Integrating Bio-Inspired Approaches with UAV-FSN Systems for Clustered Target Area Detection in Agriculture

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Abstract: *Target area detection in agriculture plays a crucial role in optimizing crop management and resource allocation. Traditional methods often lack the precision and efficiency required for modern farming practices. Integrating bio-inspired approaches with UAV-FSN systems offers a promising solution to this challenge. By harnessing principles from nature, such as swarm intelligence and reinforcement learning, it becomes possible to optimize the deployment and coordination of UAVs within FSN for clustered target area detection in agriculture. This research explores the integration of bio-inspired approaches with UAV-FSN systems for clustered target area detection in agriculture. The increasing demand for precision agriculture necessitates efficient methods for identifying target areas affected by various factors. In this study, we introduce a novel algorithm, the QL-ABC Algorithm, which combines the Artificial Bee Colony (ABC) Algorithm with Q-Learning to optimize the deployment and movement of unmanned aerial vehicles (UAVs) within flying sensor networks (FSN) for target area detection. The performance outcomes of the proposed QL-ABC Algorithm on comparison with the existing algorithms are analyzed using extensive simulation analysis with the appropriate simulation metrics: packet delivery ratio, mean end-to-end delay, and energy consumption. Results validate the usefulness of the proposed QL-ABC algorithm in accurately detecting clustered target areas in agricultural landscapes, thus contributing to advancements in precision farming practices and sustainable agriculture.*

Keywords: Flying Sensor Networks, Artificial Bee Colony Algorithm, Clustered Target Area Detection, Q-Learning, Unmanned Aerial Vehicles.

1 Introduction

In the field of agriculture, there has been the emergence on modern technologies to achieve precision and accuracy. Flying Sensor Networks comprises a network of sensors mounted on Unmanned Aerial Vehicles capable of gathering data over vast agricultural areas. These UAVs can be armed with various sensor devices such as multispectral cameras, thermal sensors, and LiDAR, enabling them to collect diverse agricultural data with high spatial and temporal resolution. The integration of FSN and UAVs offers farmers and agricultural researchers unprecedented access to real-time and comprehensive information about crop health, soil conditions, and environmental factors [1]. The agricultural sector faces numerous challenges, including resource scarcity, environmental degradation, and fluctuating market demands. Target area detection leads a primary role to address these encounters by facilitating precise and timely interventions. Identifying specific areas within agricultural fields affected by pests, diseases, nutrient deficiencies, or water stress enables farmers to implement targeted treatments, optimize resource usage, and maximize crop yields. Moreover, accurate target area detection enhances sustainability by minimizing the use of agrochemicals and reducing environmental impacts. The use of agrochemicals poses significant environmental and health risks, including soil degradation, water contamination, and adverse effects on non-target organisms. Minimizing or eliminating their use is imperative to mitigate these negative impacts and promote sustainable agricultural practices. Efforts should focus on adopting alternative methods such as organic farming, integrated pest management, and precision agriculture to reduce reliance on agrochemicals.

Bio-inspired approaches draw inspiration from biological systems and phenomena to design algorithms and strategies for solving complex problems. In agriculture, bio-inspired approaches have shown promise in optimizing various tasks, including target area detection. Examples of bio-inspired algorithms include swarm intelligence, evolutionary algorithms, and reinforcement learning. These approaches leverage principles observed in nature, such as self-organization, collective behavior, and adaptation, to enhance the efficiency and effectiveness of agricultural operations [2]. By mimicking the behaviors of organisms like bees, ants, and birds, bio-inspired algorithms can optimize the deployment and coordination of UAVs within FSN for clustered target area detection in agriculture.

The integration of bio-inspired approaches with remote sensing and flying sensor networks (FSNs) has shown promising potential in agricultural applications. Uzair et al. [3] proposed a bio-inspired video enhancement technique for small moving target detection, which could be adapted for identifying target areas in agriculture. Arafat and Moh [4] explored bio-inspired approaches for energy-efficient localization and clustering in UAV networks, which could enhance the efficiency of target area detection in agricultural landscapes. Additionally, Chen et al. [5] introduced a multi-robot distributed collaborative region coverage search algorithm based on Glasius bio-inspired neural networks, providing insights into optimizing the deployment and coordination of UAVs within FSNs for target area detection in agriculture. These studies underscore the significance of bio-inspired approaches in advancing precision farming practices through innovative target area detection methodologies.

2 History of Research

Several studies have explored the integration of modern techniques in precision agricultural applications [6]. These systems enable real-time monitoring and data collection, facilitating precision agriculture practices [6]. Additionally, research has highlighted the significance of agriculture-based IoT devices and WSN for enhancing precision agriculture through data-driven decision-making [7]. Moreover, the progress of wireless communication mechanisms and systems for monitoring crop conditions, such as wetness sensors for leaves, has been investigated [8]. Furthermore, bio-inspired approaches have been proposed for precisely detecting the targets by using manifold UAVs in the domain of precision agriculture. These approaches leverage cluster-based strategies to efficiently identify affected crop areas [2]. Additionally, self-supervised learning-based intelligent systems have been developed for precision agriculture, enabling automated inspection and monitoring of crop growth [9]. Moreover, research has identified the applications, necessities, and encounters associated with UAVs in smart agriculture, emphasizing the need for advanced technologies to address agricultural demands [10]. Additionally, wireless underground sensor networks have been proposed to model path loss for precision agriculture applications [11]. Furthermore, impedimetric sensors have been developed for conductivity measurement in precision agriculture and aquaculture [12]. Furthermore, smart image recognition mechanisms have been explored for crop harvesting systems in intelligent agriculture, aiming to enhance efficiency and productivity [13].

