UAV SWARMING APPLICATIONS FOR SEARCH AND RESCUE MISSIONS

M. Kötter[1 2], R. Brachmanski[1], M. Uijt de Haag[2]
[1] Airbus Defence and Space GmbH, Rechliner Straße, 85077 Manching, Germany
[2] Technische Universität Berlin, Flight Guidance and Air Transport, Marchstraße 14, 10587 Berlin, Germany

Abstract

This work in progress paper deals with the potential and the implementation of swarming concepts for the use case of search and rescue missions in afforested areas. Unmanned vehicles provide a valuable instrument to deal with dangerous situations as the lack of an operator reduces human exposure to environmental hazards. To ensure the mission and the funcionality of the unmanned vehicles against failures and losses, swarming is a promising solution. After defining the problem, we present the goal of this work: A robust and reliable swarming structure that is capable of being deployed close to forest fires to scout the dimension of the forest fire and search for survivors, both humans and animals. After detecting survivors, the follow-up task will be to lead them away from the fire towards safety.

Keywords

Swarming; Search and Rescue; Autonomy

ACRONYMS

MRS Multi-Robot System

UAV Unmanned Aerial Vehicle

GUI Graphical User Interface

HGV Heavy Goods Vehicle

1. INTRODUCTION

In the recent years, highly automated robotic systems have shown the potential to take over various complex tasks in different environments, including air, land, maritime, and space domains. These systems enable a personnel-efficient and cost-effective execution of hazardous and tedious missions, that can be accelerated by using (multiple) autonomous or automated agents organized in teams or swarms. An agent is here to be understood as an entity of any kind which interacts with its environment. In this work, the current state of the art for robotic swarm applications will be discussed as well as their specific use to protect humans and animals alike from fires.

1.1. Multi-Robot Systems

Teams or swarms have the potential to operate more efficiently and to be more robust in adverse conditions as opposed to single vehicle systems. As groups of humans and animals show, multiple of them can achieve tasks that a single one cannot achieve, such as hunting large prey, building complex structures or dividing and specializing on different tasks. In search and rescue missions, Multi-Robot Systems (MRSes) are capable of searching on multiple locations simultaneously or helping multiple victims of a catastrophe at the same time. According to Dias et al. [1], MRSes usually refer to multiple mobile robots, not to stationary robots as in a factory at production lines. Figure 1 shows robotic swarms and robotic teams as different subsets of MRSes in general.

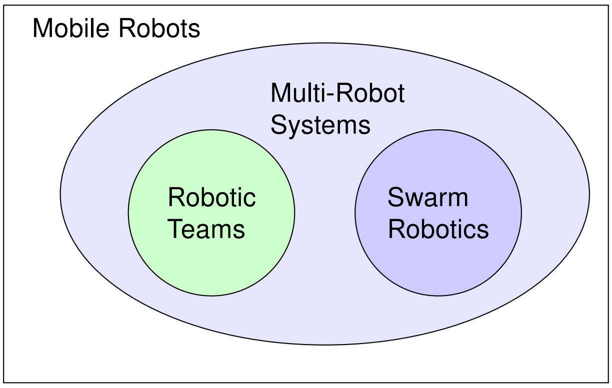

FIG 1. Multi-Robot Systems, based on Dias et al. [1], modified to also include the teaming aspect.

1.2. Autonomous or Automated Systems

Autonomous Systems are able to take responsibility off from human operators by making own decisions; this goes along with the challenge to assure the quality of the decisions. Humans heavily rely on their abil-

doi: 10.25967/630167

ity to judge actions and evaluate if a decision is good based on common sense or rules of engagement. In an autonomous system, it must be proven first that a decision making process for an autonomous agent will not cause fatal behaviour for the agent or its environment. On the other hand, autonomous decision making reduces the scope of humans. It also provides the ability to save staff for a certain task and the ability to keep staff away from potentially dangerous situations. Autonomous systems are also in advantage when it comes to reaction time and communication speed in between agents: while humans need to get information onto a man-machine interface (visual or acoustic) and need to focus on one information at a time, robotic agents can receive multiple streams of digital information and process them simultaneously. Here, the human as a bottle-neck can be minimized in the process chain, if left with only supervisory functions.

