circle is that a circle with its centre is target t and its radius is distance constraint δ , which is denoted by $c(t)$.

According to the definition, $\mathcal{L}_{c(t)} = 2\pi\delta$ is the circumference of a target-barrier circle. Furthermore, a portion of target-barrier circle is referred to as **target-barrier arc**. The target-barrier circle $c(t)$ is the blue circle in Fig. 2. Then, the minimum number of IL-UAVs required pertains to the case that all the employed IL-UAVs are distributed on $c(t)$, whose centre is t . Then, the IL-UAVs s_i and s_{i+1} are both located at the target-barrier circle, and the distance is $d_{ts_i} = d_{ts_{i+1}} = \delta$.

Besides, the connection point of the sensing regions of s_i and s_{i+1} is h , and the distance is $d_{s_i h} = d_{s_{i+1} h} = d_\epsilon$. Thus, the isosceles triangle is denoted by $\Delta ts_i s_{i+1}$, in which $th \perp s_i s_{i+1}$. Then, we have

$$\sin \theta = \frac{hs_{i+1}}{ts_{i+1}} = \frac{d_\epsilon}{\delta}, \quad (16)$$

where the angle between th and ts_{i+1} is θ .

Then, to construct the target-barrier for one target in Fig. 2, the minimum number of IL-UAVs required is

$$|\mathcal{S}(b)| = \left\lceil \frac{\pi}{\arcsin(d_\epsilon/\delta)} \right\rceil. \quad (17)$$

In the target-barrier coverage, if all IL-UAVs are located at the target-barrier circle for every target in \mathcal{T} , these target-barriers are independent of each other. Then, the number of IL-UAVs employed is $|\mathcal{S}(\mathcal{B})| = m \left\lceil \frac{\pi}{\arcsin(d_\epsilon/\delta)} \right\rceil$ for all targets.

Note that it is unnecessary to deploy IL-UAVs on each target-barrier circle when the targets are scattered densely and the distance between targets is short. To achieve a larger target-barrier for enclosing a portion of targets in \mathcal{T} , we can further reduce the number of employed IL-UAVs in the way of merging several target-barrier circles. We will start with the investigation on the method of merging two target-barrier circles.

Lemma 2. Once the distance between the two targets is shorter than $\pi\delta$, a merged target-barrier can be achieved from these two target-barrier circles.

Proof. It is easy to see $2\pi\delta$ is the circumference of a target-barrier circle. As illustrated by the red convex hull in Fig. 4, the perimeter \mathcal{L}_b of the merged target-barrier will be equal to twice the circumference of a target-barrier circle if the distance $d_{t_1 t_2} = \pi\delta$. Thus, we can easy get the result that the perimeter of a merged target-barrier is less than twice the circumference of a target-barrier circle ($\mathcal{L}_b < 4\pi\delta$) if the distance between two targets is shorter than $\pi\delta$. \square

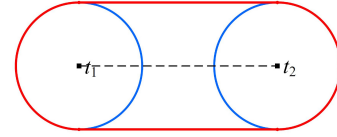


Fig. 4: The merged target-barrier of t_1 and t_2 .

Before introducing the method of merge more target-barrier circles, we present a theorem.

Theorem 1. The length of all target-barrier arcs is a fixed value in a merged target-barrier.

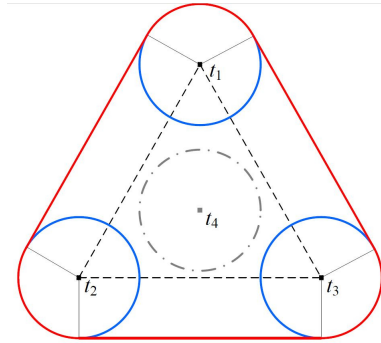


Fig. 5: The merged target-barrier of four targets.

Proof. As we know, the length of the target-barrier (a target-barrier circle) for a single target is $2\pi\delta$.

The length of two target-barrier arcs for two targets is $2\pi\delta$, which is shown in Fig. 4. The reason is that the semicircle reserves for each target-barrier arc.

As for m targets, $m > 2$, sum all angles for these m target-barrier circles is $2m\pi$, as shown in Fig. 5. $(m-2)\pi$ is equal to the sum of interior angles in m polygons, whose vertices are the m targets. Moreover, there are another $m\pi$ angles for

all target-barrier circles since that m tangent lines emerge in every two target-barriers. Thus, $2m\pi - (m-2)\pi - m\pi = 2\pi$, which is the sum of all m target-barrier arcs.