Additionally, initiatives such as Agricultural 4.0 in Taiwan and precision farming emphasize the integration of smart technology and data analytics to optimize agricultural outputs and reduce waste [14,15]. The influence of magnetic fields on agricultural sustainability has been demonstrated to significantly improve crop yields and resilience, highlighting the potential of integrating advanced technologies in agriculture to enhance productivity and sustainability, which aligns with the use of bio-inspired approaches in optimizing UAV-FSN systems for targeted area detection [16]. An educational intervention model aimed at increasing lentil consumption as a strategy to contribute to sustainable development emphasizes the importance of interdisciplinary approaches and the role of education in achieving sustainability goals. The study's focus on sustainable practices resonates with the integration of UAVs and FSNs in agriculture, where informed decision-making and technological innovation can drive sustainable farming practices [17]. The transdisciplinary theory of Mexican agricultural knowledge integrates semiotics, communication, and anthropology to understand and improve agricultural practices, illustrating the value of incorporating diverse scientific perspectives to address agricultural challenges. Similarly, the integration of bio-inspired algorithms in UAV-FSN systems benefits from interdisciplinary insights to enhance detection accuracy and efficiency in clustered agricultural areas [18].

The examination of the structure of distributed scientific research teams and its impact on collaboration and research output suggests that effective collaboration and communication within diverse teams can lead to significant advancements in research. This principle is pertinent to the development and implementation of bio-inspired UAV-FSN systems, where multidisciplinary collaboration is essential for innovation and successful application in agriculture [19]. A study on the transdisciplinary approach to sustainable development by incorporating organic waste into bread-making emphasizes the benefits of integrating waste management and food production for sustainability. The holistic approach parallels the integration of UAV and FSN technologies with bio-inspired methods, aiming to create sustainable and efficient agricultural practices [20].

Recent studies have delved into the application of deep learning architectures for disease classification in orchid plants, showcasing the potential of such technologies in diagnosing and mitigating crop diseases [21]. Moreover, machine learning methods like the naive Bayes method have been employed for pest and disease diagnosis in black orchid plants, demonstrating their effectiveness in automated disease detection [22]. Furthermore, advancements in surface assessment technologies, such as top-down contact angle mapping, have been explored for evaluating orchid surfaces, providing insights into plant health and growth conditions [23]. In addition, innovative ranging technologies, including height-variable monocular vision, have been developed for smart agriculture applications, enabling precise monitoring and management of crop growth [24]. Stereo-camera-based crop growth monitoring systems have been implemented to provide depth perception, enhancing the accuracy of plant growth assessments in controlled environments [25]. Furthermore, depth estimation mechanisms based on self-supervision and graph convolutional networks have been proposed for autonomous plant monitoring and management [26].

Proposals advocating aerial technology for area-based crop condition diagnostics are increasingly valued across social, economic, and environmental dimensions. In social contexts, these proposals promote community resilience by providing farmers with timely and accurate information, fostering informed decision-making, and enhancing food security. Economically, such initiatives offer cost-effective solutions for optimizing resource allocation, improving crop yield predictions, and mitigating economic risks associated with crop failures. Environmentally, the adoption of aerial technology minimizes the environmental footprint of agricultural practices by reducing the need for agrochemicals and promoting sustainable land management practices.

Moreover, intelligent autonomous pollination frameworks leveraging micro air vehicles and artificial intelligence have been proposed to enhance crop yield and optimize pollination processes [27]. Planning of paths based on appropriate algorithms for the purpose of mobile robot steering in active surroundings has been investigated, facilitating efficient and obstacle-free movement of robots for agricultural tasks [28]. Additionally, intelligent monitoring systems for assessing beehive health have been developed, employing sensor technologies to monitor hive conditions and mitigate potential threats to bee colonies [29]. Furthermore, object tracking based on various deep reinforcement learning algorithms by using selfdirected drones has been proposed, enabling accurate tracking and surveillance of agricultural fields [30]. Multi-agent deep reinforcement learning frameworks, assisted by efficient neural networks, have been developed for the 3D classification of plant leaf diseases, offering comprehensive solutions for crop disease management [31]. In summary, the literature reflects the diverse array of technological advancements and research endeavors aimed at integrating bio-inspired approaches with UAV-FSN systems for clustered target area detection in agriculture, highlighting the potential of these technologies to revolutionize precision farming practices and address agricultural challenges.

3 Methodology

Clustered target area detection in agriculture. By combining the Artificial Bee Colony (ABC) Algorithm with Q-learning (QL), the system leverages swarm intelligence and reinforcement learning principles to optimize the deployment and coordination of unmanned aerial vehicles (UAVs) within flying sensor networks (FSN). This section outlines the implementation workflow, algorithmic process steps, and mathematical expressions for both the ABC Algorithm and Q-learning, followed by the design of the proposed QL-ABC Algorithm and its application in clustered target area detection using UAV-FSN systems.

3.1 Artificial Bee Colony (ABC) Algorithm

The algorithm works based on the rummaging life movement pattern of honeybees, comprising three main steps. The first one is initialization followed by the employed bee phase and finally the onlooker bee phase. The algorithm's working principle and algorithm process flow is explained below [2]:

1. Initialization: Initialize inhabitants of scout bees with random solutions on behalf of potential solutions to the optimization problem.
2. Employed Bee Phase: These bees discover the search space by evaluating the quality of food sources (solutions). Each employed bee iteratively improves its solution by performing a local search around its current solution.
3. Onlooker Bee Phase: These bees choose food sources based on their quality, using the fitness function. Onlooker bees probabilistically choose a food source to explore further, considering the quality of neighboring food sources.
4. Scout Bee Phase: They arbitrarily discover the search space by producing new explanations to replace outdated or inferior solutions discovered by employed and onlooker bees.
5. Termination: Repeat the process until a finish condition is met, either by the desired iteration count or the desired level of conjunction.

