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Yosyp Albrekht,
Andrii Pysarenko

EXPLORING THE POWER OF HETEROGENEOUS UAV SWARMS THROUGH REINFORCEMENT LEARNING

The object of research is heterogeneous and homogeneous swarms of unmanned aerial vehicles (UAVs). The primary focus of this study is the comparison between heterogeneous and homogeneous UAV swarms, examining their performance in a simulated environment designed using the Python Gym library. The research involves implementing reinforcement learning algorithms, specifically the Proximal Policy Optimization (PPO), to train and evaluate the swarms.

The central issue addressed by this research is to determine which type of UAV swarm – heterogeneous or homogeneous – exhibits better performance in a defined task. The chosen task involves searching for groups of objects in an unknown area, emphasizing the ability of the swarm to adapt and efficiently locate objects in dynamic environments.

The obtained results reveal an advantage for heterogeneous UAV swarms over their homogeneous counterparts. The heterogeneous swarm has a steeper learning curve and achieves higher rewards in fewer episodes during the training phase. The key finding indicates that the varied skill set within the heterogeneous swarm allows for quicker adaptation to changing environmental conditions. The superior performance of the heterogeneous swarm is attributed to the diversity of capabilities among its UAV agents, enabling them to leverage their individual strengths to achieve better overall performance in the given task.

The practical application of these results is contingent upon the task requirements and environmental conditions. In scenarios where tasks demand diverse skills and adaptability to changing conditions, heterogeneous UAV swarms are recommended. The results suggest their efficacy in applications such as search and rescue operations, environmental monitoring, and other dynamic tasks.

In conclusion, this research provides valuable insights into optimizing UAV swarm composition for specific tasks. The results contribute both theoretically and practically by highlighting the advantages of heterogeneity in swarm capabilities.

Keywords: *reinforcement learning, robot swarms, heterogeneous swarms, UAV swarms, heterogeneous UAV swarms.*

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1. Introduction

The realm of robotics has undergone a remarkable transformation in recent years, with advancements in artificial intelligence and automation propelling unmanned aerial vehicles (UAVs) to the forefront of technological innovation. The concept of using UAVs in swarms, where multiple drones collaborate intelligently to achieve complex tasks, has captured the imagination of researchers and practitioners alike [1].

The Evolving Landscape of UAV Swarms: The integration of AI and robotics has sparked a revolution in the capabilities of unmanned aerial vehicles (UAVs), pushing the boundaries of what these aerial platforms can achieve. Traditionally employed for tasks such as remote sensing and surveillance, UAVs have evolved into dynamic and versatile entities that are increasingly sought after across various industries. This evolution has been marked by groundbreaking advancements that have transcended their conventional roles and ushered in an era of innovation.

One of the most captivating developments in this field is the emergence of UAV swarms. This concept represents a departure from the traditional single-UAV approach, as it harnesses the power of multiple drones collaborating seamlessly to accomplish tasks that were previously deemed impractical or infeasible for a single UAV. The concept draws inspiration from natural systems like bird flocks and insect colonies, where individual agents work in harmony to achieve common objectives [1].

In recent years, numerous experiments and research endeavors have aimed to uncover the potential of UAV swarms. These experiments have spanned a range of domains and applications, demonstrating the adaptability and robustness of swarm-based systems. One noteworthy experiment involved the coordination of a UAV swarm to create intricate aerial formations for artistic displays and light shows. This experiment showcased the potential for swarm-based choreography and hinted at the aesthetic possibilities inherent in this technology [2].

Another significant experiment focused on disaster response scenarios, where UAV swarms were deployed to rapidly map and assess disaster-stricken areas [3]. The swarms autonomously surveyed the affected regions, collecting crucial data that aided emergency responders in making informed decisions. This showcased the utility of UAV swarms in time-critical situations, where their collaborative efforts could provide crucial insights and support.

In the agricultural sector, UAV swarms have been put to the test for precision agriculture applications [4, 5]. These experiments involved swarms of drones equipped with specialized sensors that could monitor crop health, soil conditions, and water distribution. By analyzing the collected data, the swarm could identify areas requiring specific interventions, optimizing resource utilization and potentially increasing crop yield.