1.3. Use Case

Autonomous agents are valuable tools for the detection and treatment of natural disasters such as forest fires: they are available in large numbers to overfly forests, detect fires and map the areas affected by fires. Furthermore, they can approach the fire much closer than human pilots could safely do and detect humans and animals in danger. In addition, without a pilot, the size of rotorcraft can be reduced and small, autonomous rotorcraft can breach below the forest canopy to guide humans or chase animals away from a threat. If communication is interrupted, some of the agents are required to work as independent groups, coordinating their tasks locally.

2. SWARMING VS. TEAMING: A COMPARISON

While swarms and teams both are multi agent systems and hierarchically even, Schulte et al. [2] give an insight on the difference between swarming and teaming: a key difference is having or not having predefined roles among the members.

2.1. Swarming

In swarming, agents are held relatively simple, the complexity arises from the swarm structure [1, 3]. They are supposed to be homogenous in the truest definition of a swarm, where they have the same capabilities and are equally useful for all possible tasks. That actual swarms can deviate slightly from this, as shown in the caste system of ant or termite swarms, where they have soldiers and workers.

Another key criterion that is important for swarms is their local, decentralized behaviour; there is no central decider that controls all agents, agents are not even required to have a connection to all other swarm members. Agents make local decisions based on the local information they have.

Schulte et al. [2] also add that since swarms are decentralized and act local, addressing them for task assignments etc. is not simply done by communicating with a single agent. This communication has to be done with the swarm as a whole, which does not exist as a tangible object. Therefore, they define a swarm avatar as communication interface. This avatar represents the whole swarm, communicates with the swarm's supervisors and transmits the information from and to the individual agents.

2.2. Teaming

In teaming, on the other side, agents can fulfill specific roles and know about the other roles in their team. For fulfilling different roles, they can also be built differently to be adapted to their roles. In robotics, teams can be purely robotic or they can also include humans that work together with robots.

3. AUTONOMY VS. AUTOMATED

Often it seems that systems are called “highly automated” or “autonomous” synonymously. Adler [4] explains what seperates highly automated systems from autonomous systems in different ways concerning understanding, responsibility and dependence.

3.1. Autonomous Systems

With multiple citations, Adler [4] relays the image that autonomy stands for *independence*. However, he also goes into detail that systems today are well connected among each other to get as much data about their current situation as possible. He introduces that autonomous systems can be open or closed: while open autonomous systems are considering external information in addition to their own perception for their decisions, closed autonomous systems only rely on their own situational awareness. He points out that more information makes decisions better and faster; prediction of other agents is more useful, if these agents provide information about what they intend to do. Many open autonomous systems that work together form a digital ecosystem.

From the perspective of understanding, autonomous systems are described by Adler [4] as systems where the developers cannot directly predict how they work. Therefore, with the loss of predictability, control is minimized as well, which leads to a shift in responsibility.

Furthermore, a criterion for autonomy is if a system is able to take responsibility: Adler [4] explains here that a truly autonomous system takes own responsibility and therefore does only require little supervision.

3.2. Highly Automated Systems

In opposite to the aforementioned autonomy, highly automated systems lack these criteria an autonomous system has [4]: highly automated systems still function with almost no human interference, as they are “highly automated”, but they are not necessarily able to cope with completely unexpected, unknown situations. This also leads to the fact that these systems need supervision and human intervention in critical cases.

When it comes to understanding, these systems can be completely predicted, since everything can be programmed or planned in advance. Since humans plan or program the actions ahead, this also indicates that responsibility remains more with them as with autonomy, as they knowingly let the system act in certain ways.