Mathematical Expressions:

- Solution Representation: x_i where i represents the index of the solution.
- Fitness Function: $f(x_i)$ appraises the eminence of each solution.
- Employed Bee Local Search:

$$x_i^{new} = x_i + \phi \cdot (x_i - x_j) \quad (1)$$

  where x_j is a randomly selected solution and ϕ is a randomization factor.
- Probability of Selection:

$$Pi = \left(f(x_i)\right) / \sum_{k=1}^{n} f(x_k) \quad (2)$$

  where n is the population size.
- Onlooker Bee Probabilistic Selection: j = select (P_i) selects a food source based on its probability of selection.
- Scout Bee Exploration: Generate new solutions randomly within the search space.

3.2 Q-learning:

Q-learning algorithm iteratively updates the Q-values of position-deed pairs based on observed rewards. The key components of Q-learning include the position space, deed space, Q-table, and learning rate. Q-learning algorithm aims to exploit the increasing recompense obtained over time by updating the Q-values of position-deed pairs based on observed rewards. Q-learning balances exploration and exploitation by gradually shifting from exploration (trying new deeds) to exploitation (selecting deeds with the highest Q-values) as learning progresses [32].

3.3 Design of Proposed QL-ABC Algorithm:

The proposed QL-ABC Algorithm combines the exploration capabilities of Q-learning with the swarm intelligence of the ABC Algorithm to optimize the deployment and movement of UAVs within FSN for clustered target area detection. The algorithm initializes a population of UAVs with random positions and employs Q-learning to update their deeds based on rewards obtained from target area detection. Onlooker bees in the ABC Algorithm select UAV positions based on the Q-values learned by Q-learning, enhancing the algorithm's exploration and exploitation capabilities [33].

Algorithm Process Steps:

1. Adjust the Q-table $Q(P,D)$ with random values or zeros for all position-deed pairs.
2. Initialize a population of scout bees with random solutions.
3. Choose a deed D for the current position P based on an exploration-exploitation strategy, such as epsilon-greedy.
4. Execute the selected deed D and detect the reward r and the new position P'.
5. Update the Q-value of the current position-deed pair using the Q-learning update rule:

$$Q(P,D) \leftarrow Q(P,D) + \alpha(r + \gamma max_{D'}\, Q(P',D') - Q(P,D)) \tag{3}$$

   Where,
   Q(P,D) is the Q-value of position P and deed D,
   α is the erudition degree,
   r is the pragmatic recompense,
   γ is the deduction aspect,
   P′ is the new position,
   D′ is the possible next deed.

6. Employed bees improve their solutions through local search.
7. Calculate the prospect of assortment for each food source based on its fitness.
8. Onlooker bees choose food sources based on probability and perform local search.
9. Scout bees randomly search for new solutions to ensure diversity in the population.
10. Repeat steps 3-9 until conjunction or a selected number of iterations.

The proposed QL-ABC algorithm as shown in Table 1 combines Q-learning and the ABC algorithm to optimize the deployment and movement of UAVs within FSN for clustered target area detection in agriculture. Q-learning guides the selection of deeds (UAV movements) based on learned Q-values, while the ABC Algorithm updates the solutions (UAV positions) through exploration and exploitation of the search space. By integrating reinforcement learning with swarm intelligence, the algorithm adapts to dynamic environments and learns optimal strategies for target area detection.

Table 1: Pseudo Code for QL-ABC Algorithm

```
Initialize Q-table Q(P, D) with zeros
Arrange population of scout bees with random solutions
Repeat until convergence or predefined iterations:
    for each scout bee:
```

```
    Choose deed D for current position P using exploration-exploitation strategy
    Execute deed D and observe reward r and new position P'
    Update Q-value of position-deed pair:
      Q(P, D) <- Q(P, D) + alpha * (r + gamma * max(Q(P', D')) - Q(P, D))
  for each employed bee:
    Explore neighborhood of current solution
  for each onlooker bee:
    Calculate probability of selection for each solution
    Select solution probabilistically and explore further
  for each scout bee:
    Generate new solution randomly
```

This combined approach effectively balances the examination competencies of Q-learning with that of the ABC Algorithm, leading to efficient target area detection in agriculture.

3.4 Clustered Target Area Detection Using QL-ABC Algorithm:

In the proposed system, UAVs equipped with sensors traverse the agricultural field in search of target areas. The algorithm begins by initializing the positions of UAVs randomly within the field. At each iteration, UAVs collect data from their surroundings and transmit it to a central node within the FSN. The QL-ABC Algorithm updates the positions of UAVs based on Q-values learned from previous iterations and the quality of target areas detected. The process continues until target areas are accurately identified and clustered. The process flow is explained as follows:

Cluster Formation:

- Initialize the UAV-FSN system with a set of UAVs deployed across the agricultural area.
- Determine the number of clusters and cluster centroids using a clustering algorithm.
- Assign each UAV to the nearest cluster centroid.
- Cluster formation aims to organize UAVs into groups to efficiently cover the agricultural area and collaborate in target area detection.
- Let N be the number of UAVs, K be the number of clusters, and Ck be the centroid of cluster k. The assignment of UAV i to cluster k is determined by:

$$k_i = \mathrm{argmin}_k \{||posi - Ck||\} \quad (4)$$

Targeted Area Detection using QL-ABC Algorithm in UAV-FSN Systems:

