UDC 504.064.36:514.18:519.8 **doi: 10.32620/reks.2025.1.21**

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EXPLORING THE POSSIBILITIES OF MADDPG FOR UAV SWARM CONTROL BY SIMULATING IN PAC-MAN ENVIRONMENT

This paper explores the application of the Multi-Agent Deep Deterministic Policy Gradient (MADDPG) for model training to control UAV swarms in dynamic and adversarial scenarios. Using a modified Pac-Man environment, Pac-Man represents a target UAV, and Ghosts represents the UAV swarm that counteracts it. The grid-based representation of Pac-Man mazes is used as an abstraction of a two-dimensional terrain model, which serves as a plane of pathways with obstacles that correspond to the UAV flight conditions a t a certain altitude. The proposed approach provides a clear discretization of space, simplifying pathfinding, collision avoidance, and the planning of reconnaissance or interception routes by combining decentralized local autonomy with centralized training, which enables UAVs to coordinate effectively and quickly adapt to changing conditions. This study evaluates the performance of MADDPG-trained model-controlled adversaries against heuristic navigation strategies, such as A and Breadth-First Search (BFS). Traditional Rule-Based Pursuit and Prediction Algorithms inspired by the behaviors of Blinky and Pinky ghosts from the classic Pac-Man game are included as benchmarks to assess the impact of learning-based methods.* ***The purpose*** *of this study was to determine the effectiveness of MADDPG-trained models in enhancing UAV swarm control by analyzing its adaptability and coordination capabilities in adversarial environments by computer modeling in simplified missions-like 2D environments. Experiments conducted across varying levels of terrain complexity revealed that MADDPG-trained model demonstrated superior adaptability and strategic coordination compared to the rule-based methods. Ghosts controlled by a model trained via MADDPG significantly reduce the success rate of Pac-Man agents, particularly in highly constrained environments, emphasizing the potential of learning-based adversarial strategies in UAV applications such as urban navigation, defense, and surveillance.* ***Conclusions.*** *MADDPG is a promising robust framework for training models to control UAV swarms, particularly in adversarial settings. This study highlights its adaptability and ability to outperform traditional rule-based methods in dynamic and complex environments. Future research should focus on comparing the effectiveness of MADDPG-trained models with multi-agent algorithms, such as Expectimax, Alpha-Beta Pruning, and Monte Carlo Tree Search (MCTS), to further understand the advantages and limitations of learning-based approaches compared with traditional decision-making methods in collaborative and adversarial UAV operations. Additionally, the exploration of 3D implementations, integrating maze height decomposition and flight restrictions, as well as incorporating cybersecurity considerations and real-world threats like anti-drone systems and electronic warfare, will enhance the robustness and applicability of these methods in realistic UAV scenarios.*

Keywords: *multi-agent reinforcement learning; navigation; adversarial UAV strategies; computer modelling.*

1. Introduction

The rapid advancement of unmanned aerial vehicles (UAVs) has transformed numerous industries, ranging from logistics and disaster response to surveillance and agriculture. UAVs are increasingly being employed for their ability to operate autonomously, even in complex and obstacle-ridden environments, enabling applications such as reliable data transmission and communication in hard-to-reach areas as shown in papers [1, 2]. However, effective coordination and navigation strategies for UAV swarms remain critical challenges, particularly in dynamic and adversarial environments where swift decision-making and adaptability are required according to review from the paper [3]. In addition, recent advancements in UAV swarm technology have emphasized the importance of high-speed communication links and flexible control strategies to enhance collaborative decision-making and coordination among UAVs, particularly in dense urban environments where efficient, autonomous operation improves reliability and reduces mission time, as highlighted in previous studies [4].

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

In this context, multi-agent reinforcement learning (MARL) techniques, such as Multi-Agent Deep Deterministic Policy Gradient (MADDPG), have gained traction for their potential to solve complex coordination problems — as demonstrated by the analysis in paper [5] and for improving target tracking, as evidenced by the review in paper [6] through collaborative learning.

The adoption of MARL solutions, particularly MADDPG, for UAV control has demonstrated promising results in areas such as path optimization that shown in papers [7, 8], collision avoidance as highlighted in [5, 9], and resource allocation demonstrated in the researches [10, 11]. These methods enable agents to operate with a degree of autonomy while considering both individual objectives and team-wide goals. This is essential for tasks like surveillance missions described in previous studies [12, 13] or disaster relief operations researched in [14]. Despite these advancements, challenges persist in evaluating MARL approaches in environments that accurately simulate real-life scenarios, especially those involving adversarial agents or unpredictable dynamics, as shown in the study [15].