As a result, we can conclude that there is a fixed value ($2\pi\delta$) for the length of all target-barrier arc. \square

Note that we assume that all targets know their locations. In the actual agricultural applications, ILs-IoTs should first construct to kill insects and monitor the insect population. Then, we utilize the phototactic feature of migratory insects to calculate the insect density by the discharge frequency of the ILs fixed on the ground. And the highest density locations are the locations of targets.

C. Algorithm

A merged algorithm is proposed to optimise a target-barrier set using the minimum number of IL-UAVs from our discussions.

To achieve the optimal target-barrier set \mathcal{B}_{min} , we first construct a target-barrier enclosing all targets. Based on Theorem 1, we can get the perimeter \mathcal{L}_b of the merged target-barrier

$$\mathcal{L}_b = \mathcal{L}_{cp} + 2\pi\delta, \quad (18)$$

Note that \mathcal{L}_{cp} is the perimeter of a convex polygon, whose vertices set is the outside targets, e.g., the targets $\{t_1, t_2, t_3\}$ in Fig. 5. Resort to the Graham scan algorithm, it can be easily to generate the convex polygon. The common tangent of every two target-barrier circles will be obtained if each polygon edge moves along the normal line with δ . Then, for constructing the merged target-barrier, the minimum number of IL-UAVs is

$$|\mathcal{S}(b)| = \left\lceil \frac{\pi}{\arcsin(d_\epsilon/\delta)} \right\rceil + \left\lceil \frac{\mathcal{L}_{cp}}{2d_\epsilon} \right\rceil. \quad (19)$$

These IL-UAVs are all deployed on the merged target-barrier b , which includes all target-barrier arcs and common tangents.

Next, resort to the Kruskal algorithm, we can construct the minimum spanning tree \mathcal{G} . Then, the targets are denoted by the vertices and the distance between two targets t_i and t_j is represented by $e_{t_it_j}$. Moreover, to facilitate the next computation, we sort all edges in the descending order.

Each edge in \mathcal{E} is repeat removed and two convex polygons are generated using the Graham scan algorithm for the first edge. Besides, each target in the merged target-barrier can be regarded as a simple point convex polygon, whose perimeter is zero. Furthermore, let a line convex polygon denote two targets, between whose the distance is the perimeter.

Thus, resort to the convex polygons accompanying their corresponding target-barrier arcs, we can achieve two optimal target-barriers. If the perimeter of \mathcal{B}_{min} is greater than the summation, which is the sum of these two target-barriers and $2\pi\delta$, the optimal target-barrier set \mathcal{B}_{min} will be updated. Given v elements in the optimal target-barrier set \mathcal{B}_{min} , the minimum number of required IL-UAVs is

$$|\mathcal{S}(\mathcal{B}_{min})| = v \left\lceil \frac{\pi}{\arcsin(d_\epsilon/\delta)} \right\rceil + \sum_{k=1}^v \left\lceil \frac{\mathcal{L}_{cp}}{2d_\epsilon} \right\rceil. \quad (20)$$

Algorithm 1 The merged algorithm

Input: A set of targets \mathcal{T} , the distance constraint δ

Output: The optimal set of target-barriers using the minimum number of IL-UAVs required, \mathcal{B}_{min}

- 1: Construct the convex polygon cp_0 of all targets
- 2: $\mathcal{L}_{b_0} \leftarrow \mathcal{L}_{cp_0} + 2\pi\delta$
- 3: $\mathcal{B}_{min} \leftarrow \{b_0\}$
- 4: Generate a minimum spanning tree $\mathcal{G} = (\mathcal{T}, \mathcal{E})$
- 5: Descending sort of $e_{t_it_j}$ in \mathcal{E}
- 6: **for** $e_{t_it_j}$ in \mathcal{E} **do**
- 7: Remove $e_{t_it_j}$
- 8: Construct convex polygons cp_i and cp_j
- 9: $\mathcal{L}_{b_i} \leftarrow \mathcal{L}_{cp_i} + 2\pi\delta$ and $\mathcal{L}_{b_j} \leftarrow \mathcal{L}_{cp_j} + 2\pi\delta$
- 10: **if** $\mathcal{L}_{b_i} + \mathcal{L}_{b_j} + 2\pi\delta < |\mathcal{B}_{min}|$ **then**
- 11: $\mathcal{B}_{min} \leftarrow \{b_i, b_j\}$
- 12: **end if**
- 13: **end for**
- 14: **return** \mathcal{B}_{min}

Algorithm 1 describes our designed method. Due to the Graham scan algorithm with the complexity of $\mathcal{O}(m \log m)$ in time, the optimal deployment problem for the ϵ -target-barrier coverage can be solved in $\mathcal{O}(m^2 \log m)$ in time. And m denotes the number of targets that we should be protect with the designed ϵ -target-barriers.

