

Awasthi, Shrutarv et al.

Article

Micro UAV Swarm for industrial applications in indoor environment: A systematic literature review

Logistics Research

Provided in Cooperation with:

Bundesvereinigung Logistik (BVL) e.V., Bremen

Suggested Citation: Awasthi, Shrutarv et al. (2023) : Micro UAV Swarm for industrial applications in indoor environment: A systematic literature review, Logistics Research, ISSN 1865-0368, Bundesvereinigung Logistik (BVL), Bremen, Vol. 16, Iss. 1, pp. 1-43, https://doi.org/10.23773/2023_11

This Version is available at:

<https://hdl.handle.net/10419/297215>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by/4.0/>

Micro UAV Swarm for industrial applications in indoor environment – A Systematic Literature Review

S. Awasthi^{1*}, M. Fernandez-Cortizas², C. Reining¹, P. Arias-Perez², M. A. Luna²,
D. Perez-Saura², M. Roidl³, N. Gramse¹, P. Klokowski³ and P. Campoy²

Received: 27 April 2023 / Accepted: 28 September 2023 / Published online: 20 November 2023
© The Author(s) 2023 This article is published with Open Access at www.bvl.de/lore

ABSTRACT

This contribution provides a systematic literature review of micro aerial vehicle (MAV) swarms for indoor industrial applications. First, an initial list of **1997** publications that complies with predefined inclusion criteria was surveyed by reviewers. Next, **185** publications that comply with the Selection Process were analyzed based on localization, control, guidance system, safety and security, MAV charging, communication, artificial intelligence, and applications. The analyzed researches could possibly be deployed in the industrial application of production, logistics and supply chain or transferable into this field. The publications encompassed within this study can be classified under Technology Readiness Level (TRL)

4. Some works do strive to offer solutions tailored to industrial tasks, the validation of their findings predominantly occurs through simulations or controlled laboratory environments. The findings provide an overview of the state-of-the-art specifications, the technologies used by MAVs, trends and outline a future road map for further research from a practitioner's perspective.

KEYWORDS: MAV swarm · indoor · logistic · supply chain

1 INTRODUCTION

Industry 4.0 is a vision that evolved to optimize production and manufacturing processes – from raw material procurement to customer satisfaction [1]. Logistics is an essential component of an industry as it ensures the link between suppliers, manufacturers, and customers [2]. Its goal is to guarantee customer satisfaction by assuring the delivery of suitable goods to the right customers at the right time and place and in the economically most efficient way [3]. Furthermore, in the context of industry 4.0, the logistic sector is being digitized, optimized, and automated to reduce inaccuracies while ensuring the effortless sharing of information in real time. Introducing unmanned aerial vehicles (UAV) to logistics processes signals an accelerated transformation to automation. In the EU, logistics, warehousing, and storage represent up to 15% of the current costs [4]. In the US, warehousing constitutes 30% of the total logistics cost [5], underlining the potential for cost savings. Audi tested the use of UAVs for automated transport of parts in factory halls [6, 7]. Thus, there is a growing interest to optimize and automate the operations in warehouse and production facilities.

It is speculated that the UAV logistics and transportation market will reach \$ 29.06 billion by 2027 with an annual growth rate of almost 21 % [8].

✉ Shrutarv Awasthi^{1*}
Miguel Fernandez-Cortizas²
Christopher Reining¹
Pedro Arias-Perez²
Marco Andres Luna²
David Perez-Saura²
Moritz Roidl³
Nils Gramse¹
Patrick Klokowski³
Pascual Campoy²

¹ Chair of Material Handling and Warehousing, Technical University Dortmund, Joseph-von-Fraunhofer-Straße 2-4, Dortmund, 44227, Germany.

² Computer Vision and Aerial Robotics Group, Centre for Automation and Robotics UPM-CSIC, Universidad Politécnica de Madrid, Calle José Gutiérrez Abascal 2, Madrid, 28006, Spain.

³ Fraunhofer Institute for Material Flow and Logistics (IML), Joseph-von-Fraunhofer-Straße 2-4, Dortmund, Germany.

* Corresponding author. E-mail: shrutarv.awasthi@tu-dortmund.de;

Additionally, the market research report by Polaris had valued the global drone logistics and transportation market at \$ 350.5 million in 2021 and forecast it to grow at a compounded annual growth rate of 55.20% till 2030 [9]. UAVs have shown high potential in the logistics sector and are speculated to be the next big thing [10]. Since the modern supply chains are complex, dynamic, and technology-driven, there is a need for flexible logistics systems that can optimize the supply chain. Small and lightweight UAVs can traverse efficiently in a cluttered and constrained indoor environment (such as a warehouse or a factory). They can contribute significantly towards optimization of the supply chain [11]. UAVs perfectly fit into the Industry 4.0 setting, where intelligent objects are networked and exchange data with each other [12].

Micro UAV or Micro Aerial Vehicle (MAV) refers to small, lightweight, flying robots weighing less than 2 kg [13–16]. However, none of the works [13–16] clarify if they consider the weight of MAV with or without payload. This publication assumes a MAV to weigh less than 2 kg without payload. However, we believe the maximum take-off weight of a UAV would be a better classification parameter, as many countries consider the maximum weight of a UAV (including payload) while designing the regulations [17]. MAVs are classified into fixed-wing, fixed-wing hybrid, single-rotor, and multi-rotor [18]. Multi-rotor UAVs are the most popular due to their high mobility, ability to take off vertically, affordability, and ease of building. The increased maneuverability can minimize the overall costs of the supply chain by optimizing various logistics tasks such as warehousing, route planning, inventory management, transportation, and surveillance. Therefore, this work

considers multi-rotor MAVs. However, Micro UAVs are resource-constrained; for instance, they have a limited flight time due to the battery capacity, carry a limited number of sensors, and have a limited payload and speed [19]. MAV swarms can offer a solution to overcome the limitations faced by a single MAV.