To address these challenges, game-based environments have emerged as effective platforms to simulate complex agent interactions and navigation tasks. The Pac-Man game, which is widely recognized for its intricate navigation dynamics, offers a unique testbed, as it used in the paper [16] to explore UAV coordination strategies in a simplified yet representative setting. By leveraging this environment, we can emulate scenarios where UAVs must navigate, evade adversaries, and achieve mission objectives—paralleling real-world applications like urban navigation, as shown in the paper [17], and military missions, as researched in [18, 19].

The modified Pac-Man environment used in this study represents a novel approach for simulating UAV operations. In this setup, the agents' roles are redefined: Pac-Man serves as a stand-in for a UAV tasked with navigating complex terrain to achieve specific goals, such as reaching designated targets (capsules). Conversely, the Ghosts embody adversarial forces that intend to disrupt the mission. This configuration not only allows for testing the efficacy of MARL methods like MADDPG but also facilitates a direct comparison with traditional navigation algorithms, such as Breadth-First Search (BFS) and A* search, as well as pre-defined heuristic behaviors modeled after the original game's Blinky and Pinky algorithms described in the articles [20, 21].

The primary objective of this research was to evaluate the potential of MADDPG-trained neural network models in controlling adversarial teams (e.g., Ghosts) against various navigation strategies, thereby assessing its suitability for swarm-based UAV missions. By juxtaposing the performance of MADDPG-trained model with the traditional and heuristic-based algorithms, we aim to identify its strengths and limitations in dynamic and adversarial settings. This study's findings are expected to contribute valuable insights into MARL's applicability to UAV navigation, with potential implications for advancing coordination mechanisms in real-world multi-agent systems for UAV swarm coordination in navigation and path planning as well as for adversaries' environments and missions like military applications, surveillance, and rescue operations.

The article is structured as follows. Section 2 presents an analysis of the current state of the issue under study. Section 3 describes the objective of this study was to evaluate the efficiency and coordination capabilities of UAV swarms controlled by a trained MADDPG model. Section 4 outlines the materials and methods used in this study, detailing the modified Pac-Man environment as a simulation framework for UAV control, algorithms, and models. Section 5 presents the experimental setup designed to evaluate agents' performance and stages of experiments. Section 6 presents the results of the experiments, comparing the performance of MADDPG-trained models to that of the heuristic algorithms and rule-based methods at varying levels of complexity. Section 7 provides a detailed discussion of the findings, highlighting their alignment with previous studies, identifying limitations, and exploring the implications for real-world UAV applications. Finally, Section 7 concludes the paper by summarizing the key contributions, highlighting MADDPG's potential in training neural network models for UAV swarm control, and proposing directions for future research, including the integration of cybersecurity considerations and exploration of additional multi-agent algorithms.

2. State of the Art

Pac-man Game Applicability for Navigation. The Pac-Man game, initially designed as a recreational pursuit, has emerged as a valuable platform for studying navigation and decision-making in controlled environments as it used in the papers [16, 22]. The game presents a dynamic, grid-based environment where an agent navigates complex mazes to balance objectives, such as target acquisition and adversary evasion. These attributes make Pac-Man an effective abstraction for real-world navigation tasks, where UAVs may need to traverse urban environments, avoid obstacles, and fulfill mission objectives under time constraints like the challenges of the papers [23, 24].

Studies [16, 25] have demonstrated how Pac-Man can be used as a model to develop and evaluate navigation algorithms. The structured grid layout simulates real-world navigation challenges, and its adversarial dynamics provide an opportunity to explore algorithms in competitive settings. For instance, the game has been employed to test reinforcement learning strategies, enabling researchers to assess the trade-offs between exploration and exploitation in decision-making, as shown in the paper [25].

BFS Algorithm for Navigation and UAVs. The Breadth-First Search (BFS) algorithm, which is a classic graph traversal method, is widely recognized for its simplicity and optimality in unweighted environments. BFS operates by exploring all possible paths from a given node level by level, ensuring that the shortest path to a target is found, as described in [26]. In the context of UAV navigation, BFS has been employed for tasks requiring exhaustive search in structured environments, such as grid-based path planning or obstacle detection that described in [27, 28].