4. SWARMING: STATE OF THE ART

Autonomous robotic swarms are already under research in different aspects – definitions and requirements are already given. As presented in section 2, swarms differ from other forms of multi-agent systems by each agent focussing on a local environment to achieve a global behaviour of the whole swarm. With that come some definitions that the agents must fulfill to form said swarm, as Dias et al. [1] introduce:

- **Decentralization:** swarms are defined as being decentralized, it is a main feature. Each agent makes its own decisions without depending on a central decision hub.
- **Self-organization:** the agents are managing themselves based on feedback they receive from their environment.
- **Homogenity:** swarms are made of similiar agents that do not specialize on certain tasks. Every agent should be able to be swapped and still function in its new place.
- **Small individual competency:** single agents are expected to be as simple as possible; they alone are not supposed to perform all tasks that the swarm can accomplish as a whole.
- **Distribution of information:** information is mainly shared locally among neighbours. Swarm agents are not necessarily aware of the state of all other agents.
- **Robustness:** the swarm continues to work properly if agents fail or get damaged. This forbids dependence on individuals.
- **Scalability:** agents can be added and removed without compromising the swarms operationability. This is also important to ensure robustness.
- **Parallelism:** since each agent decides for itself, all decicions are made parallel to each other and do not need to be processed sequentially. This prevents a swarm from running into member limits based on processing-capacity or communication band width.

This offers advantages and challenges for implementing swarms in commercial (i.e. non-research) applications. Swarms are – by definition – independent from the actual number of agents and from steady connections to each agent, however, this requires higher degrees of automation or autonomy and lessens the control operators can have on both, the individual agents as well as the swarm as a whole.

4.1. State of Research

As Dias et al. [1] present over their work, there is a broad list of projects where swarming behaviour and swarming applications are being researched. However, until now, no information about successful commercial applications that fulfill the aforementioned criteria is to be found. Becker [5] also contributes that legal requirements are a challenge to be overcome before a commercial swarm can be implemented, as authorities demand guaranteed safety before such systems are deployed in public places.

Nevertheless, Dias et al. and Osaba et al. [1, 3] provide a lot of current research projects working on swarming applications. The research projects deal with all possible aspects of swarms such as communication among agents, communication with an operator, different behaviours such as collision avoidance among swarm members and other aspects. These projects show that a lot of progress is made in this field and swarm robotics are being prepared for their commercial implementation, as soon as it is ready and legal.

4.2. Communication

Since swarms operate on a local basis and react to their neighbours, communication is an important topic to exchange information with neighbours and identify each other. In some applications, long range communication towards their swarm avatar or far agents in some usecases might be required as well.

Trianni and Dorigo [6] introduce the three different modes of communication, assumed from the animal kingdom:

- Stigmergy / indirect communication
- Direct interaction
- Direct communication

Stigmergy, or *indirect communication* refers to agents using their environment for communicative purposes. The environment can serve for this carrying pheromones placed by other agents, as ants do. The environment can also refer to a construction, as termites base their behaviour on how far they get with building a nest: depending on the progress of the nest construction, their behaviour changes. Tang et al. [7] show that a possibility to implement stigmergy in robotic agents is the usage of pheromones implemented on RFID tags which are placed in the environment.

Direct interaction describes communication via physical contact. Ants show the behaviour to pull other ants in a certain direction with the intent to make the other ants follow them. When they want to share information about food sources, they give them food samples from this source to make them aware that this food source is available. Another possibility for ants to make a nest-mate follow them is *antennation*, where ants tap each other with their antennas. Trianni and

Dorigo [6] mention that direct interaction is usually not used for robotic agents as it is usually not intended for them to have contact. A technical example, however, could be for trains or Heavy Goods Vehicles (HGVs) to check if the train cars or the truck trailers are attached to each other by measuring the forces on the coupling.

Direct communication is the method of communication best known to humans: Sending signals from one agent to another. These can be visual clues like dances or gestures, acoustic signals like talking or – in most cases for robotic agents – radio frequency communication.

These different forms of communication are suitable for different applications and form a library from which in the development of a swarm different communication methods can be implemented depending on the specific needs of the developed swarm.

4.3. Decision-Making

Pinto et al. [8] introduce a cognitive architecture that combines a decentralized manner in the low levels of decision making with a centralized level for higher level decisions, where also human supervisors can interact with the system. Basic decisions are made on the individual agents themselves to provide flexibility, however, if agents make decisions of greater impact, these decisions are requested; a central decision-maker then accepts or denies these requests to avoid conflicting actions. Their usecase is the inspections of dams and slopes in mining and power generation to detect deformation damages to the structures.