A MAV swarm is a group of MAVs that use algorithms to work collaboratively and achieve a specific goal. The desired collaborative behavior emerges from the interactions between the MAVs and the environment through the sensors and actuators. This behavior is inspired by the animals cooperating as a team to achieve a common goal [19]. For instance, migratory birds often fly in echelon formations to save energy [20]. A MAV swarm allows individual MAVs to be configured into a team to perform tasks that would otherwise require a large, task-specific, monolithic UAV [21]. In addition, the individual MAVs can sense, share information autonomously, and make appropriate decisions.

The swarming system can be centralized, decentralized, or hybrid. Communication occurs between a MAV and a central station in a centralized system. A central station could be a Ground Control System, or one of the members of the MAV swarm could act as a central control. Centralized swarming does not require communication among the MAVs. If the MAVs want to share the data with another MAV, it can be passed through the central station. In decentralized swarming, MAVs do not require a central station to communicate with others. Each MAV in the swarm can be independently autonomous, intelligent, and have computational capabilities. These two systems are explained in Section 4.1. A hybrid system combines

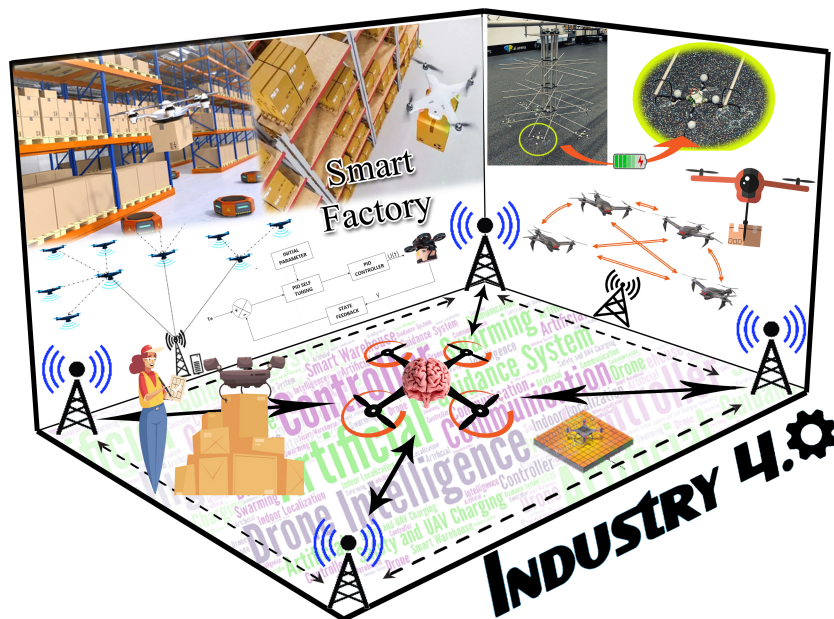


Fig. 1: Visualizing the idea of MAV swarms using various technologies to perform tasks in an industrial environment

centralized and decentralized systems to mitigate the disadvantages when used individually. In a hybrid system, the swarm can have multiple central control stations, and the individual MAVs also have limited sensing and computational capabilities. The swarm control is primarily decentralized and distributed among the MAVs in the swarm [22]. One can decide on the type of swarming system to use based on the end goal while considering the swarming system's adaptability, robustness, scalability, and fault tolerance [23].

While research on UAVs for supply chain and logistics has gained popularity over the last couple of years [8], there is a lack of literature reviews focused on using UAVs to optimize the supply chain or automate operations in an indoor industrial setting. Therefore, this contribution aims to perform a systematic literature review (SLR) on a swarm of MAVs operating indoor industrial environments such as production, manufacturing, warehouses, and factories. The industrial environment is mainly enclosed, consisting of constrained spaces, with humans working alongside other machines, and has many static and dynamic obstacles. Thus, making it suitable for MAVs to be deployed in such an environment [10].

Figure 1 aims to visualize the goal of this review. It depicts a swarm of autonomous MAVs working indoors such as in a warehouse. The MAVs are able to communicate amongst themselves and also with a ground station. They are able to localize within the warehouse and able to avoid static and dynamic obstacles. These MAVs exhibit real-time decision-

making capabilities and compute optimal paths, even within intricate and cluttered surroundings. Moreover, they are capable of working collaboratively to complete a task. In the event that a MAV is low on battery it autonomously navigates to a charging station to recharge and another fully charged MAV takes its place. The MAVs autonomously perform diverse tasks such as stock taking, surveillance, and transportation with minimal human intervention. Importantly, it is imperative to ensure the safety of human coexistence with MAVs. The report by Roland Berger emphasizes that the full potential of UAVs will only be realized when autonomous operations become the norm, and the full potential of artificial intelligence (AI) is harnessed [24].

Table 1 presents a list of industries that have adopted UAVs to automate a range of industrial activities. The list has been gathered from diverse sources, including company websites, blogs, and news reports. The analysis of the list highlights that UAVs have found significant utility in inventory management. However, the realm of autonomous localization within indoor environments remains a formidable challenge. Although UAVs exhibit immense potential, their integration into industrial sectors for tasks like transportation, pick and place operations, and surveillance is still in its nascent stages. The current implementation of UAVs in industrial settings is not entirely autonomous; a certain degree of human intervention is necessary, such as for charging, initialization, mapping and addressing technical issues. Remarkably, the concept of fully autonomous UAV swarms collaborating harmoniously

Table 1 presents a list of industries that have adopted UAVs to automate a range of industrial activities.