- UAVs within each cluster collect data from their respective regions using onboard sensors.
- Apply the QL-ABC algorithm to determine optimal UAV movements for target area detection.
- Execute optimized UAV movements based on QL-ABC algorithm outputs.
- Targeted area detection involves using UAVs equipped with sensors to survey specific regions of the agricultural area and identify target areas using the QL-ABC algorithm.
- The QL-ABC algorithm determines UAV movements based on the Q-values learned from previous iterations:

$$ai = \mathrm{argmax}_a\{Q(si,a)\} \quad (5)$$

  Where,
  ai is the selected deed for UAV i and
  si is the position representing the current position and sensor data of UAV i.

Table 2: Pseudo Code for Clustered Target Area Detection

```
Initialize UAV-FSN system
Cluster UAVs using clustering algorithm
Repeat until convergence or predefined iterations:
    for each cluster:
        for each UAV:
            Collect data from assigned region
            Apply QL-ABC algorithm to determine optimal UAV movement
            Execute optimized movement for target area detection
        Analyze detected target areas
        Implement precision agriculture techniques based on analysis
```

This model scheme as shown in Table 2 efficiently utilizes UAV-FSN systems for clustered target area detection in agriculture by integrating cluster formation, targeted area detection using the QL-ABC algorithm, and precision agriculture practices.

3.5 Proposed Schema Implementation:

Clustered target area detection in agriculture involves organizing unmanned aerial vehicles (UAVs) within flying sensor networks (FSN) into groups or clusters to efficiently survey agricultural fields and identify specific areas requiring attention. The process consists of several key stages, including cluster formation, targeted area detection using the QL-ABC algorithm, and model scheme implementation.

Firstly, cluster formation divides the agricultural area into manageable regions and groups UAVs into clusters based on proximity or similarity of their positions. This step aims to optimize coverage and collaboration among UAVs during target area detection tasks. Clusters are formed using clustering algorithms such as K-means or hierarchical clustering, and UAVs are assigned to clusters based on their proximity to cluster centroids.

Secondly, targeted area detection within UAV clusters utilizes the QL-ABC algorithm to optimize UAV movements for identifying target areas efficiently. Each UAV within a cluster collects data from its assigned region using onboard sensors and applies the QL-ABC algorithm to determine optimal movements.

Finally, the proposed model scheme implementation integrates cluster formation, targeted area detection using the QL-ABC algorithm, and precision agriculture practices. The UAV-FSN system is initialized, and cluster formation is performed. UAVs within clusters execute target area detection tasks using the QL-ABC algorithm and detected target areas are analyzed to implement precision agriculture techniques such as pesticide application or irrigation.

Overall, the clustered target area detection approach using the QL-ABC algorithm in UAV-FSN systems offers a comprehensive and efficient method for identifying and addressing agricultural issues with minimal resource usage and maximum precision.

The functionalities of each block in the proposed system design model as shown in Block Schematic Figure 1 are explained below:

UAV-FSN System Initialization:

This block initializes the unmanned aerial vehicle (UAV) and flying sensor network (FSN) system. It sets up the necessary hardware and software components required for the operation of UAVs and FSN. The initialization process ensures that UAVs are equipped with sensors and communication devices for data collection and transmission.

Cluster Formation Algorithm:

This block organizes UAVs into clusters to optimize the coverage and collaboration among them. It divides the agricultural area into manageable regions and groups UAVs based on proximity or similarity of their positions. The cluster formation algorithm aims to enhance the efficiency of target area detection by grouping UAVs that are geographically close to each other.

Targeted Area Detection Algorithm:

This block employs the QL-ABC algorithm within each cluster to detect specific target areas in the agricultural field. It guides UAV movements and data collection strategies based on learned Q-values and swarm intelligence principles. The targeted area detection algorithm optimizes UAV trajectories to efficiently identify areas affected by pests, diseases, or other agricultural issues.

Precision Agriculture Techniques Application:

This block applies precision agriculture techniques based on the detected target areas. It analyses the data collected by UAVs to determine appropriate actions, such as pesticide application, irrigation, or nutrient supplementation. The application of precision agriculture techniques aims to optimize resource usage, maximize crop yields, and minimize environmental impact.