Shah and Vachhani [9] propose a concept opposite to the idea of Pinto et al. [8]: They completely leave out inter agent communication and let the agents solely act and decide upon their own local perception. The agents' goal is to aggregate at a predefined point in the environment around them. Shah and Vachhani [9] also explain that their aggregation algorithm reaches similar performance as other algorithms that use local or even global communication.

4.4. Task Allocation

Khaluf et al. and Lee et al. [10, 11] all offer local approaches for agents to decide whether to assume an open task or not.

Khaluf et al. [10] represent the currently available tasks as a graph where tasks are nodes and some tasks are connected via edges. They employ a local *Ant Colony Optimization* implementation that is run on each agent independently to determine on different factors (deadline, how many agents already work on it) whether an agent should switch tasks via an edge or stay. Due to this design, agents can only switch to tasks that are connected to their current tasks via an edge.

Lee et al. [11] deal with a threshold based algorithm: They assume that every agent can work on every task, but agents have individual priorities for what tasks to work on. Therefore, the agents use a threshold value they compare to the importance of the task to evaluate whether they should work on it or not. Agents decide to work on tasks if the threshold is exceeded: if agent A “prefers” task T_1, but not task T_2, it has a low threshold for T_1 and a high threshold for T_2. Even if the importance of T_1 is relatively low, A will still work on it. On the other hand, if the importance of T_2 is relatively low for A, A will not work on it. However, if no agent works on T_2 and its importance grows, at some point, it exceeds the high threshold value of A for it and A will still work on it, even though this task is not among the priorities of this agent.

4.5. Usecases for Aerial Swarms

Aerial swarms have a wide variety of possible applications, as Dias et al. [1, 3, 5] name: a promising field for these swarms are search and rescue missions, as multiple vehicles can scan more area to find people and animals in need of help. A great number of Unmanned Aerial Vehicles (UAVs) is able to search at multiple places at the same time to increase the chances of finding more living beings like those in need. In case some living beings are avoiding the searching agents (i.e. scared animals, escaping suspects searched for by police), it is also harder to flee from or lose contact to multiple searchers spread out through the environment. An additional advantage of unmanned agents in search and rescue missions is that these missions are often performed in dangerous areas, like close to natural desasters like forest fires, volcanoes, etc. By using unmanned vehicles to find survivors, rescuers are less exposed to danger.

Given their airborne nature, these UAVs do not only excel at searching missing entities, but also at checking the condition and the processes of those with known locations. So are aerial swarms promising for future inspection of traffic, constructions and farms. Especially constructions that are not easy to reach and walk along, such as road networks, power lines or offshore wind parks, could be inspected easier by UAVs. Therefore, inspection and supervision are suitable applications for these swarms as well. To a certain degree, the agents can also intervene, for example when managing traffic.

UAVs can also map unknown areas. This is, again, faster when using multiple vehicles to simultaneous scan multiple places at once. Mapping can be necessary for example in search and rescue missions to guide rescuers towards victims or victims towards safety. Therefore, doing this unmanned can help guiding humans and animals out of risky situations.

5. GOALS OF THIS RESEARCH

A robust and reliable swarming structure is to be developed that is capable of being deployed close to forest fires in order to scout the dimension of the forest fire and possibly the fire's direction of movement and then search for survivors, both humans and ani-