In the context of environmental monitoring, UAV swarms have been deployed to study wildlife behaviors and ecosystem dynamics. These experiments allowed researchers to gather data from multiple vantage points simultaneously, providing a comprehensive view of complex ecosystems. This approach unveiled insights that would have been challenging to obtain using traditional single-UAV methods.

As these experiments and research initiatives demonstrate, UAV swarms hold immense promise across a wide array of applications. The ability to combine the strengths of individual drones within a collaborative framework enables the accomplishment of tasks that are beyond the scope of a single UAV. This not only enhances efficiency and effectiveness but also opens new doors to innovation in industries ranging from entertainment and disaster management to agriculture and environmental conservation.

The developments and insights from these experiments have paved the way for further exploration into the capabilities of UAV swarms. It's evident that the synergy achieved through collaborative efforts of multiple drones holds transformative potential for addressing complex challenges and driving progress in AI, robotics, and beyond. Continuing to unlock the mysteries of swarm dynamics and reinforce their capabilities through advanced techniques like reinforcement learning, the horizon of possibilities for UAV swarms expands even further, promising a future where these aerial collectives revolutionize the way people interact with and harness technology.

The paper [6] discusses the significance of swarm robots in various fields and highlights the growing interest in improving the evolutionary capabilities of their strategies. It points out that strategy evolution in swarm robotics systems has been a subject of research in both industry and academia, particularly for complex applications with diverse task scenarios.

One of the key observations made in the paper is the limited focus on simultaneously improving both evolutionary efficiency and strategy performance in existing studies. Additionally, it notes that strategies evolved under global information may struggle to fully adapt to distributed task scenarios.

To address these issues, the paper introduces a novel approach called TORCH (heterogeneous – homogeneous swarm coevolution). TORCH employs a swarm coevolution mechanism to accelerate the evolution process. Notably, it introduces the use of a behavior expression tree, which expands the search space for evolved strategies. Importantly, TORCH enables swarm robots' strategies to evolve under local information conditions, making them more adaptable to distributed task scenarios.

The paper backs up its claims with extensive experiments, including a comparison with three methods based on homogeneous swarm evolution and parameter expression. The results of these experiments demonstrate the superiority of TORCH in terms of improving evolutionary efficiency and enhancing strategy performance.

In paper [7], there is a discussion about the Swarmanoid Project, which is a futuristic research project following the Swarmbots Project, that is part of the research related to heterogeneous swarms of robots. This project is funded by the European Commission and involves five research labs in different parts of Europe, including Belgium, Italy, and Switzerland.

Unlike many current studies in swarm robotics that focus on similar robots, the Swarmanoid Project aims to create a diverse swarm of small autonomous robots that can operate in a fully 3-dimensional indoor environment. This swarm includes three types of robots: eye-bots, hand-bots, and foot-bots.

The main idea of this project is to form a swarm of robots with each type having its own special skills:

– Eye-bots are good at seeing and supervising. They can fly or stick to the ceiling, allowing them to explore the area quickly and find targets or interesting objects.
– Hand-bots are designed to pick up and move things located on walls, shelves, or tables. They can climb walls and obstacles by using a rope to attach to the ceiling.
– Foot-bots are wheeled robots with a strong grip that they use to connect with other foot-bots, carry hand-bots, or transport objects.

The paper also mentions that the Swarmanoid Project is combining elements of mobile swarm robotics with humanoid robotics, and the specialization of each robot type is a key part of achieving humanoid swarming. Additionally, the paper says that it will present the hardware capabilities of these robots in the following sections, and it mentions the development of a simulation environment to make it easier to test and prototype robot behaviors.

The next steps on the Swarmanoid project aiming on enrichening the potential of the heterogeneous swarms in their flexibility and robustness were described in [8].