Ref.	Company	Swarm	Application
[25]	Doks. innovation GmbH	No	Inventory Management. Semi autonomous charging. Prior environment mapping required to localize the UAV.
[26]	Aeriu Smart Solutions Kft.	No	Inventory Management. Manual charging. Prior environment mapping required to localize the UAV.
[27]	Corvus drones	Yes	Crop, flowers, and plant management
[28]	Amazon	No	Inventory Management and outdoor delivery. Semi-autonomous outdoor localization.
[29]	FedEx	No	Inventory Management and outdoor delivery. Semi-autonomous outdoor localization.
[30]	Walmart	No	Inventory Management and outdoor delivery. Semi-autonomous outdoor localization.
[31]	IKEA	Yes	Inventory management. Semi-autonomous localization
[32]	DSV	Yes	Inventory Management. Manual charging. Prior environment mapping required to localize the UAV.
[33]	Ceva Logistics	Yes	Inventory Management. Manual charging. Prior environment mapping required to localize the UAV.
[34]	Hardis Group	Yes	Inventory Management. Manual charging. Prior environment mapping required to localize the UAV.
[35]	Aucxis	No	Inventory Management. Manual charging. Prior environment mapping required to localize the UAV.

to execute tasks remains relatively uncommon. The existing gaps in realizing fully autonomous UAVs within industrial contexts have motivated us to delve into researching technologies capable of bridging these gaps. Consequently, this pursuit has led us to formulate the research questions that are elaborated at the end of this section.

Furthermore, as most of the research on MAV swarms in an indoor environment is relevant for industries, in this work, all the publications from the previous ten years related to MAV swarms operating indoors are considered. This work focuses on the technology aspect rather than the business and management aspect. The Technology Readiness Level (TRL) is used in this work to assess the advancement of a technology from its initial theoretical or conceptual stage (TRL 1) to its deployment and utilization in real-world settings (TRL 9) [36]. The different levels are explained in detail in Appendix B. This work also aims to help new researchers who would like to begin research in MAVs in indoor logistics by giving them an overview of the technological developments and trends in this field. Considering the points mentioned above from a production and logistics practitioner's perspective, we seek answers to the following research questions:

1. Which localization technologies are preferred, and how accurate and cost-effective are they?
2. What type of guidance, navigation, and control (GNC) methods are used in MAV swarms, and how does each contribute to system autonomy?
3. MAVs are considered suitable for indoors. What are the safety concerns regarding deploying MAVs in industries?
4. What are problems faced to achieve 24/7 operation of the MAV swarm and what approaches are discussed to resolve them?
5. What are the most suitable swarm communication systems for an indoor industrial application?
6. What is current trend seen for MAV swarms in industries with regards to AI?
7. What are the tasks that are being or could potentially be performed using MAVs in industries?
8. What are the research gaps regarding deployment of MAV swarm in industries?
9. What is the future scope regarding deployment of MAV swarm in industries?

The scope of this contribution is to answer the above questions by conducting a systematic literature review.

The remainder of this review is structured as follows. Section 2 presents the SLR methodology. In Section 3, this contribution is demarcated from related surveys to underline its novelty value. Section 4 gives a descriptive analysis of the eight categories: localization, control, guidance system, safety and security, UAV charging, communication, artificial intelligence, and applications. Every category has a subsection at the end to discuss the

relevant findings. Section 5 presents some observations based on all the relevant publications. Finally, this review concludes by answering the research questions in Section 6.

2 METHOD OF LITERATURE REVIEW

This SLR is based on the guidelines suggested by [37] and the process followed is similar to [38]. This work includes all the published works from 1 Jan 2011 – 30 Dec 2021 that is available to researchers to get a mental picture of the overall academic activity. Moreover, we also included some relevant literature from the year 2022. Google Scholar (GS) facilitates literature discovery by indexing every scholarly document it finds. A detailed list of the sources of Google Scholar can be found in [39]. GS has a more comprehensive coverage than Scopus, Web of Science and also IEEE Explore, and includes the great majority of the documents that they cover [40].

This work excludes works centered on agriculture, outdoor settings, or military applications. The reasoning behind omitting military-oriented research stems from the understanding that military tasks are largely geared towards outdoor and combat scenarios. Nevertheless, we acknowledge the potential relevance of certain military studies that could hold implications for indoor applications. Moreover, we also excluded student degree theses, patents, and paid content to ensure the quality of the work. The rationale for omitting patents lies in their non-peer-reviewed nature, which complicates the assurance of their quality and validity. However, it's acknowledged that certain patents may offer valuable insights into industrial trends. For this reason, all patents encountered have been cataloged in Appendix C. The detailed method, inclusion criteria and selection process adopted in this work are explained in Appendix A.

3 UNIQUENESS OF THIS REVIEW

A total of 37 literature reviews were identified during the selection process, as explained in Section 2. Among those, five were relevant to this review and are listed in Table 2. They are being discussed at this point to emphasize the novelty value of this contribution. In Table 2, a short content description is given regarding the commonalities and differences to. The five relevant reviews are listed in chronologically descending order.

Analyzing the articles in Table 2, Rejeb et al. focuses on the business and management aspect of using UAVs in the supply chain [8]. Dias et al. focus on swarm robotics in general. Therefore, they do not include all researches in the field of indoor UAV swarm focused at indoor logistics [43]. Skrinjar et al. focuses on only the localization techniques used in indoor environment [44], Obeidat et al. covers only the applications of UAVs [41]. Ucgun et al. reviews

Table 2: Related literature reviews

Ref.	Year	Author & Description
[8]	2021	A Rejeb et al. perform a SLR to examine the potential and challenges for UAVs to be integrated in supply chain. They focus towards the managerial aspect and the benefits for an organization on incorporating UAVs in the supply chain. They do not delve into the technological aspect of UAVs.
[41]	2021	Obeidat et al. presenta survey on indoor localization and localization detection techniques. The localization systems in the survey include satellite-based navigation, inertial navigation systems, magnetic-based navigation, sound-based technologies, optical-based technologies, and RF-based technologies. The authors compare the localization systems in terms of accuracy and cost. Finally, they give an overview of the most common localization algorithms and methods.
[42]	2021	Ucgun et al. survey the wired and wireless charging stations for charging batteries used in rotary-wing UAVs. The authors compare the charging stations based on energy efficiency and reliability.
[43]	2021	Dias et al. review fundamental concepts related to swarm robotics, frameworks, simulators, platforms, basic behaviors and tasks, tools, and application fields in swarm robotics. They also discuss the techniques currently applied to solve the field problems and the research tools used.
[44]	2018	Jasmina et al. review the contributions of UAVs in logistic processes such as delivery and warehouse operations. The authors highlight the advantages of incorporating UAVs in logistics.

only the charging stations for UAVs [42]. None of the related surveys focuses on the technological aspect of MAV swarms in indoor or industrial environments. Therefore, this SLR aims to bridge this research gap.