Although computationally expensive in large-scale or high-dimensional settings, BFS remains a benchmark for comparing more sophisticated pathfinding techniques. In the Pac-Man environment, BFS is often used to model deterministic navigation strategies, allowing researchers to evaluate its performance relative to adversarial dynamics and other algorithms, as highlighted in [16, 25].

A* Algorithm in Navigation and UAVs. The A* algorithm, which is an extension of BFS, incorporates heuristics to optimize search efficiency. By combining the actual cost of reaching a node with the estimated cost to the target, A* achieves superior performance in environments where computational efficiency is critical according to the research [29]. This makes A* particularly suitable for UAV pathfinding tasks, where real-time decisions are essential for avoiding collisions and reaching designated waypoints as shown in the paper [30].

In UAV applications, A* is often used to plan optimal paths in obstacle-rich environments, including urban terrains and disaster zones considered in [31, 32]. The algorithm's adaptability to varying heuristics further enhances its applicability to scenarios that require both precision and flexibility.

MADDPG Background and Usage. The Multi-Agent Deep Deterministic Policy Gradient (MADDPG) [33] is a state-of-the-art MARL framework designed for continuous and discrete multi-agent environments that explained in the article [33]. The proposed algorithm extends Deep Deterministic Policy Gradient (DDPG) by incorporating a centralized training mechanism with decentralized execution, which makes it highly effective for environments with multiple interacting agents, as described in [33].

MADDPG has demonstrated remarkable success in solving complex coordination problems across various domains, including autonomous driving, that shown in the paper [34], robotic control, demonstrated in the papers [35, 36], and UAV swarm control [19]. Its ability to handle dynamic and adversarial scenarios, such as UAV swarm coordination and competitive games, highlights its versatility and robustness [19].

In adversarial setups, MADDPG's centralized training allows agents to learn from shared experiences, which enhances their ability to predict and counter opposing agents' strategies according to the [33].

This study leverages MADDPG to control adversarial agents (Ghosts) in the Pac-Man environment, providing insights into its potential for real-world UAV applications that require coordination and adaptability.

For UAV swarm control, the proposed approach is a procedure that blends decentralized decision-making with centralized training. Each UAV uses local sensory inputs for navigation while exchanging critical data—such as positions and obstacle detections (that corresponds to maze walls treated as terrain obstacles in proposed 2D modelling environment)—through adaptive communication protocols, as previously researched in the paper [19]. This framework supports basic route planning and swarm coordination in near-realistic scenarios and forms the theoretical basis of the proposed model.

A hierarchical control architecture further refines coordination by combining high-level strategy generation with precise low-level execution. MADDPG makes trained neural network models formulate cooperative maneuvers that balance mission goals and adversarial conditions, while controllers like PID or model predictive control ensure accurate flight dynamics. Although our work focuses on the theoretical aspects of these algorithms, their application to dynamic real-world settings requires additional experiments and simulation modifications using actual terrain data.

3. Problem Statement

The objective of this research was to evaluate the effectiveness of the Multi-Agent Deep Deterministic Policy Gradient (MADDPG) in training neural network models for enhancing UAV swarn control in dynamic and adversarial scenarios. To guide UAV swarm control processes, we propose a layered procedure: each UAV relies on environment data that simulates getting data from local sensors in real UAV to manage immediate collision avoidance and pathfinding while simultaneously sharing critical positional and environmental updates with fellow swarm members through adaptive communication protocols. At the same time, a centralized training mechanism integrates these distributed experiences, refining cooperative policies that enable the swarm to handle adversarial conditions, navigate maze-like terrain, and adapt swiftly to changing environments. Specifically, this study aimed to assess the effectiveness and coordination capabilities of UAV swarms controlled by a MADDPG-trained model when countering a target UAV, represented by Pac-Man, in a modified simulation 2D environment.

This study explores the effectiveness of MADDPG-trained models when acting as adversarial agents against heuristic navigation strategies, such as A* and Breadth-First Search (BFS). In addition, this study compares these learning-based adversarial strategies with traditional rule-based algorithms inspired by the behaviors of Blinky and Pinky from the classic Pac-Man game.