Heterogeneous vs. Homogeneous Swarms: As the capabilities of UAVs expand, so does the potential to diversify the swarm composition. Heterogeneous and homogeneous UAV swarms represent two distinct paradigms:

Heterogeneous Swarms: Heterogeneous swarms consist of UAVs with varied capabilities. These capabilities can include differences in speed, sensor ranges, communication methods, and maneuverability. By leveraging this diversity, heterogeneous swarms aim to optimize performance in tasks that demand a range of skills. In research [9] it was found that the heterogeneous swarms tend to base upon the jobs the individual UAV performs better.

Homogeneous Swarms: In contrast, homogeneous swarms comprise UAVs with uniform capabilities. Each member of the swarm possesses identical attributes, creating a more standardized and streamlined approach. This model is particularly suited for tasks where a singular, specialized skillset suffices. Compared to heterogeneous, the homogeneous swarm tend to gather in groups to outperform the opponent [9].

There is no necessity in comparison between a set of UAVs that are controlled separately, as in [10] there was already done a comparison between a UAV swarm, with centralized control and a set of UAVs that are controlled separately.

A common problem in UAV swarms is the necessity of having all the modules of the swarm to have identical characteristics. The homogeneity of the swarm has some advantages such as easier setup, an easier learning process. There are not many research documents on heterogeneous swarms, still, their usage can provide several advantages.

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Different abilities of the UAVs can increase the possibilities of the swarm itself. In this article, there was an attempt to emerge into the evolving landscape of heterogeneous and homogeneous UAV swarms, exploring how different reinforcement learning strategies can influence their efficacy.

The aim of research includes the creation of a model of heterogeneous UAV swarm and its comparison with a homogenous swarm containing similar types of UAVs and measured their capabilities in the same environment to determine which type of the swarms have better performance.

Finding the answer to this question can lead to improvement in UAV swarm usage in a variety of fields from agriculture to military usage.

2. Material and Method

In pursuit of understanding the impact of swarm composition on performance, a comprehensive experiment harnessing the capabilities of the Python Gym library was designed. This experiment is composed of several key elements:

Environment Creation: To faithfully replicate real-world challenges, an environment was developed that presents tasks, suitable for UAV swarms. Specific focus was on evaluating the swarm's ability to search for groups of objects in an unknown area. After the experiment starts the objects start moving in the area and performing a random movement. UAV agents are getting points for every step they are in a radius of an object, and getting points deducted for every second when they are not near any of the objects and also when any of the objects is not covered by at least one UAV agent.

UAV Agent Specification: The experiment includes two swarm configurations: heterogeneous and homogeneous. Heterogeneous swarms encompass UAVs with distinct capabilities, while homogeneous swarms consist of UAVs that share identical attributes. The difference of the UAV agents is the next: the first type of agents has a maximum speed of 3 points and counts as following the object when it is in the 4 points radius. Whereas the second type of agents has maximum speed of 1 point but detects and starts getting points in the 10 points radius.

Reinforcement Learning Algorithms: Central to the experiment's execution are the Deep Q-Network (DQN) and Proximal Policy Optimization (PPO) algorithms. These algorithms serve as the foundation for the swarms' learning processes, guiding their actions and decisions as they navigate the environment.

Experiment Setup: Before diving into the execution phases, it's essential to outline the core elements of the experiment setup. Let's define some key terms and formulas:

State (S)*:* The state of the environment perceived by the UAV swarm, encompassing information about its position, neighboring objects, and task-specific cues.

Action (A)*:* The decision made by the UAV swarm in response to its current state. This action determines the next step the swarm takes within the environment.

Reward (R)*:* The numerical value that quantifies the immediate benefit or cost associated with a specific action taken by the UAV swarm. A positive reward encourages favorable actions, while a negative reward discourages undesirable behaviors.

The calculation of the reward can be defined as follows:

$$R(s, a, s') = r(s, a, s') + \gamma \cdot V(s') - V(s),$$

where $R(s, a, s')$ represents the reward obtained from transitioning from state s to state s' by taking action a; $r(s, a, s')$ is the immediate reward obtained from the environment as a result of action a; $V(s')$ is the estimated value function for state s', representing the expected cumulative reward that can be obtained from state s' onward; $V(s)$ is the estimated value function for the current state s; γ is the discount factor, which balances the importance of immediate rewards versus future rewards.