4 DESCRIPTIVE ANALYSIS OF LITERATURE CORPUS

1997 publications were obtained from the inclusion criteria and were analyzed based on the selection criteria. 185 of them made it to Stage IV as their full text satisfied the Selection Criteria. Table 3 illustrates the number of contributions per stage. In this work, the publications that reached Stage IV are considered for further analysis.

Figure 2 depicts the distribution of all the 37 relevant literature reviews. Seven literature reviews cover swarm behavior, algorithms, applications, challenges, swarm optimization, and advancements in swarm robotics: grouped under the swarm category. The guidance system (GS) category consists of reviews focusing on path planning, collision avoidance, and routing algorithms. This category has eight reviews. There are two reviews related to UAV swarms in logistics. Analyzing Figure 2 reveals that more than 60% of all the related reviews are from the years 2020 and 2021. GS and Swarm's categories dominate in terms of quantity. The Navigation System category consists of publications focusing on localization and map building [45].

Localizing a UAV indoors is fundamental when developing an autonomous UAV swarm. Among all the research that reached the final stage, most of them focused on localization. Therefore, based on our criteria, localization is one of the most researched fields, and we

Table 3: Examined Publications per Stage.

Stage	No. of Publications
(I) Keywords	1997
(II) Title	805
(III) Abstract	371
(IV) Full Text	185

discuss it in section 4.1. Once localized, a UAV needs to have a precise and stable flight. A controller can direct a UAV's flight and is regarded as the brain of a UAV. Thus, the UAV controllers are discussed in section 4.2. A sound guidance system would ensure a collision-free path for a UAV swarm and will be discussed in section 4.3. Safety is paramount when deploying a UAV swarm indoors and is discussed in section 4.4. Communication among MAVs and MAVs to a base station is essential to achieve a swarm behavior and will be discussed in section 4.6. Subsequently, works incorporating AI on UAVs are discussed in section 4.7. Incorporating the technologies mentioned above on a MAV, it is possible to use MAVs in industries. Therefore, in section 4.8, we look at the works that have deployed MAV swarms for various industrial applications.

4.1 Localization

Among the 185 papers that reached stage IV, 27 papers were focused on indoor drone swarm localization, adhering to the selection criteria in Table 13. Yearwise distribution of these publications can be observed in Table 5. One can observe that there has been a substantial increase in the number of relevant publications from 2019 to 2021.

A key challenge in designing truly autonomous UAVs is the UAV localization problem. UAV localization is

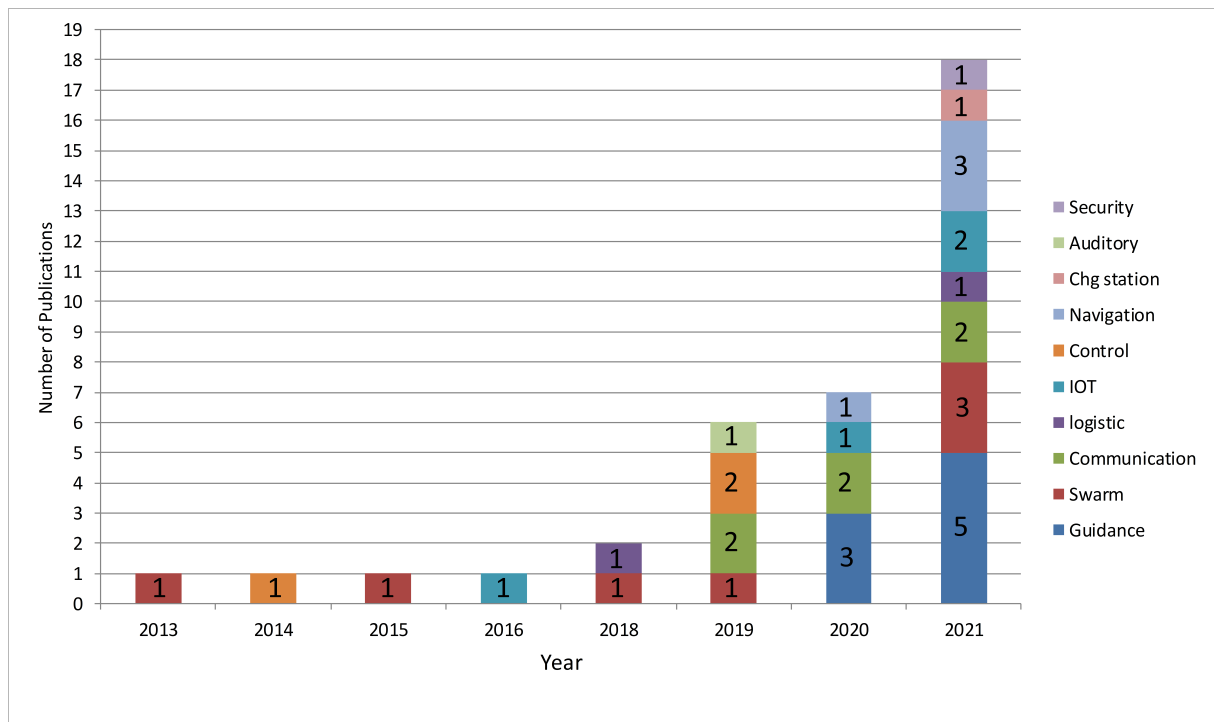


Fig. 2: Distribution of literature reviews by year

determining a UAV's position (e.g., coordinates) relative to a global reference frame or a local reference frame. Accurate knowledge about the 3D position is essential for UAVs to navigate autonomously to different points in space and perform aerial coverage tasks such as exploration and mapping.