To achieve the objective, a modified Pac-Man environment was utilized to simulate various levels of terrain complexity, providing a controlled yet dynamic framework for experimentation, where the grid-based representation of mazes is used as an abstraction of a two-dimensional terrain view serving as a model of a plane of pathways with obstacles that correspond to the conditions of UAV flight at a certain altitude, that provides a clear discretization of space, simplifying pathfinding, collision avoidance, and the planning of reconnaissance or interception routes. The Pac-Man serves as a target UAV by completing tasks while navigating mazes, such as collecting objectives and avoiding adversaries. The Ghosts, acting as a swarm of adversarial UAVs, were controlled either by MADDPG-trained models or by rule-based algorithms for comparison. Through this setup, the study investigates the ability of MADDPG-trained models to dynamically adapt to changing scenarios, reduce the success rates of Pac-Man agents, and outperform rule-based methods in adversarial settings. This study aims to measure the effectiveness of MADDPG-trained models in simulated UAV mission scenarios and highlight their potential for real-world UAV applications, such as urban navigation, surveillance, and defense operations.

4. Materials and Methods

The modified Pac-Man environment serves as a simplified yet dynamic framework for modeling UAV control strategies in adversarial settings. This environment adapts the classic Pac-Man game mechanics to simulate navigation, decision-making, and team-based coordination tasks, with Pac-Man acting as a UAV and the Ghosts representing adversarial forces. The goal is to evaluate the effectiveness of various algorithms, including heuristic-based and machine learning-based approaches, under diverse conditions.

Game Conditions:

Pac-Man Objectives: The primary goal is to eat all capsules (analogous to UAVs completing mission-critical tasks, such as scanning all designated targets) while avoiding adversarial Ghosts (representing hostile UAVs or environmental threats, emphasizing evasion and survivability). Points are awarded for specific actions that emphasize efficiency and adaptability:

– **Eating a capsule: +500 points** (reflects a significant milestone in a UAV mission, such as successfully completing a high-priority task or neutralizing a major threat).

– **Eating food: +10 points** (analogous to secondary or routine objectives, such as collecting environmental data or securing minor waypoints).

– **Eating a Ghost (during the scared timer): +200 points** (represents a UAV taking a tactical advantage over an adversary, such as disabling a hostile drone or exploiting a momentary weakness in the system).

Penalties: A time penalty of **-1 point per move** is applied to discourage inactivity, ensuring the agents prioritize efficient navigation (similar to fuel or battery depletion penalties in UAV missions, where prolonged delays can compromise success).

Scared Timer: Upon eating a capsule, Ghosts become vulnerable (scared) for the next **10 moves**, during which they can be eaten by Pac-Man (akin to UAVs gaining a temporary tactical advantage, such as deploying countermeasures or exploiting an adversary's signal disruption).

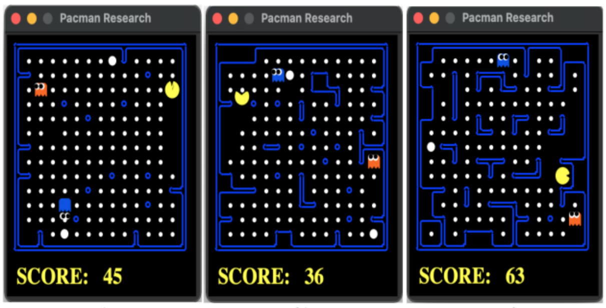
Environment Setup:

Mazes: Three distinct layouts (SM1, SM2, SM3) with increasing wall density were designed to simulate different levels of navigation complexity:

– **SM1:** 15x15 grid, 2 Ghosts, 2 capsules, 10% walls (See Fig. 1a) - low complexity, suitable for UAVs in open terrain;

– **SM2:** 15x15 grid, 2 Ghosts, 2 capsules, 25% walls (See Fig. 1b) - moderate complexity, akin to UAVs navigating semi-urban areas;

– **SM3:** 15x15 grid, 2 Ghosts, 2 capsules, 40% walls (See Fig. 1c) - high complexity, resembling dense urban environments or forests.



a) b) c)

Fig. 1. Maze layouts used in the experiments:
a) SM1 – low complexity, b) SM2 – moderate complexity,
c) SM3 – high complexity

This variety allows testing the adaptability of algorithms to different levels of spatial complexity and adversarial dynamics.

Pac-Man Agents:

1. **Random Agent:** Implements random decision-making for movement, serving as a baseline for comparing performance (equivalent to a UAV without pre-defined or learned strategies).
2. **BFS Search Agent:** The BFS search algorithm utilizes an algorithm for deterministic pathfinding, optimizing movement to the nearest objective in unweighted scenarios (useful for UAVs in structured environments, such as grid-based search areas).
3. **A Search Agent*:** This algorithm employs the A* algorithm, combining actual path cost and heuristic estimations to efficiently navigate through a maze (analogous to UAVs using GPS and terrain data for optimized pathfinding).