Policy (π)*:* The strategy or set of rules that the UAV swarm employs to decide which action to take in a given state. Reinforcement learning algorithms seek to optimize this policy over time.

Value Function (V)*:* A function that estimates the expected cumulative reward the UAV swarm can attain from a given state, following a specific policy. It helps the swarm evaluate the potential benefits of being in a particular state.

3. Results and Discussion

The algorithm for training the UAV swarm using reinforcement learning can be outlined in pseudocode as follows:

```
begin
init_state = initialize the UAV environment
params = define reinforcement learning parameters
model = define neural network model
metrics = define metrics
N = number of episodes
T = number of timesteps
S = number of UAVs in the swarm
for training_episode = 0 to N do:
environment = init_state
for time_step = 0 to T do:
for i = 0 to S do:
observe_current_state(UAV[i])
set_next_decision(UAV[i])
        endfor
environment = next_step(model, environment)
calculate_reward(environment)
update_network(model, params)
endfor
record_metrics_for_episode(reward, training_episode,
metrics)
endfor
create_diagram(metrics)
end
```

The experiment unfolded in two phases: training and comparison.

Training Phase: Utilizing the chosen reinforcement learning algorithms, training processes for both heterogeneous and homogeneous UAV swarms were initiated. Throughout the training process, key metrics such as convergence speed, learning progress, and total rewards were tracked. The training went for 100000 episodes.

Comparison: In comparison phase, after both of the environment had the training, the results were added into one diagram, to get the difference between the systems. The results of the reward graph are available in Fig. 1.

Fig. 1 shows that the heterogeneous swarm has a steeper learning curve and higher reward maximum, which means that it can achieve the result faster an in more efficient way.

The result of the experiment proved the hypothesis that the heterogeneous swarms can show better performance on the same environment compared to homogeneous.

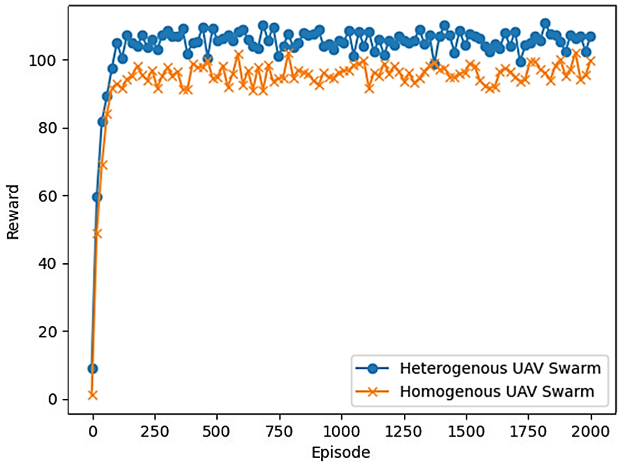

Fig. 1. Comparison of the rewards of heterogeneous and homogeneous systems for the first 2000 episodes

The findings of the experiment may be used in further experiments on UAV swarms by improving the capabilities of those swarms by incorporating the heterogeneity to the model.

Creating the virtual model of the UAV swarm had some necessary limitations: the physics of the UAV agents was simplified, the battery power was not counted, the same way as the weight of the drones. The same way the environment was simplified there was no disturbance (no electromagnetic jammers or any other obstacle) also there was a limited space of movement where the experiment was executed.

Future research could delve deeper into optimizing the composition of heterogeneous swarms for specific task requirements. Additionally, exploring more advanced reinforcement learning techniques and algorithms could unlock even greater potential for UAV swarms in various applications.

There are some steps to improve the research by adding the advanced physical behavior of the UAV agents, and by increasing the number of different types of agents in the system.

Other way in developing the current study would be to set a number of areas with different landscape and different complexity of the hidden objects. This experiment could answer the question if the heterogeneous UAV swarms would be better the harder the environment is for searching objects.