Global localization methods for indoor UAVs using external systems such as motion tracking cameras are accurate and have low computational complexity. However, the coverage area of each motion-tracking camera is limited, and the cameras must be positioned in such a way as to ensure that they can see all the objects that need to be tracked, which could be a problem in a crowded warehouse. The number of motion tracking cameras required depends on several factors, such as the accuracy requirement and size of objects to be tracked. Therefore, such systems are limited in operation space, are expensive, and thus, are not practical for a large industrial setting. Local localization methods determine the position of a robot within a specific local area, typically indoors or in a small outdoor space, unlike global localization, which involves determining the position of a robot anywhere in the world. Local localization methods use onboard sensors and are independent of any external systems, therefore suitable for indoor industrial environments [46] [47].

In a collaborative drone swarm system, knowledge of the relative pose of neighboring UAVs is imperative. Algorithms developed for MAV systems can be either centralized, decentralized, or distributed. In a centralized approach, the data from all individual

sensor nodes is transmitted to a central node. The central node performs the computation for all the sensor nodes and shares the information with them. Thus, the computation is performed only once, which decreases the computation cost. The central node is also utilized for the coordination, communication, and task allocation between MAVs [48]. Centralized algorithms can produce globally optimal solutions; however, the overall system (or centralized system) is prone to failure if the central node fails or a communication problem occurs.

On the other hand, decentralized and distributed algorithms do not depend on a single node for communication. A single point of failure is removed, increasing the robustness and scalability with a more computationally efficient solution for a multi-UAV system. Systems employing these algorithms are also referred to as decentralized and distributed systems. These systems do not depend on a single node for communication and are tolerant of errors. A UAV can perform computations by relying directly on its sensors' measurements (decentralized) or by combining them with information communicated by neighboring UAVs (distributed). Distributed algorithms enable swarms of UAVs to gather information from disjoint locations simultaneously, which makes the swarm more robust to sensor failures since there is some redundancy in the system. A major drawback with the decentralized and distributed approach is that an individual MAV would require on-board sensors and computational capabilities, which will increase the weight and power consumption of the MAV. Moreover, there is

latency due to the lag induced by computations and communication decay due to the number of interactions among the swarm members [49, 50].

4.1.1 Localization Techniques

Localization techniques can also be classified into range-free and range-based localization, as shown in Figure 3. Range-based algorithms are more accurate than range free. Therefore, range-based localization techniques are mostly preferred for Indoor MAV swarm and will be discussed in this work [51].

Lateration: Lateration involves the determination of the robot's position based on distance measurements between the target and nodes. The position of the nodes is known. For instance, to estimate the location of a target in a 2D plane, three nodes with known locations are required [49]. In trilateration, three nodes are used to estimate the location. If more than three nodes are used, the technique is called multilateration. Lateration is used in approaches such as Time of Arrival (TOA), Two-Way Ranging (TWR), and Received Signal Strength Indication (RSSI).

TOA is the absolute time instant when a radio signal from a transmitter reaches a remote receiver. Differential measurements between TOA can also be used to compute distance, Time Difference of Arrival (TDOA). TDOA is less affected by radio reflection and is more accurate than TOA in the NLOS (Non-Line of Sight) situation. [50, 52].

In RSSI, the distance between the transmitter and receiver is estimated by measuring signal strength at the receiver. Differential measurements can also be used to compute distance (DRSSI) [50, 53].

In TWR, the Time of Flight of a radio frequency signal between the anchor and the node is measured, which is then multiplied by the speed of light to get the distance [49]. [54], [55], [56], and [57] use TWR to achieve localization.

Angulation: It is a direction-based technique using information about angles between nodes instead of

distances. It is used in the Angle of Arrival (AOA) approach.

In AOA, node location is estimated using the angle of arrival of two anchors' signals at the node. Unlocalized nodes use the triangulation method to evaluate their locations. AOA requires additional hardware, which makes it challenging to use with a drone swarm. Moreover, this technique is severely affected by NLOS situations [49, 50, 58].

Dead Reckoning (DR): The DR technique is used to estimate the present location of a moving object using a known previous location and velocity information over some time. The errors are cumulative as new position estimates are calculated solely from previous estimates. Typical sensors used for dead reckoning in robotics include wheel encoders, optical flow, and inertial measurement units (IMUs). An IMU is commonly used for dead reckoning. It consists of accelerometers, gyroscopes, and magnetometers, measuring triaxial acceleration and angular velocities. [41, 59].

4.1.2 Localization Technologies

The techniques mentioned above are commonly used with various technologies for localizing MAVs indoors. Some of the essential technologies are explained below:

Optical Based: The optical signal is an electromagnetic signal. Here, Infrared (IR) and Laser light-based technologies are discussed. Laser sensors are used for positioning. These sensors transmit a laser and analyze the reflected light. The time between transmission and reception of a short laser pulse is measured using a TOF system. This type of sensor is called light detection and ranging sensor (LIDAR). A drawback of LIDAR is the high computational cost which may affect the response in real-time applications [60]. IR systems are composed of a transmitter and a receiver. These systems require a Line of Sight (LOS) between transmitter and receiver, as IR cannot penetrate through solid objects such as doors and walls. IR systems are easy to deploy,