V. PERFORMANCE EVALUATIONS

In this section, we provide illustrative results to evaluate the performance of the merged algorithm for the optimal deployment problem.

A. Effectiveness of the Algorithm

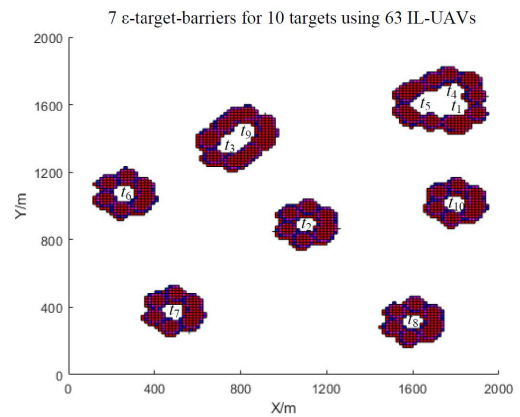


Fig. 6: An example of the ϵ -target-barrier coverage.

We present an example to verify the effectiveness of our algorithm to land the minimum IL-UAVs and construct an ϵ -target-barrier coverage. We adopt the exponential attenuation probabilistic model, and the parameters are setting according to [45] for simulations. The predetermined threshold is $\epsilon = 0.5$. As shown in Fig. 6, $t = 10$ targets, i.e., pest control areas,

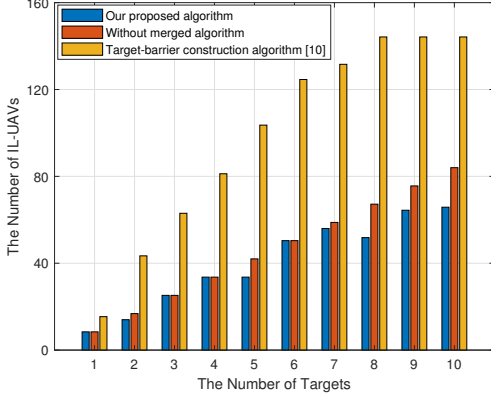


Fig. 7: The number of required IL-UAVs versus the number of targets in different methods.

are uniformly distributed in the farmland at random with areas of $2000\text{m} \times 2000\text{m}$. At the beginning, based on the distance constraint $\delta = 100\text{m}$, we construct 10 target-barrier circles. Each target-barrier circle requires 7 IL-UAVs, and 70 IL-UAVs are required in total for 10 target-barrier circles. By executing our proposed algorithm, we sort out 7 ϵ -target-barriers for 10 targets, using 63 IL-UAV nodes.

B. Advantage of the Algorithm

The following simulations are executed to verify the advantage of the proposed algorithm over those without the merged method or the target-barrier construction in [13]. Moreover, the effect of the number of targets, m , the distance constraint δ , and the predetermined threshold ϵ on the number of required IL-UAVs, n are respectively investigated. Note that the target-barrier construction algorithm is an IL-UAV selection method, which needs to deploy a vast number of IL-UAVs in advance. In our simulations, the farmland is set to be a square with a size of $2000\text{m} \times 2000\text{m}$, where all targets are uniformly distributed at random. The exponential attenuation probabilistic model is taken as our testing probabilistic model, and the parameters are set according to [45] for our simulations.

First, we examine the number of required IL-UAVs, n , versus the number of targets, $m \in [1, 10]$. The distance constraint is set to $\delta = 100\text{m}$, and the predetermined threshold is set to $\epsilon = 0.5$ for the ϵ -target-barrier. As shown in Fig. 7, we can find that our algorithm is the one with the minimum number of IL-UAVs in the construction of ϵ -target-barriers for various number of targets. Compared with the target-barrier construction algorithm, the benefit from our merged algorithm is that the number of required IL-UAVs is drastically reduced. Besides, we observe that the number of required IL-UAVs is increased along with the number of targets increasing. However, once the number of targets is larger than 6, the number of required IL-UAVs will not be continuously increased as the number of targets increases. This is because that most of the ϵ -target-barriers will be merged by our proposed algorithm.

Second, the number of required IL-UAVs, n , is examined versus the distance constraint $\delta \in [50\text{m}, 140\text{m}]$. The predetermined threshold is set to $\epsilon = 0.5$ for the ϵ -target-barrier,

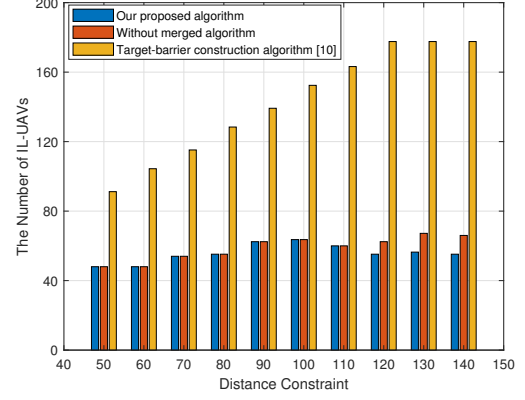


Fig. 8: The number of IL-UAVs versus the distance constraint in different methods.