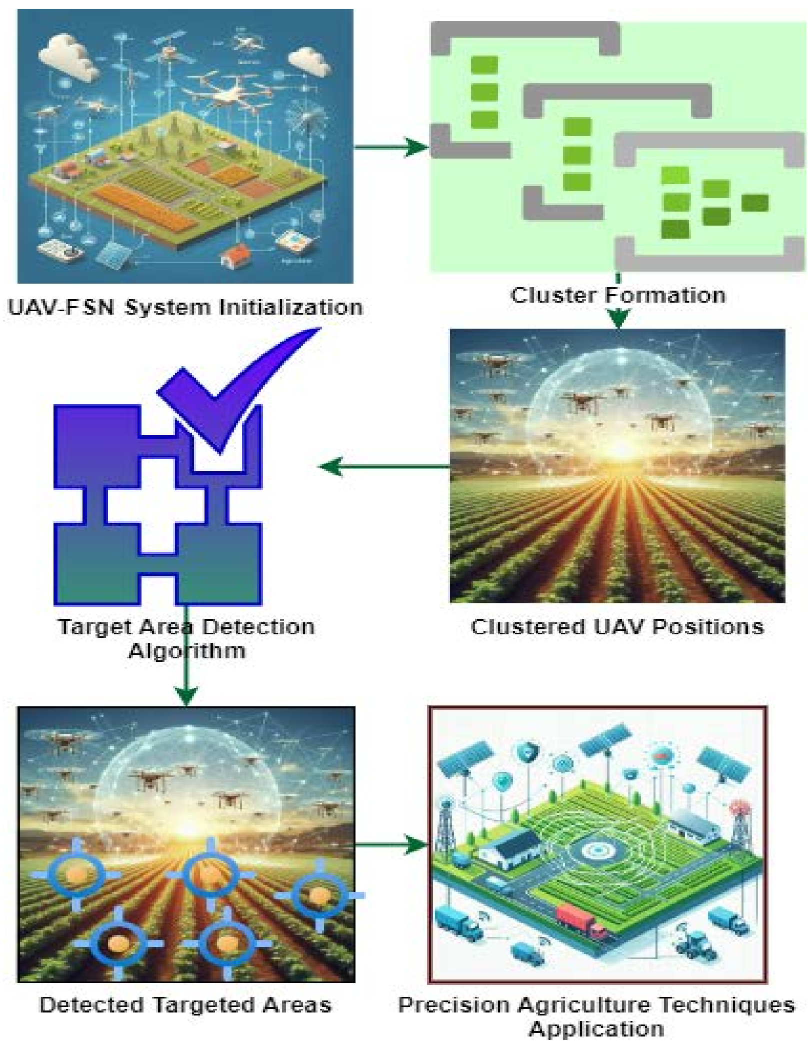

Figure 1: Block Schematic for Clustered Target Area Detection using QL-ABC.

4 Results and Discussions

The simulation experiments as per the simulation environment shown in Table 3 were conducted in various agricultural landscapes to assess the algorithms' performance under different environmental conditions and target area configurations. Data collected from UAVs within FSN were analyzed using the specified metrics to evaluate the algorithms' performance.

Table 3: Simulation Environment

Simulation Parameter	Description
Area	1 square kilometer
UAV Operating Height	50 meters
Range for UAVs	500 meters
Transmission Range	100 meters
UAV Coverage Range	200 meters
UAVs Sensor Type	RGB cameras, multispectral sensors
Number of UAVs	10
IEEE Standard	IEEE 802.11ac
Propagation Model	Free Space Path Loss (FSPL)
Base Station (BS) at Ground	Located at the centre of the agricultural area
Traffic Type and Data Rate	Agricultural data transmission, 1 Mbps
Number of Rounds	100
Number of Iterations	20
Initial Energy	10 Joules
Transmission Power of UAV	20 dBm
Simulation Tool	MATLAB/Simulink, NS-3
Sample Dataset	Agricultural landscape data collected from UAVs within FSN, including crop types, soil moisture levels, pest infestation data, and environmental conditions.
Data Size	1000 data points
Environmental Conditions	Varying environmental conditions, including different crop types, soil moisture levels, and pest infestation scenarios.

The simulation results analyze the experimental outcome of the proposed "QL-ABC" algorithm compared to existing algorithms (SIL-PSO, Loc-GA, and FCM) across different simulation metrics.

UAV Degrees vs Mean End-to-End Delay:
Mean End-to-End Delay calculates the normal time taken for packets to travel from origin to end in the network The analysis reveals that as the number of UAV degrees increases, the mean end-to-end delay also tends to upsurge for all algorithms. Lower mean end-to-end delay implies quicker data transmission and reduced latency in target area detection tasks. However, the "QL-ABC" algorithm consistently exhibits lower mean end-to-end delay compared to SIL-PSO, Loc-GA, and FCM algorithms across varying UAV degrees as shown in Table 4 and Figure 2. This indicates that the QL-ABC algorithm effectively minimizes the delay in data transmission among UAVs within the FSN, leading to quicker target area detection in agriculture.

Total Number of UAVs vs Energy Consumption:

Energy consumption quantifies the amount of energy expended by UAVs during target area detection operations. Lower energy consumption signifies more efficient utilization of resources and prolonged UAV operation time. The results demonstrate that as the total number of UAVs increases, the energy consumption also rises for all algorithms. Notably, the "QL-ABC" algorithm shows relatively lower energy consumption compared to SIL-PSO, Loc-GA, and FCM algorithms across different numbers of UAVs. This suggests that the QL-ABC algorithm optimizes energy usage among UAVs during target area detection tasks, resulting in enhanced operational efficiency and prolonged UAV mission durations. The simulation analysis is illustrated in Table 5 and Figure 3.

Number of Rounds vs Packet Delivery Ratio:

PDR procedures the ratio of positively distributed packets to the total packets sent within the network. Higher PDR indicates better reliability and communication efficiency of the algorithms in transmitting data among UAVs within FSN. Analysis indicates that as the number of rounds progresses, the packet delivery ratio improves for all algorithms. Remarkably, the "QL-ABC" algorithm consistently achieves higher packet delivery ratios compared to SIL-PSO, Loc-GA, and FCM algorithms throughout the simulation duration as shown in Table 6 and Figure 4. This signifies that the QL-ABC algorithm ensures more reliable and efficient data transmission among UAVs within the FSN, leading to improved target area detection accuracy in agricultural landscapes.