Ghost Agents:

1. **Rule-Based Pursuit and Prediction Algorithms:** Inspired by Blinky and Pinky from the classic Pac-Man game [20, 21], these algorithms implement predefined behavioral rules. The **Pursuit Algorithm** aggressively follows the Pac-Man's current position, while the **Prediction Algorithm** anticipates future movements to simulate simple adversarial UAV strategies.
2. **Neural Network Ghosts:** Controlled as a coordinated team by a model trained using Multi-Agent Deep Deterministic Policy Gradient (MADDPG) [33]. This approach enables Ghosts to collaborate, anticipate Pac-Man's movements, and dynamically adapt their strategies (paralleling adversarial UAV swarms learning to counteract a target UAV).

MADDPG Implementation:

The proposed MADDPG model was trained using a centralized training and decentralized execution approach proposed in the paper [33]. The Ghosts (as agents) learned optimal policies by interacting with the environment and adjusting their strategies based on Pac-Man's actions. The training process emphasized collaborative behavior, exploiting adversarial opportunities to maximize their effectiveness as a team (similar to UAV swarms optimizing interception strategies in real-time).

5. Simulation

Objective of the Experiments:

The experiments were designed to evaluate the performance of Pac-Man and Ghost agents across all mazes. The gathered metrics include the following:

1. **Average Score:** Points accumulated by Pac-Man during gameplay.
2. **Average Game Time:** The time in seconds before a game is concluded (reflecting operational efficiency, analogous to measuring how quickly a UAV completes its mission).
3. **Win Rate:** The percentage of games in which Pac-Man successfully ate all capsules (analogous to UAVs achieving mission goals without interception).

The mazes used in the simulation are approximations of real-world terrains, whether urban or natural, with obstacles representing buildings, trees, or other impediments. These obstacles simulate the UAV flight conditions at certain altitudes, where navigation and obstacle avoidance are critical. This approach allows testing the adaptability of algorithms in scenarios that closely mimic real-life challenges faced by UAVs in dynamic and constrained environments.

Experiments and Comparison:

- **Phase 1:** Experiments were conducted against Ghosts controlled by the **Rule-Based Pursuit and Prediction Algorithms** (Blinky and Pinky algorithms from classic game [20, 21]). For each Pac-Man agent (Random, BFS, A*), 100 games were played in each maze configuration (SM1, SM2, SM3), and performance metrics were generated in tabular format.
- **Phase 2:** The same experiments were repeated with Neural Network Ghosts controlled by the MADDPG-trained model, following the same structure (3 Pac-Man agents x 3 mazes x 100 games).

6. Results

6.1. Performance in SM Maze 1

In SM Maze 1, A* Search and BFS Search agents demonstrated comparable performance against Rule-Based Pursuit and Prediction Algorithms, achieving win rates of 63% each, with average game times of approximately 3.4 s. However, when facing Ghosts controlled by the MADDPG-Trained Model, the A* agent's win rate decreased to 53%, while BFS maintained a slightly higher win rate of 60%. Notably, the MADDPG-Trained Model-Controlled Ghosts prolonged the game duration for all agents compared to Rule-Based Ghosts, indicating their enhanced adaptability and dynamic strategies (See Table 1).

The Random agent performed poorly across all scenarios with no wins; thus, it lacks strategic navigation and serves as a baseline for comparison.

6.2. Performance in SM Maze 2

The increased wall density in SM Maze 2 poses additional challenges. Against Rule-Based Ghosts, BFS outperformed A*, achieving a win rate of 68% compared to A*'s 58%. However, when facing MADDPG-Trained

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

Model-Controlled Ghosts, performance declined sharply: BFS managed only a 10%-win rate, while A* recorded no wins. This indicates that the adaptability of MADDPG-Trained Model-Controlled Ghosts became more pronounced in complex terrains (See Table 2).

Table 1

Performance in SM Maze 1

Pac-Man Agent	Ghost Agents	Average Score	Average Time (s)	Win Rate (%)
Random	Rule-Based Algorithms	72.97	3.47	0.00
A* Search	Rule-Based Algorithms	891.81	3.42	63.00
BFS Search	Rule-Based Algorithms	861.50	3.41	63.00
Random	MADDPG-Trained Model	169.34	7.66	0.00
A* Search	MADDPG-Trained Model	763.47	2.78	53.00
BFS Search	MADDPG-Trained Model	853.17	3.06	60.00

Table 2

Performance in SM Maze 2

Pac-Man Agent	Ghost Agents	Average Score	Average Time (s)	Win Rate (%)
Random	Rule-Based Algorithms	54.37	2.50	0.00
A* Search	Rule-Based Algorithms	738.69	3.64	58.00
BFS Search	Rule-Based Algorithms	851.76	3.49	68.00
Random	MADDPG-Trained Model	127.14	3.72	0.00
A* Search	MADDPG-Trained Model	47.16	1.78	0.00
BFS Search	MADDPG-Trained Model	161.18	2.86	10.00

The Random agent's scores and win rates remained negligible, thereby reducing the difficulty of navigating without strategic guidance in more complex mazes.