mals. After detecting survivors, the follow-up task will be to lead them away from the fire towards safety. With humans, this is easier as humans can understand the good intentions behind the drone's deployment and can follow the drone to safe areas, as appropriate acoustic and visual messages (e.g., voice or display "follow me") are provided. Animals may not understand that a drone is trying to save them, see the drones as threats additional to the fire, and try to avoid them as well. Therefore, if drones trigger a flight response in animals, the strategy to make them move away from danger must be adjusted. If perceived as a threat, the drones have to "push" animals out instead of "pulling" them in. To be flexible and applicable to various situations, the swarming algorithm implemented on the swarm members must be usable for an arbitrary number of agents being deployed. However, as a swarm is meant to have its agents working together, a minimum number of agents might be necessary to accomplish certain tasks. In case of fire or obstacles, communication between the agents can be compromised. Therefore, the swarm needs to be operational even if the communication is compromised.
Even though wild fires can be a threat to wild life, there are other threats that wild life can be exposed to which can be even more difficult for the animals to avoid by themself; animals can see and smell fire, which gives many of them the opportunity to escape from it by themselves. Only some animals might get trapped and need some support to find a way out. Other threats, however, can be more difficult or impossible for them to perceive and evade: Certain toxins that could be accidentally or illegally released into nature could be tasteless and odorless, or radioactive material could be released after an accident at a nuclear power plant. Since the animals cannot perceive such threats, they will not escape by themselves and depend on help by humans.
After chasing animals away, it depends on the individual situation, which other steps might be necessary to assure the continuation of the animals' safety.
To accomplish the detection of burning areas and living beings from sensor data, artificial intelligence is a necessary element of the implementation. To cope with unreliable communication, a decentralized layout of the swarm is a promising solution to both, not depending on a centralized planning unit as well as not relying on data of all other agents for short term tactical decisions (micro management). This also reduces the computation demand for large numbers of agents. Long term strategical decisions (macro management) are still possible and reasonable on a few, bigger platforms with enhanced power supply and computational capacity, if the swarm is set up heterogeneously or if such units are hierarchically placed above the swarm. Figure 2 shows the seamless transition between micro and macro management. Some border has to be found what happens on the agents' local level (decided within the swarm) and is decided over the swarm (commanded to the swarm). To guide survivors out of an area,

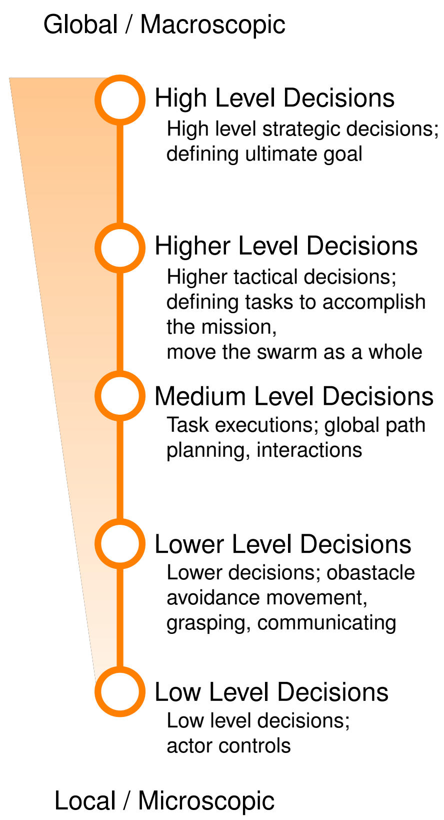

FIG 2. Decision levels in the swarm.

the safest route has to be determined, which might for example be accomplished using potential field methods or search-based pathfinding. If an animal has to be chased away from danger, it has to be determined which routes have to be cut off by agents that the animal might try to evade the agents and endanger itself.
Figure 3 shows the possible function dependence graph, which describes how the different functions to be implemented work together to achieve a functioning demonstrator. The functions are divided into the different categories "Input / Output", "Perception", "Communication", "Behaviour" and the "Demonstrator".
The functions therefore are seperated into what they contribute to the system. Especially the behavioural part is of interest, as here, the swarm-internal decisions are made as well. By deciding which agents assume which tasks and which tasks are to be done how, the swarm will achieve its own characteristics.

6. PREPARATION OF A SIMULATION ENVIRONMENT

The first step to develop a useful swarming behaviour is a simple, 2.5 dimensional simulation to test first algorithms and see how the decentralized decisions affect the swarm as a whole. For that, such simulation is under current development. It will feature a simple representation of a forest with trees aligned on a grid and predator and prey animals roaming around, as shown in figure 4. Further, this simulation will