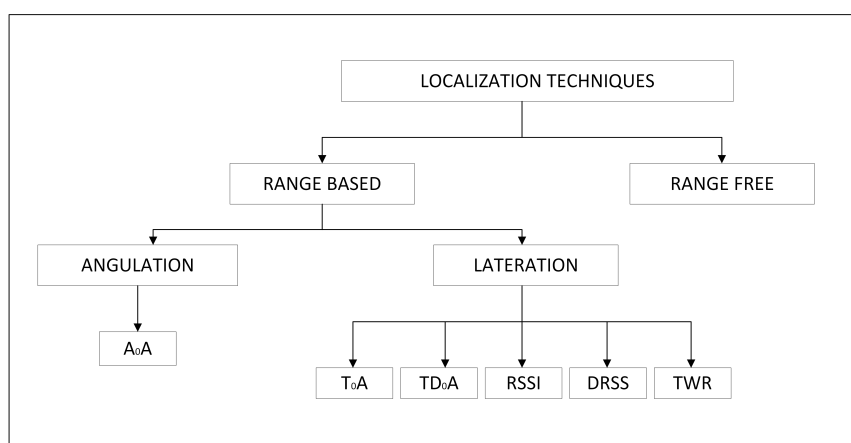


Fig. 3: Localization Techniques

lightweight, small in size, inexpensive, and mostly use the trilateration technique to estimate the location of a node[41]. IR is generally used for short-range, preferably under 5m, as its performance degrades for more considerable distances. Roozing et al. present a low-cost IR tracker with a general-purpose point-based pose estimation algorithm for localizing a MAV. The authors compared the accuracy against measurements from an onboard IMU and external stereo vision system [61].

Vision Based: Vision-based systems use a camera for localization and could be included in optical systems. As more than half of the publications use a camera for localizing a MAV, we categorize the vision-based systems separately in this work. Vision-based systems are considered the future of indoor navigation technology. They utilize RGB-D images from a monocular camera or multiple cameras to train and learn the models for localization. The wide availability of low-cost, low-power, lightweight cameras and advancements in computer vision techniques have made real-time vision processing much more practical. The pictures or videos captured by the camera can be processed onboard, or in an external system [62]. These systems can provide accuracy in several centimeters in environments with good visibility and well-defined features. However, accuracy can be affected by occlusions, lighting conditions, and environmental changes.

Visual odometry is widely used in robotics to estimate the motion of a robot (translation and rotation) in real-time using sequential images obtained from the camera. The main drawback of VO is that the accumulated errors may be significant. Visual odometry-based methods can be divided into feature matching (matching features over several frames), feature tracking (matching features in adjacent frames), and optical flow techniques [63]. Optical flow is one of the most commonly used techniques used for image-based navigation. Approaches based on optical flow estimate the motion based on the analysis of the sequence of frames caused by the relative movement between an object and camera [60]. In addition, fiducial markers such as Aruco or QR codes are also used to localize UAVs. The markers can be placed on the UAVs or fixed at known locations in the hall, enabling the UAVs to compute their location relative to the marker.

Fusing the Vision sensors measurements with other sensors, such as inertial or RF sensors, can improve UAV localization estimation, as shown in Figure 4. Li et al. use a deep neural network (DNN) based architecture on images from a monocular camera to achieve relative localization between MAVs. They use relative position estimates from UWB for labeling, and subsequent training of the DNN in a self-supervised way [64]. Their method is suitable for an industrial setting. However, the field of view of the AI Deck camera is limited to 87 degrees which could result in inaccuracies when flying

in constricted spaces. Zhang et al. use a servo camera to tackle the problem of restricted Field-of-View (FoV). They fuse UWB, VIO, and servo camera measurements to achieve localization accuracy of around 6 cm. In addition, Aruco markers are pasted on UAVs to enable other UAVs to detect and identify them [65]. The servo camera setup can compensate for the drift but not eliminate it. Using markers for identification is unsuitable when numerous drones are to be deployed, mainly due to the limited number of unique tag IDs[66]. Furthermore, a robot with many moving parts requires frequent maintenance and increases the probability of failure. An industry would want robust robots requiring low maintenance.

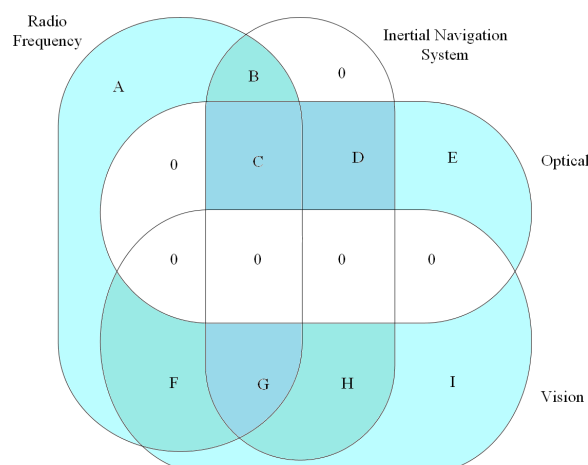
Holter et al. propose a visual relative localization system that monitors a 360 degree FoV using a spherical camera. They put fiducial markers on UAVs for detection and achieved a relative localization error of around 4 cm [67]. Finally, Nadler et al. present the design of two lightweight bearing-only sensors with low power consumption [68]. The first is a camera-based sensor using a spherical mirror placed in front of the lens to enable 360° field of view. The second one is a laser-based beacon together with a photo-diode-based sensor. They do not use odometry and achieve a mean localization error of 15 cm.

Cao et al. propose VIR-SLAM, a SLAM approach combining monocular camera and inertial measurements, to achieve visual-inertial odometry. To correct the drift error, authors use a UWB ranging with a static anchor placed in the environment. The drift is corrected when the anchor is visible to the camera. The authors perform a map fusion and implement collaborative SLAM to get the state estimation. They reported a start-to-end error of 4.8cm in 2D. However, in the z direction, the accumulated error was much bigger [57]. Chen et al. propose a visual multi-robot localization method based on stereo ORB-SLAM2 to obtain the state information and build the sparse local maps for UAVs [69].

Pavliv et al. present an approach to detect, localize, and track a drone swarm relative to a moving human using a headset with an embedded camera and IMU. They use a deep neural network(DNN) for drone detection. Their approach does not use artificial markers and is a step towards achieving human swarm interaction indoors, which is helpful in applications such as security, surveillance, and inspection [66].