6.3. Performance in SM Maze 3

In the most challenging scenario (SM Maze 3) with 40% wall density, all agents experienced significant performance reductions. Against Rule-Based Ghosts, A* marginally outperformed BFS in both score and win rate (55% vs. 53%). Against Ghosts controlled by the MADDPG-Trained Model, BFS's performance declined further, achieving only a 19%-win rate compared to A*'s 43%. This highlights MADDPG-trained model's superior ability to adapt to constrained environments, mirroring the UAV swarm behavior in dense urban terrains (See Table 3).

Table 3

Performance in SM Maze 3

Pac-Man Agent	Ghost Agents	Average Score	Average Time (s)	Win Rate (%)
Random	Rule-Based Algorithms	48.90	3.59	0.00
A* Search	Rule-Based Algorithms	1134.65	4.23	55.00
BFS Search	Rule-Based Algorithms	1003.78	3.91	53.00
Random	MADDPG-Trained Model	77.14	4.43	0.00
A* Search	MADDPG-Trained Model	886.50	3.62	43.00
BFS Search	MADDPG-Trained Model	280.26	2.34	19.00

As expected, the Random agent failed to navigate effectively, which demonstrates the impact of increased maze complexity on performance.

6.4. Summary and Key Observations

1. Ghosts **controlled** by the MADDPG-Trained Model significantly reduced Pac-Man agent win rates**,** particularly in complex mazes (SM Maze 2 and SM Maze 3), demonstrating their adaptability and strategic coordination.

2. A* Search generally outperformed BFS in simpler settings, but BFS demonstrated greater resilience in mazes with higher wall density.

3. The Random agent's negligible performance confirmed its role as a baseline for evaluating the strategic value of navigation algorithms.

4. Increased maze complexity (wall density) heavily influenced agent performance, emphasizing the importance of adaptable strategies for UAV operations in constrained environments.

5. These results affirm MADDPG's potential for training models to control adversarial UAV swarms, offering valuable insights into real-world applications, such as urban navigation, defense, and cooperative adversarial tasks.

7. Discussion

The findings of this study align with previous research, demonstrating the advantages of reinforcement learning-based approaches, such as MADDPG, in multi-agent coordination and adversarial tasks. In comparison to the traditional algorithms explored in a previous paper [33], which addressed the challenges of non-stationarity and variance in multi-agent domains, the proposed MADDPG-Trained Model proved effective in dynamic and competitive scenarios. Similar to Lowe et al.'s findings, the MADDPG model in our experiments exhibited enhanced coordination strategies and adaptability, especially in complex environments such as SM Maze 2 and SM Maze 3, where wall density and adversarial interactions added significant complexity. These results further validate the potential of MADDPG for UAV swarm control in real-world settings.

The comparison between heuristic navigation algorithms and rule-based models mirrors the findings of Salem et al. (2024) [16] and Zou (2021) [25], who identified the superior performance of A* in pathfinding tasks due to its optimality and efficiency. However, our experiments revealed that Ghosts controlled by the MADDPG-Trained Model significantly disrupted the performance of A*, reducing its win rate to 43% in the most challenging maze. This highlights the limitations of static pathfinding algorithms in adversarial contexts and supports Zou's argument that reinforcement learning is a more robust solution for competitive environments [25].

Moreover, the dynamic adaptability of MADDPG-controlled agents observed in this study complements the results of Bachiri et al. (2023) [37], who demonstrated the utility of MADDPG in managing dynamic demands in electric vehicle charging networks. Similar to UAV coordination challenges, EV charging scenarios require real-time decision-making under constraints, and MADDPG's centralized training and decentralized execution strategy has proved instrumental in both domains [37].

Finally, our results echo the findings of Ding et al. (2022) [38], who emphasized the importance of trajectory optimization and coordination in hybrid action space environments. The ability of MADDPG-trained Ghosts to adapt their trajectories dynamically to counter Pac-Man's strategies reflects its capacity to address complex multi-agent problems, underscoring its relevance for UAV swarm operations in constrained and competitive environments.