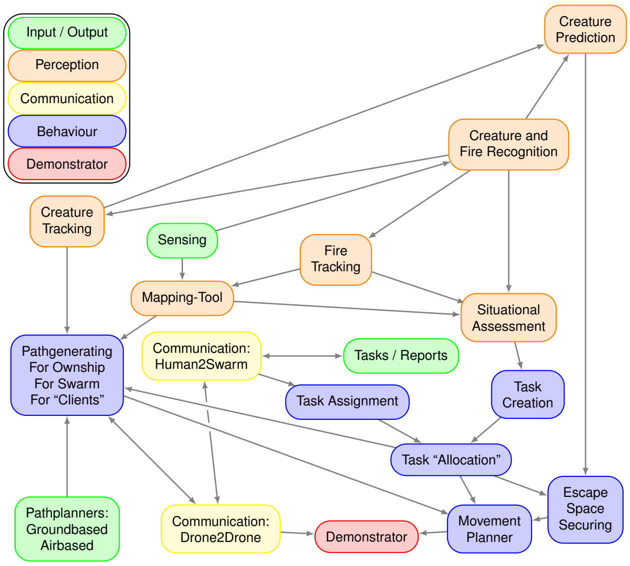

FIG 3. Function dependence graph.

feature both multi-rotor UAVs as well as fixed wing ones. The multi-rotor UAVs are the main agents of the swarm and can move both above and in between the trees to look for animals and interact with them. The fixed wing aircraft are mainly for reconnaissance, but also are able to relay communication between other agents as well as possibly supplying additional computation power for high level, macroscopic decisions. They always remain at altitude above the forest and do not directly interact with animals. Additional to trees, bushes, stones and ponds as obstacles, threats are introduced: fire, poison and nuclear material. Around them, danger zones are defined, while safe zones are defined where animals are to be guided. The animals all flee from fire and from low flying drones, however, they do not take notice of poison and radioactive material. The swarm then has the task to chase all animals into green zones. The algorithms for each of the tasks depicted in figure 3 are to be determined by testing different options, except of perception algorithms which are not regarded or possible in this simple simulation, as it is not photo realistic.
If the swarm is able to achieve its goals in the 2.5 dimensional environment, a three dimensional environment will be the next step to produce a more realistic scenario for the agents. After this, an implementation on actual drone hardware is due.

7. SUMMARY AND OUTLOOK

In this work in progress paper, we introduce the research project we are working on and define a goal to be reached in the end of the project. Autonomous or highly automated swarms of UAVs offer a lot of potential to improve use cases such as search and rescue missions, while also bringing challenges like the need to guarantee safe operation as no human operator can quickly intervene in critical situations.

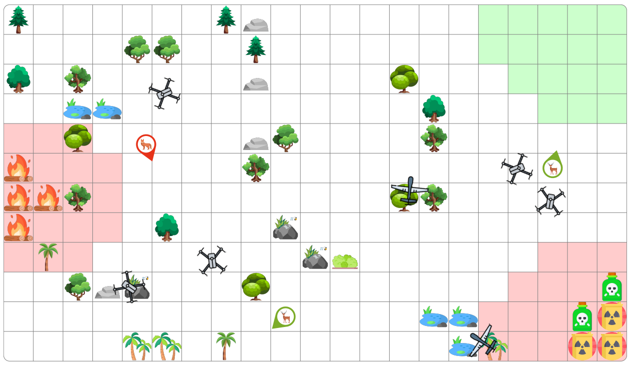

FIG 4. A graphical representation of the first simulation environment for this research. This grid based world is supposed to be the main element of the GUI. [12]

Therefore, a robotic swarming concept is to be developed for search and rescue missions, where humans and animals are guided away from threats. An emphasis is to be put on the rescue of animals as they are not able to cooperate with drones and are therefore more challenging to be guided away from danger in afforested areas.
In the current step, a 2.5 dimensional simulation software is to be developed to test first software concepts for this swarming application. Within this simulation environment, both UAVs and animals are implemented. The UAVs are then fitted with algorithms to control their swarming behaviour, how to move through their environment and how to interact with animals. After successfully implementing a swarming concept in 2.5 dimensions, a three dimensional simulation will be the next step before implementing a swarming demonstrator using physical hardware.