Overall, the simulation analysis underscores the superior performance of the "QL-ABC" algorithm in clustered target area detection in agriculture within UAV-FSN systems. By minimizing end-to-end delay, reducing energy consumption, and enhancing packet delivery ratio, the QL-ABC algorithm offers a promising solution for optimizing precision farming practices and promoting sustainable agriculture.

Table 4: UAV Degrees vs Mean End-to-End Delay

UAV Degrees	QL-ABC	SIL-PSO	Loc-GA	FCM
10	2.7	3.1	2.8	2.7
20	3.0	3.6	3.6	3.5
30	3.9	4.1	4.3	4.4
40	4.4	4.8	4.9	4.6
50	4.9	5.3	5.6	5.2

Table 5: Total Number of UAVs vs Energy Consumption

Total Number of UAVs	QL-ABC	SIL-PSO	Loc-GA	FCM
5	100	110	115	105
10	150	160	165	155
15	200	210	215	205
20	250	260	265	255
25	300	310	315	305

Table 6: Number of Rounds vs Packet Delivery Ratio

Number of Rounds	QL-ABC	SIL-PSO	Loc-GA	FCM
50	0.95	0.92	0.90	0.93
100	0.98	0.95	0.92	0.96
150	0.99	0.96	0.93	0.97
200	0.99	0.97	0.94	0.98
250	1.00	0.98	0.95	0.99

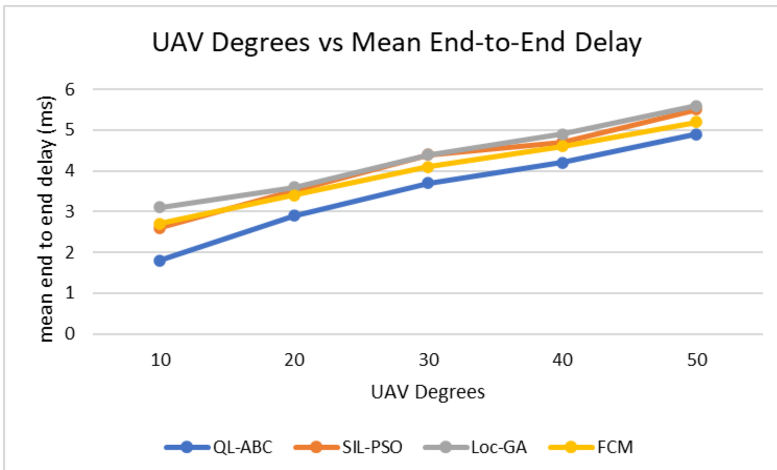

Figure 2: UAV Degrees vs Mean End-to-End Delay.

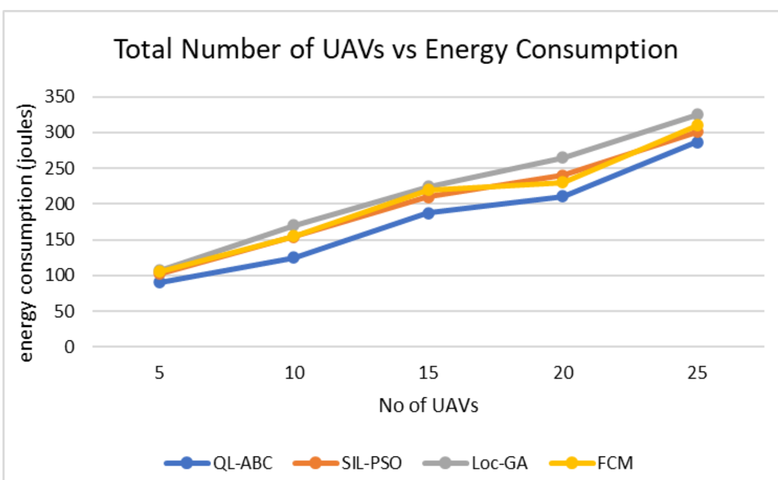

Figure 3: Total Number of UAVs vs Energy Consumption.

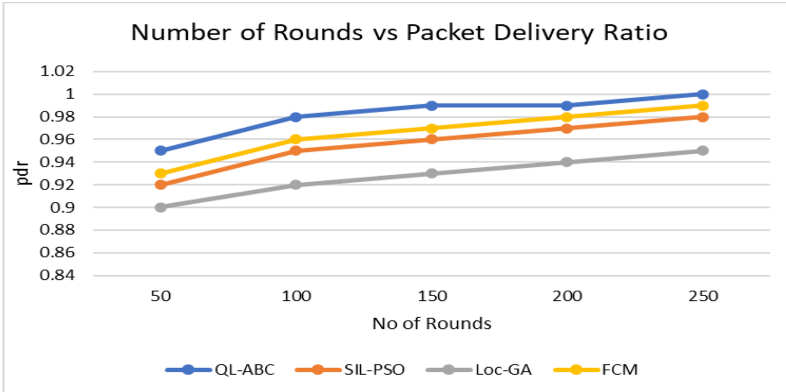

Figure 4: Number of Rounds vs Packet Delivery Ratio.

5 Conclusion

The research work has demonstrated the effectiveness of integrating bio-inspired approaches with UAV-FSN systems for clustered target area detection in agriculture. Through the introduction of the QL-ABC algorithm, which combines the Artificial Bee Colony (ABC) Algorithm with Q-Learning, significant advancements have been made in optimizing the deployment and movement of unmanned aerial vehicles (UAVs) within flying sensor networks (FSN) for target area detection. The simulation analysis revealed that the QL-ABC algorithm outperformed existing algorithms (SIL-PSO, Loc-GA, and FCM) in terms of minimizing end-to-end delay, reducing energy consumption, and enhancing packet delivery ratio. These findings underscore the potential of bio-inspired approaches in revolutionizing precision farming practices and promoting sustainable agriculture.