and there are $m = 10$ targets distributed at random in the given region. The simulation results are shown in Fig. 8, where our algorithm always utilises fewer IL-UAVs for the coverage for various distance constraints. However, once the distance constraint is less than 110m, the number of required IL-UAVs in our algorithm is the same as that without merged algorithm. This is because that many sparse scenarios of targets are generated from the small distance constraint, while more dense scenarios are generated from larger distance constraint, and more target-barriers will be merged. Furthermore, we observe that the number of required IL-UAVs is no longer changed when the distance constraint is larger than 120m, in the target-barrier construction algorithm [45], mainly because the same set of IL-UAVs are selected when the IL-UAVs are deployed in advance.

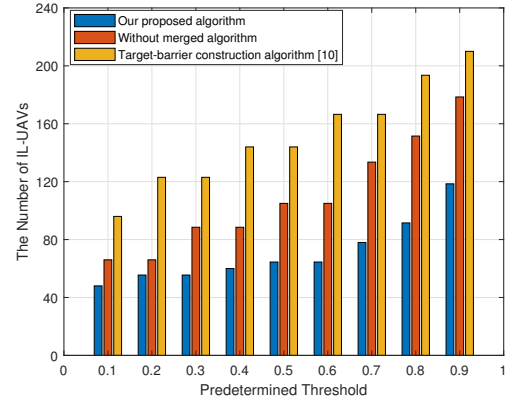


Fig. 9: The number of required IL-UAVs versus the predetermined threshold in different methods.

Third, we examine the number of required IL-UAVs, n , versus the predetermined threshold $\epsilon \in [0.1, 0.9]$. The predetermined threshold is set to $\epsilon = 0.5$ for the ϵ -target-barrier. The distance constraint is set to $\delta = 100\text{m}$ for the ϵ -target-barrier, and there are $m = 10$ targets distributed at random in the given region. The simulation results are shown in Fig. 9, where our proposed algorithm always utilises fewer IL-UAVs concerning

various predetermined thresholds, compared with the other two algorithms, while the number of required IL-UAVs is gradually increased as the pre-defined threshold increases. However, the number of required IL-UAVs will not be changed if there is little variation with the predetermined threshold. The reason behind this is that the detection probability changes along with the distance between the adjacent IL-UAVs. Then, we have to deploy more IL-UAVs for a larger predetermined threshold to construct the ϵ -target-barrier coverage. However, there is a certain number of IL-UAVs to construct any target-barrier.

VI. CONCLUSION AND DISCUSSION

A. Summary

Motivated by the advantage of ILs-IoTs and UAVs for pest control, this paper introduced a novel IL-UAV design to form IL-IoUAVs. We formulated the target-barrier coverage using the probabilistic sensing model and defined an ϵ -target-barrier coverage model for IL-IoUAVs. To solve the optimal deployment problem of IL-UAVs, the target-barrier circle is introduced. And we utilised the properties to convert the problem of an IL-IoUAV formulation into a minimisation of the length of all target-barrier problem. Then, a merged algorithm is proposed to solve the problem of how to minimise the number of required IL-UAVs. Finally, the simulation results demonstrated the effectiveness and advantages of the proposed algorithm, and the designed IL-IoUAVs can be competent for pest control in green agriculture.

Although this paper focuses on the optimal deployment problem of IL-UAVs that is solved by the ϵ -target-barrier coverage, several limitations need to be considered for better applications in green agriculture. On the one hand, improving energy management strategy should be considered since the power sources of IL-UAVs available are inadequate for a long time task. On the other hand, the price of each IL-UAV is higher than the IL node fixed on the ground. Therefore, efforts to lower hardware costs in the IL-IoUAV implementations, together with maximizing system performance, need to be implemented.

B. Future Work

For future work, we plan to conduct further research in the following three aspects.

- Since the mobility of IL-UAVs can support a more resilient deployment, how to combine IL-UAVs with IL nodes fixed on the ground to construct a new IL-IoUAVs framework is another work in the future.
- Due to the power limitation of IL-UAVs and ILs-IoTs, we plan to explore a network state model combining network coverage distribution and energy distribution. And the multi-objective optimization will be established involving better coverage performance and less energy consumption.
- Different kinds of insects are usually present diverse phototaxis and activity time, which will affect the deployed locations of each IL-UAV. With the development of data forecast, how to schedule IL-UAVs through the whole night for pest control is another work in the future.

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