Frame-based cameras record the entire frame at a pre-defined rate and capture unnecessary information. Moreover, under fast camera motions, the data may have motion blur, large displacements, and occlusions between consecutive frames [70]. These factors could result in inaccurate localization using cameras for fast-moving UAVs. Event cameras can detect movements thousands of times faster than standard frame-based cameras and could be used for localizing UAVs. They do not capture full images but rather asynchronously output the intensity change for each pixel. The EC has

Fig. 4: The distribution of publications based on the localization technologies used.



low latency (in order of microseconds), low power consumption, high dynamic range, and low bandwidth demands [71] [72]. None of the works in Figure 3 use an EC. There has been a sharp spike in the number of publications using EC for localization and ego-motion estimation. The list of publications has been well organized in a GitHub repository [73].

Radio Frequency (RF): RF waves can penetrate materials like walls and human bodies. The penetrating characteristics of RF waves reduce the multi-path effects and identify the user position with precise accuracy [90]. The position accuracy of an RF-based Ultra wide-band (UWB) system depends on the line of sight (LOS) conditions between the UWB anchors, and tags [91, 92]. UWB methods primarily utilize triangulation and angulation techniques [41]. UWB ranging or localization is rarely used as a standalone system. Instead, it is often integrated with other sensors such as IMU, optical, or sound sensors to improve the overall accuracy [93]. Many works use the Extended Kalman filter (EKF) for full pose estimation of a UAV [54, 55, 78, 80].

UWB offers many advantages, such as high-bandwidth transmission, low power consumption, robustness against interference, and centimeter-level accuracy performance. Thus, making it suitable for Warehouse management [94], Internet of things [95], industries [94], and other logistic applications [96]. Xianjia et al. overview the UWB-based networking and localization for robotic system [93].

Radio frequency identification (RFID) is also widely used for indoor localization. Dimitriou et al. propose a moving system instead of a fixed network of RFID antennas and readers, which could be deployed in warehouses, manufacturing, industry, or retail stores. A moving robot/MAV which hosts radio frequency identification (RFID) equipment aims to locate passive RFID tags attached to objects in the surrounding area. They achieved a mean localization error ranges between

Table 4: References corresponding to distribution of Figure 4

Representation	Count	Papers Reference
A	3	[74–76]
C	1	[77]
B	5	[52, 54, 55, 78, 79]
D	1	[80]
E	2	[53, 61]
F	4	[56, 64, 81, 82]
G	5	[57, 58, 83–85]
H	3	[66, 86, 87]
I	3	[67, 88, 89]

30 and 40 cm[97]. Furthermore, Orgeira et al. use RFID received signal strength measures and sonar values to develop a positioning system within a manufacturing plant for an indoor light part delivery UAV [94].

MAV swarms for indoor deployments face multiple challenges, such as a lack of infrastructure, limited sensors, limited computing power, and low-bandwidth communication. Purohit et al. propose a location-less coverage system that allows a resource-constrained MAV sensor swarm to collaboratively and efficiently attain sensing coverage of a target. They disperse anchor nodes(MAVs) in an area while maintaining radio connectivity among the nodes. Subsequently, explorers (MAVs) move and sense the environment while collecting radio signatures from anchor nodes. The explorers receive high-level commands from the base station to follow a defined path. Their method suits applications such as surveillance, search & rescue, or nuclear radiation monitoring [98].

Vision-based methods are intrinsically scalable but are sensitive to the visibility of the markers or UAVs. Marker-less detection requires heavy onboard

computation, which is problematic. However, relative localization based on wireless communication between UAVs is light, low-cost, and omnidirectional [55]. Steup et al. present a UWB-based localization technique suitable for a MAV swarm. Each drone is equipped with a UWB transceiver module for communication and distance measurement. Drones in a swarm can switch between a swarm member and an anchor node. The authors recorded the localization error to be predominantly in the range of $\pm 2\text{m}$ [74]. High positioning accuracy and low latency are essential to deploy drones in an industrial setting. In traditional UWB localization techniques, each tag performs a separate ranging process with all anchors thus, incurs a high system delay. Lee et al. propose a UWB-based positioning technology that reduces the network's overhead. They removed the overhead of distinguishing between nodes as anchors or tags. Each node performs the same operation. They separated the ranging and information transmission processes using an out-of-band network. The authors reported a positioning error of 32.89 cm [75].

Wei Sun presents a system to sense the relative position of nano drones in a swarm using RFID. Passive RFID tags are attached to each drone, and the relative position of all the RFID-tagged drones is estimated based on the spatial-temporal phase profiling [76]. Choi et al. present a lightweight UWB-VIO-based relative positioning method that combines UWB with VIO to perform device-to-device positioning without requiring pre-installed infrastructure or pre-learning. In addition, the authors incorporate intelligent virtual anchor generation control and adaptive ranging, which reduces computing complexity and power consumption. Moreover, it also makes the system robust against NLOS environments [85]. Generally, in a UWB setup, multiple fixed modules (anchors) are installed before they can localize one or multiple moving modules (tags). Natter et al. propose a method to remove the need for tedious initial manual setup. The authors disperse the MAVs in an environment and deploy them as anchors incrementally. Any flying MAV relies on both odometry and landed MAVs for localization [77].

Li et al. propose a technique to estimate the relative position of multiple UAVs by fusing the measurements from an IMU, an optical flow sensor, and a UWB. They use an EKF for state estimation [55]. Few other publications also use a similar approach with a variant of EKF to achieve localization with an error of less than 1 m [52, 54, 78]. Liu et al. propose a tight fusion method for 3D UAV localization by fusing the WiFi round-trip time and an IMU. They used an outlier EKF and reported it to perform better than the classic EKF [79].

The accuracy of RF-based localization systems can be affected by the density and distribution of RF sources, interference from other wireless devices, and the presence of walls and other obstructions. Therefore, the choice of localization technology to use depends

on the specific requirements and environment of the application. RF-based methods are typically better suited for indoor environments and can provide accuracy in several meters [99]. However, other localization technologies, such as vision or ultrasonic-based systems, can be more accurate and reliable in certain situations, such as in environments with high levels of RF interference or where a high degree of accuracy is required.