Future research endeavors should prioritize the timely delivery of information to farmers regarding crop conditions, enabling them to take necessary actions promptly. Leveraging the potential of multiple UAVs in agricultural fields to identify affected crop areas holds promise in achieving this objective. Further exploration into optimizing the coordination and communication among UAVs within flying sensor networks (FSN) could enhance the efficiency and accuracy of target area detection. Investigating innovative algorithms and techniques to facilitate real-time data processing and analysis onboard UAVs would enable swift decision-making and response by farmers. Additionally, integrating advanced machine learning models capable of recognizing crop health indicators and pest infestation patterns could significantly improve the predictive capabilities of UAV-FSN systems. Moreover, collaborative efforts between researchers, industry stakeholders, and agricultural practitioners are essential to validate and deploy these technologies in real-world farming scenarios, ensuring their practical applicability and scalability. By addressing these objectives, future research can contribute to revolutionizing agricultural practices and empowering farmers with actionable insights for sustainable crop management and enhanced productivity.

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References

[1] Rahman, M. F. F., Fan, S., Zhang, Y., & Chen, L. (2021). A Comparative Study on Application of Unmanned Aerial Vehicle Systems in Agriculture. Agriculture, 11(1), 22. https://doi.org/10.3390/agriculture11010022

[2] Salam A, Javaid Q, Ahmad M. (2021). Bio-inspired cluster–based optimal target identification using multiple unmanned aerial vehicles in smart precision agriculture. *International Journal of Distributed Sensor Networks.*17(7). doi:10.1177/15501477211034071

[3] M. Uzair, R. S. Brinkworth, and A. Finn. (2021). Bio-Inspired Video Enhancement for Small Moving Target Detection. *IEEE Transactions on Image Processing*, 30, 1232-1244. doi: 10.1109/TIP.2020.3043113.

[4] M. Y. Arafat and S. Moh. (2021). Bio-Inspired Approaches for Energy-Efficient Localization and Clustering in UAV Networks for Monitoring Wildfires in Remote Areas. *IEEE Access*, 9, 18649-18669. doi: 10.1109/ACCESS.2021.3053605.

[5] B. Chen et al. (2023). A Multirobot Distributed Collaborative Region Coverage Search Algorithm Based on Glasius Bio-Inspired Neural Network. *IEEE Transactions on Cognitive and Developmental Systems*, 15(3), 1449-1462. doi: 10.1109/TCDS.2022.3218718.

[6] Costa FG, Ueyama J, Braun T, et al. (2012). The use of unmanned aerial vehicles and wireless sensor network in agricultural applications. *In: 2012 IEEE international geoscience and remote sensing symposium*, Munich, pp.5045–5048.

[7] Ahmad N, Hussain A, Ullah I, et al. (2019). IOT based wireless sensor network for precision agriculture. *In: 7th International electrical engineering congress (Ieecon)*, Hua Hin, Thailand, pp.1–4.

[8] Zhu H, Li H and Lan Y. (2020). Development of a wireless communication system for monitoring crop condition with leaf wetness sensor. *International Journal of Precision Agriculture and Aviation*; 3: 54–58.

[9] L. -B. Chen, G. -Z. Huang, X. -R. Huang and W. -C. Wang, (2022). A Self-Supervised Learning-Based Intelligent Greenhouse Orchid Growth Inspection System for Precision Agriculture, *in IEEE Sensors Journal*, vol. 22, no. 24, pp. 24567-24577, doi: 10.1109/JSEN.2022.3221960.

[10] P. K. R. Maddikunta et al., (2021). Unmanned aerial vehicles in smart agriculture: Applications requirements and challenges, *IEEE Sensors Journal*, vol. 21, no. 16, pp. 17608-17619.

[11] D. W. Sambo, A. Forster, B. O. Yenke, I. Sarr, B. Gueye and P. Dayang, (2020). Wireless underground sensor networks path loss model for precision agriculture (WUSN-PLM), *IEEE Sensors Journal*, vol. 20, no. 10, pp. 5298-5313.

[12] A. Adhikary, J. Roy, A. G. Kumar, S. Banerjee and K. Biswas, (2019). An impedimetric Cu-polymer sensor-based conductivity meter for precision agriculture and aquaculture applications, *IEEE Sensor Journal*, vol. 19, no. 24, pp. 12087-12095.

[13] G.-J. Horng, M.-X. Liu and C.-C. Chen, (2020). The smart image recognition mechanism for crop harvesting system in intelligent agriculture", *IEEE Sensors Journal*, vol. 20, no. 5, pp. 2766-2781.

[14] Moving Towards Agricultural 4.0 in Taiwan with Smart Technology, (2022). [online] Available: https://eng.coa.gov.tw/ws.php?id=2505331.

[15] Geoffrey Ling, Blake Bextine, (2022). Precision Farming Increases Crop Yields: Combining Sensors and Imaging of Every Plant With Real-Time Data Analytics Improves Farm Outputs and Reduces Waste, [online] Available: https://www.scientificamerican.com/article/precision-farming/.