Contact address:

marco.koetter@airbus.com

References

[1] Pollyanna G. Faria Dias, Mateus C. Silva, Geraldo P. Rocha Filho, Patrícia A. Vargas, Luciano P. Cota, and Gustavo Pessin. Swarm robotics: A perspective on the latest reviewed concepts and applications. *Sensors*, 2021.

[2] Axel Schulte, Felix Heilemann, Sebastian Lindner, and Diana Donath. Tasking, teaming, swarming: design patterns for human delegation of unmanned vehicles. In *Advances in Human Factors in Robots, Drones and Unmanned Systems: Proceedings of the AHFE 2020 Virtual Conference on Human Factors in Robots, Drones and Unmanned Systems, July 16-20, 2020, USA*, pages 3–9. Springer, 2021.

[3] Eneko Osaba, Javier Del Ser, Andres Iglesias, and Xin-She Yang. Soft computing for swarm robotics: New trends and applications. *Journal of Computational Science*, 39:101049, 2019. ISSN: 1877-7503. DOI: https://doi.org/10.1016/j.jocs.2019.101049.

[4] Rasmus Adler. Autonomous or merely highly automated – what is actually the difference?, 2019. https://www.iese.fraunhofer.de/blog/autonomous-or-merely-highly-automated-what-is-actually-the-difference/ [Accessed: 19.08.2024].

[5] Susan Becker. Drone swarms: Scaling up for a new level of efficiency, 2022. https://www.elsight.com/blog/drone-swarms-scaling-up-for-a-new-level-of-efficiency/ [Accessed: 20.08.2024].

[6] Vito Trianni and Marco Dorigo. Self-organisation and communication in groups of simulated and physical robots. *Biological cybernetics*, 95:213–231, 2006.

[7] Qirong Tang, Fangchao Yu, Yuan Zhang, Lu Ding, and Peter Eberhard. A stigmergy based search method for swarm robots. In *Advances in Swarm Intelligence: 8th International Conference, ICSI 2017, Fukuoka, Japan, July 27 – August 1, 2017, Proceedings, Part II 8*, pages 199–209. Springer, 2017.

[8] Milena F Pinto, Leonardo M Honorio, Aurélio Melo, and Andre LM Marcato. A robotic cognitive architecture for slope and dam inspections. *Sensors*, 20(16):4579, 2020.

[9] Dhruv Shah and Leena Vachhani. Swarm aggregation without communication and global positioning. *IEEE Robotics and Automation Letters*, 4(2):886–893, 2019.

[10] Yara Khaluf, Seppe Vanhee, and Pieter Simoens. Local ant system for allocating robot swarms to time-constrained tasks. *Journal of Computational Science*, 31:33–44, 2019.

[11] Wonki Lee, Neil Vaughan, and Daeeun Kim. Task allocation into a foraging task with a series of subtasks in swarm robotic system. *IEEE Access*, 8:107549–107561, 2020.

[12] Freepik, justicon, Iconjam, Mihimihi, Chanut is Industries, Dreamcreateicons, and bastian 5. Icons for gui,. https://www.flaticon.com/free-icon/palm-tree_3850525 [Accessed: 17.07.2024], https://www.flaticon.com/packs/tree-8 [Accessed: 17.07.2024], https://www.flaticon.com/de/kostenloses-icon/uav_8598680 [Accessed: 17.07.2024], https://www.flaticon.com/de/kostenloses-icon/quadrocopter_11888164 [Accessed: 17.07.2024], https://www.flaticon.com/free-icon/bonfire_2435606 [Accessed: 17.07.2024], https://www.flaticon.com/free-icon/pond_7441425 [Accessed: 17.07.2024], https://www.flaticon.com/free-icon/barrel_544409 [Accessed: 17.07.2024], https://www.flaticon.com/free-icon/poison_3953029 [Accessed: 17.07.2024], https://www.flaticon.com/packs/zoo-12 [Accessed: 17.07.2024], https://www.flaticon.com/free-icon/bushes_8029287 [Accessed: 18.07.2024], https://www.flaticon.com/free-icon/rocks_7053536 [Accessed: 18.07.2024] and https://www.flaticon.com/free-icon/stone_7996088 [Accessed: 18.07.2024].