In summary, this study builds upon and extends existing research, demonstrating MADDPG's capacity to train robust adversarial neural network models for UAV swarm control. The proposed approach leverages a layered control architecture that combines decentralized local decision-making with centralized training, thereby facilitating dynamic route planning and real-time coordination in near-realistic, obstacle-rich 2D environments. The comparison of the proposed learning-based strategies with heuristic and rule-based approaches further highlights the potential of learning-based strategies to excel in dynamic and adversarial settings.

8. Conclusions

This study evaluated the performance of a model trained by the Multi-Agent Deep Deterministic Policy Gradient (MADDPG) in controlling a Ghost team against traditional Rule-Based Pursuit and Prediction Algorithms in a modified Pac-Man environment to simulate navigation and adversarial scenarios relevant to UAV control. The findings demonstrated the MADDPG-trained model's superior adaptability and strategic coordination, particularly in complex and constrained environments, highlighting its potential for training UAV swarms in real-world scenarios.

Key observations include the significant reduction in win rates for Pac-Man agents when facing Ghosts controlled by the MADDPG-trained model, which highlights the efficacy of learning-based adversarial strategies. A* Search exhibited better performance in simpler settings, whereas BFS Search demonstrated resilience in more complex mazes, emphasizing the importance of matching navigation algorithms to specific terrain complexities for UAV operations.

This study affirms MADDPG's value in UAV applications requiring real-time decision-making and adversarial interaction, such as urban navigation, surveillance, and defense. By combining decentralized local autonomy with centralized training, the proposed approach enables UAVs to coordinate effectively and quickly adapt to changing conditions. The results also underscore the potential for learning-based approaches to outperform traditional rule-based methods in dynamic multi-agent settings. Moreover, integrating real-world data and sophisticated communication strategies can further enhance these findings, thereby facilitating a smooth transition from theoretical modeling to practical swarm deployment.

Future research will focus on extending experiments to include other multi-agent algorithms, such as Expectimax, Alpha-Beta Pruning, and Monte Carlo Tree Search (MCTS), to further explore collaborative and adversarial strategies in UAV swarm control. In addition, scaling to larger and more complex environments will help assess the scalability and robustness of these methods under real-world-like conditions. In the case of a 3D implementation, the problem requires decomposition into maze heights depending on the restrictions on UAV flight heights, introducing the restrictions on the possible heights for drones in a certain area, as well as maze heights (different), considering maze heights, organizing them, and considering decomposition then.

The integration of cybersecurity considerations, as discussed by Veprytska and Kharchenko [39], can provide valuable insights into assessing and mitigating AI-powered threats in UAV systems and ensure the reliability of adversarial strategies and their applications in secure missions. Modeling real threats such as anti-drone systems, electronic warfare (EW), and other military factors can further enhance the realism of such simulations. The cybersecurity-informed safety models for UAV operations by Illiashenko et al [40]. also highlights the importance of aligning AI-based methodologies, such as MADDPG, with robust safety and protection frameworks to address vulnerabilities in adversarial settings. Further research could focus on adding appropriate threat models and integrating algorithms to dynamically revise routes depending on changing risk parameters.

Advances in hybrid sensor networks, as explored by Skorobohatko et al. [41], can enhance the operational reliability of UAV swarms, particularly for missions requiring environmental and emergency monitoring. Techniques for reliable LiFi communication in obstacle-ridden environments, as presented by Leichenko et al. [2, 42], may complement future MADDPG experiments by addressing challenges in multi-agent coordination under communication constraints. Similarly, Chen et al.'s [43] work on human-in-the-loop control mechanisms opens possibilities for integrating human oversight into UAV adversarial strategies, enhancing adaptability in complex real-world missions. Further consideration could include the use of real circumstances in the flight of UAVs (swarms, groups), which are associated with terrain and obstacles of both natural and human activity (industry, urban obstacles, etc.).

These directions not only aim to improve the scalability and robustness of learning-based models and align MADDPG's capabilities with interdisciplinary advancements to create more resilient, efficient, and secure UAV swarm control systems.