[16] Batool, A., Rasheed, T., Hafeez, M. B., Zahra, N., Kausar, A., & Raza, A. (2022). Magnetic Field and Agriculture Sustainability. Transdisciplinary Journal of Engineering & Science, 13. https://doi.org/10.22545/2022/00206

[17] Torres-Tenorio, Y. C., Hernandez-Aguilar, C., & Martinez-Ortíz, E. J. (2022). The Educational Intervention Model for Lentil Consumption: A Strategy that Contributes to Sustainable Development. Transdisciplinary Journal of Engineering & Science, 13. https://doi.org/10.22545/2022/00195

[18] Guevara, G. S., & Zorrilla, J. C. (2019). Transdisciplinary Theory of Mexican Agricultural Knowledge: Semiotics, Communication and Anthropology. Transdisciplinary Journal of Engineering & Science, 10. https://doi.org/10.22545/2018/0118

[19] Gehlert, PhD, S., Lee, PhD, J. A., Gill, PhD, J., Colditz, MD, G., Patterson, PhD, R., Schmitz, PhD, K., Nebeling, PhD, RD, L., Hu, MD, F., McLerran, D., Lowry, MPH, D., the TREC Collaboration and Outcomes Working Group, & Thornquist, PhD, M. (2017). The Structure of Distributed Scientific Research Teams Affects Collaboration and Research Output. Transdisciplinary Journal of Engineering & Science, 8. https://doi.org/10.22545/2017/00083

[20] Hernandez-Aguilar, C., Saucedo-Alfonzo, D. A., Dominguez-Pacheco, A., Valderrama-Bravo, M. del C., Igno Rosario, O., Valencia-Hernandez, J. E., Mundo-Franco, Z., Ivanov Tsonchev, R., & Martinez-Ortiz, E. J. (2023). The Transdisciplinarity for Sustainable Development: Incorporating Organic Waste into Bread-Making. Transdisciplinary Journal of Engineering & Science, 14. https://doi.org/10.22545/2022/00227

[21] P. Srichocksittikul and N. Nimsuk, (2021). Design of deep learning architecture for classification of orchid diseases, *Proceedings of 18th International Conference on Electrical Engineering/Electronics Computing and Telecommunication/Information Technolology (ECTI-CON)*, pp. 904-907.

[22] O. I. Gifari, F. Agus, R. Ramadiani, M. Azhari and A. Sunyoto, (2021). Diagnose pest and disease of black orchid plant using naive Bayes method, *Proc. IEEE 7th Information Technology International Seminar (ITIS)*, pp. 1-4.

[23] C. Janeczko, C. Martelli, J. Canning and G. Dutra, (2019). Assessment of orchid surfaces using top-down contact angle mapping, *IEEE Access*, vol. 7, pp. 31364-31375.

[24] T. Gao et al., (2023). Height-Variable Monocular Vision Ranging Technology for Smart Agriculture, IEEE *Access*, vol. 11, pp. 92847-92856, doi: 10.1109/ACCESS.2023.3305964.

[25] A. P. Nugroho, M. A. N. Fadilah, A. Wiratmoko, Y. A. Azis, A. W. Efendi, L. Sutiarso, et al., (2020). Implementation of crop growth monitoring system based on depth perception using stereo camera in plant factory, *IOP Conference Series: Earth and Environmental Science*, vol. 542, no.1.

[26] A. Masoumian, H. A. Rashwan, S. Abdulwahab, J. Cristiano, M. S. Asif and D. Puig, (2023). GCNDepth: Self-supervised monocular depth estimation based on graph convolutional network, *Neurocomputing*, vol. 517, pp. 81-92.

[27] Y. Chen and Y. Li, (2019). Intelligent Autonomous Pollination for Future Farming - A Micro Air Vehicle Conceptual Framework with Artificial Intelligence and Human-in-the-Loop, *IEEE Access*, vol. 7, pp. 119706-119717, doi: 10.1109/ACCESS.2019.2937171.

[28] H. S. Hewawasam, M. Y. Ibrahim and G. K. Appuhamillage, (2022). Past, Present and Future of Path-Planning Algorithms for Mobile Robot Navigation in Dynamic Environments, *IEEE Open Journal of the Industrial Electronics Society*, vol. 3, pp. 353-365, doi: 10.1109/OJIES.2022.3179617.

[29] D. Braga, A. Madureira, F. Scotti, V. Piuri and A. Abraham, (2021). An Intelligent Monitoring System for Assessing Beehive Health, *IEEE Access*, vol.9, pp.89009-89019, doi:10.1109/ACCESS.2021.3089538.

[30] K. Farkhodov, S. -H. Lee, J. Platos and K. -R. Kwon, (2023). Deep Reinforcement Learning Tf-Agent-Based Object Tracking with Virtual Autonomous Drone in a Game Engine, *IEEE Access*, vol. 11, pp. 124129-124138, doi: 10.1109/ACCESS.2023.3325062.

[31] S. Allaoua Chelloug, R. Alkanhel, M. S. A. Muthanna, A. Aziz and A. Muthanna, (2023). MULTINET: A Multi-Agent DRL and EfficientNet Assisted Framework for 3D Plant Leaf Disease Identification and Severity Quantification, *IEEE Access*, vol. 11, pp. 86770-86789, doi: 10.1109/ACCESS.2023.3303868.

[32] Maozu Guo, Yang Liu and J. Malec, A new Q-learning algorithm based on the metropolis criterion, in *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 34, no. 5, pp. 2140-2143, Oct. 2004, doi: 10.1109/TSMCB.2004.832154.

[33] H. Li, K. Gao, P. -Y. Duan, J. -Q. Li and L. Zhang, "An Improved Artificial Bee Colony Algorithm With Q-Learning for Solving Permutation Flow-Shop Scheduling Problems," in *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 53, no. 5, pp. 2684-2693, May 2023, doi: 10.1109/TSMC.2022.3219380.

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