The impact of martial law conditions has affected on the research the next way: due to the rule of no flight zone in the whole country it was not possible to have any real world test of any aspect of the research. These experiments should be finished as the restriction for usage of the UAVs in the country will be cancelled.

4. Conclusions

The heterogeneous UAV swarm demonstrated an advantage over its homogeneous counterpart in the given experiment.

The reward of the heterogeneous UAV swarm's performance in average is 12.9 % better in comparison to the homogeneous swarm. Where the first one is peaking in average at 105 points the latter could achieve 93 points. This percentage remain in 2 % margin in different random setups of the environment.

The heterogeneous swarm exhibited a steeper learning curve, achieving higher rewards in fewer episodes. This observation suggests that the varied skill set within the swarm enabled quicker adaptation to changing environments.

The comparison of the reward graphs gave the opportunity to state that heterogeneous swarms are faster in finding object in comparison with homogeneous swarms.

All the results can be explained by the fact that due to the difference between the agents, they were able to utilize their best parameters to achieve better performance.

The results can be useful in both theoretical and practical perspective. From theoretical side, the results give the opportunity to continue the improvement of the UAV swarms and the possibility to incorporate different types of UAV agents to possibly improve their behavior in different scenarios during other experiments. From practical perspective, the results can be a starting ground on the development of a more efficient and useful UAV swarm model that would be useful in different types of tasks.

Conflict of interest

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

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Data availability

The manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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✉***Yosyp Albrekht,*** *Postgraduate Student, Department of Information Systems and Technologies, National Technical University of Ukraine «Igor Sikorsky Kyiv Polytechnic Institute», Kyiv, Ukraine, e-mail: yosyp.albrekht@gmail.com, ORCID: https://orcid.org/0000-0003-0093-6397*

Andrii Pysarenko, *PhD, Associate Professor, Department of Information Systems and Technologies, National Technical University of Ukraine «Igor Sikorsky Kyiv Polytechnic Institute», Kyiv, Ukraine, ORCID: https://orcid.org/0000-0001-7947-218X*

✉*Corresponding author*

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**Kostyantyn Kharchenko,
Oleksandr Beznosyk,
Bogdan Bulakh,
Ganna Ishchenko,
Vadym Yaremenko**

THE DEVELOPMENT OF THE METHOD OF OPTIMIZING COSTS FOR SOFTWARE TESTING IN THE AGILE MODEL

The object of research in the article is the process of testing and operating software with cost minimization. In the Software Development Life Cycle, depending on the chosen option of the flexible methodology, special attention is focused on testing software versions both in the process of passing iterations and in the process of releasing alpha, beta and production versions.

This article is devoted to the problem of developing a method for software testing cost optimization method that estimates the test cost function and the losses cost function from the occurrence of an error.

Using the optimization method (for example, the first-order descent method) from the two functions of testing costs and estimating the losses caused during operation, it is possible to calculate the optimal cost of testing and operating the software product.

The results obtained show that with the correct assessment of a cost function and a loss function such calculations allow to significantly save money and time for the production of the next version of the software product.

These results are explained by the fact that the method of optimizing the cost function finds the optimum point and allows to pre-estimate the budget and risks during the development and operation of the software.

The article provides several examples of the calculation and optimization of testing costs within the proposed concept for one iteration in a flexible software development cycle.

The results of the study can be used in practice, provided that the functions of estimating costs for testing and compensation for losses caused during the operation of the software are set correctly. Experienced managers and project supervisors determine these functions quite accurately for a certain number of iterations, which makes it possible to apply the method of finding the minimum budget costs for testing and operating a software product.

Keywords: *agile, SCRUM, software development life cycle, testing, QA, risk management.*

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1. Introduction

The constant development of IT and programming methodologies requires new methods of planning and forecasting the quality of the resulting software product and information system.

One of the key aspects of software development is testing. In flexible methodologies, such as Agile, software testing stages play an important role, which directly affect the quality of the proposed solution and, accordingly, the cost of operating the information system [1–3].