Contributions of authors: conceptualization, methodology – **Yakovlev Sergiy, Novikov Artem, Gushchin Ivan;** formulation of tasks, analysis **– Yakovlev Sergiy, Novikov Artem;** development of model, software, verification **– Novikov Artem, Gushchin Ivan;** analysis of results, visualization **– Novikov Artem;** writing – original draft preparation – **Novikov Artem, Gushchin Ivan;** writing – review and editing **– Yakovlev Sergiy.**

Conflict of Interest

The authors declare that they have no conflict of interest concerning this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

This study was conducted without financial support.

Data Availability

The work has associated data in the data repository.

Use of Artificial Intelligence

The authors have used artificial intelligence technologies within acceptable limits to provide their own verified data, as described in the research methodology section.

Acknowledgments

In the process of preparing this study, the authors express their sincere gratitude to Volodymyr Yanovsky for the valuable ideas that were taken into account in the process of analysis and development of solutions, consultancy, and pieces of advice provided, which significantly improved the quality of the work.

All the authors have read and agreed to the published version of this manuscript.

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Received 24.11.2024, Accepted 17.02.2025

ДОСЛІДЖЕННЯ МОЖЛИВОСТЕЙ MADDPG ДЛЯ КОМАНДНОГО УПРАВЛІННЯ БПЛА ПРИ МОДЕЛЮВАННІ В СЕРЕДОВИЩІ PAC-MAN

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У статті досліджується застосування алгоритму Multi-Agent Deep Deterministic Policy Gradient (MADDPG) для навчання моделей, що використовуються для управління роями БПЛА в динамічних та антагоністичних сценаріях. Використовуючи модифіковане середовище Pac-Man, де Pac-Man представляє цільовий БПЛА, а Примари — рій БПЛА, що протидіє йому. Представлення лабіринтів Pac-Man у вигляді сітки використовується як абстракція двовимірної моделі рельєфу, що виступає у ролі площини шляхів з перешкодами, відповідними до умов польоту БПЛА на певній висоті. Запропонований підхід забезпечує чітку дискретизацію простору, спрощуючи пошук шляхів, уникнення зіткнень та планування маршрутів для розвідки чи перехоплення, поєднуючи децентралізовану місцеву автономію з централізованим навчання, що дозволяє БПЛА ефективно координувати дії та швидко адаптуватися до мінливих умов. Дослідження оцінює продуктивність антагоністів, керованих моделями, навченими за допомогою MADDPG, у порівнянні з евристичними стратегіями навігації, такими як A та Пошук у ширину (BFS). Традиційні алгоритми переслідування та прогнозування, натхненні поведінкою Примар Блінкі та Пінкі з класичної гри Pac-Man, використовуються як еталон для оцінки впливу методів на основі навчання. **Метою цього дослідження** є визначення ефективності моделей, навчених за MADDPG, у покращенні управління роями БПЛА шляхом аналізу їхньої здатності до адаптації та координації в антагоністичних середовищах, завдяки застосуванню комп'ютерного моделювання в спрощеному подібному до контексту реальних місій двовимірному середовищі. Експерименти, проведені на різних рівнях складності ландшафту, показали, що MADDPG-тренована модель демонструє кращу адаптивність і стратегічну координацію в порівнянні з методами на основі правил. Примари, керовані моделлю, навченою за допомогою MADDPG, значно знижують рівень успіху агентів Pac-Man, особливо в умовах із високими обмеженнями, що підкреслює потенціал стратегій на основі навчання для застосувань БПЛА, таких як міська навігація, оборона та спостереження. **Висновки.** MADDPG демонструє себе як перспективна платформа для навчання моделей управління роями БПЛА, особливо в антагоністичних умовах. Дослідження підкреслює його адаптивність і здатність перевершувати традиційні методи на основі правил у динамічних та складних середовищах. Майбутні дослідження будуть зосереджені на порівнянні ефективності моделей, навчених за допомогою MADDPG, з багатоагентними алгоритмами, такими як Expectimax, AlphaBeta Prun-ning та Monte Carlo Tree Search (MCTS), щоб краще зрозуміти переваги і обмеження підходів на основі навчання у порівнянні з традиційними методами прийняття рішень у спільних і антагоністичних операціях БПЛА. Крім того, дослідження 3D-реалізацій, що включають розподіл висоти лабіринту та обмеження на польоти, а також інтеграцію аспектів кібербезпеки та реальних загроз, таких як системи протидії дронам і засоби електронної боротьби, можуть підвищити надійність і практичну застосовність цих методів у реалістичних сценаріях використання БПЛА.

Ключові слова: багатоагентне навчання з підкріпленням; навігація; антагоністичні стратегії БПЛА; комп'ютерне моделювання.

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