Inertial Navigation System (INS): An inertial navigation system (INS) employs inertial measuring units (IMU) such as an accelerometer and gyroscope to continuously calculate by dead reckoning the position, orientation, and velocity of a moving object [100].

Sound Based: Sound waves have a lower velocity than electromagnetic waves; this makes time synchronization easier and leads to high accuracy when estimating ToF. Localization using sound can be classified as ultrasonic and acoustic-based navigation systems. Liu et al. review various acoustic-based indoor localization systems [101]. Baisiri et al. present a suitable method to localize a swarm of MAVs. A single beacon MAV circles around a reference point in space while emitting continuous linear chirps of predefined frequency. MAVs are equipped with an onboard audio-based relative positioning system to measure the bearing of the beacon MAV without needing a communication network [47].

4.1.3 Discussion

The publications in Table 5 use external positioning systems such as optitrack or vicon or stereo-based systems as the ground truth to estimate a UAV position. Excepting six publications [52, 54, 55, 61, 64, 98], the others have not mentioned the weight and size of the UAVs deployed, and neither is it possible to compute the total weight and size of UAVs with onboard equipment. Therefore, we cannot comment on the preferred physical parameters of UAVs in a swarm working indoors. Homogeneous swarms consist of UAVs of the same model and similar computing characteristics. In a cluttered indoor environment, accurate NLOS operation of a swarm is essential. However, the methods used by only three publications are suitable for non-line of sight (NLOS) operation [54, 102, 103]. If not mentioned, we considered the swarm homogeneous, centralized, and not suitable for NLOS. The publications are also classified based on the ease of reproducing their work. Suppose a publication provides the link to an external repository with the code or explains clearly the step-by-step process of implementing their method. In that case, that publication is considered easily reproducible.

Analyzing Figure 4, one can infer that IMUs are not used alone for the localization task. A combination of UWB, INS, and Optical-based methods is the most popular. Based on our search criteria, we only found one publication each for localization using sound-

Table 5: Classification of publications focused on indoor localization of UAV swarm.
 NLOS: Non line of sight, I: Indoor, O: outdoor, OD: outdoor dataset, S: Simulation, C: Centralized,
 DC: De-centralized, D: Distributed, H: Homogeneous, NH: Non Homogeneous, Y: Yes, N: No

Pub.	[53]	[61]	[47]	[80]	[87]	[54]	[52]	[56]	[84]	[86]	[69]	[67]	[55]
Year	2012	2013	2014	2017	2017	2018	2018	2019	2020	2020	2020	2020	2020
Test Env.	I	I	S,O	S	I	I	I	I,O	O	I	S	I	S,I
Scheme	DC	C	C	DC	C	DC	C	DC	DC	C	C	C	C
NLOS	N	N	N	N	N	Y	N	N	N	N	N	N	N
Swar	H	H	H	-	H	H	H	H	H	NH	H	H	H
Ease Rep.	N	N	N	Y	N	Y	N	N	N	N	N	N	Y
Pub.	[102]	[65]	[74]	[66]	[89]	[58]	[57]	[64]	[78]	[88]	[83]	[79]	[85]
Year	2021	2021	2021	2021	2021	2021	2021	2021	2021	2021	2021	2022	2022
Test Env.	I,OD	I,O	I,O	I,	S,O	I,O	I	D	I	S,I,O	S,I	I	I
Scheme	DC	DC	C	C	DC	DC	D	DC	DC	DC	D	C	C
NLOS	Y	N	N	N	N	N	N	N	N	N	N	Y	Y
Swarm	H	H	-	-	H	-	H	H	H	H	NH	H	H
Ease Rep.	Y	N	Y	N	N	Y	N	Y	N	N	N	N	N

based [47] and Ultra Violet Direction and Ranging (UVDAR) techniques [89]. [86] uses measurements from a magnetometer, gyroscope, and optical flow to estimate the position. Only two out of the 16 Optical based techniques use IR system [53]. The others use a camera sensor.

The metrics for measuring localization accuracy vary depending on the algorithm and application domain. The metrics used are: mean position error, average error, root mean square error (RMSE), mean absolute error, mean square error, position error, and absolute trajectory. However, two other works used position error in pixels [64] and deviations from the ideal trajectory [53] as the metric. Ten publications used RMSE as the metric. The localization accuracy results varied with the flight duration and the number of drones. Thus, there is no single standard metric to measure the accuracy of drone swarms' indoor localization, making it challenging to compare the accuracy of the approaches used by various publications.

Among the 25 publications, only one work allows the temporary join or exit of the UAVs at run-time, referred to as plug-and-play [102]. Plug-and-play makes the swarm more robust and scalable and remains a relatively open research area. Scalability and robustness are essential properties for deploying a swarm indoors. One publication focused on the localization of UAVs specifically for an industrial environment. All 25 publications conducted testing and demonstrated their findings in simulated conditions or in a laboratory setting. Therefore, all of these publications can be classified as belonging to TRL 4. There is a lack of research concentrating on deploying UAV swarms in the industry, making it challenging for industries to gain full benefits from research in the indoor localization of MAV swarms.

4.2 Control

The control part constitutes a core part of a UAV. It controls the aircraft's stability and controls each movement robustly and precisely. In this survey, we consider UAV swarms, so we divide this control layer into three levels: the single UAV controller, collaborative control, and formation control.

In the first level, isolated low-level controllers are required to maintain the angular stability of each MAV relaying only in IMU sensors or even the position stability when localization sensors are involved in this control level. These low-level controllers are usually implemented when a commercial autopilot, like Ardupilot or Pixhawk, or a commercial MAV, like a DJI Tello or a Crazyflie, is purchased. However, the vast majority of these low-level controllers only provide attitude control, so the position of the MAV can drift over time. Therefore, a high-level controller is needed when more precise control is required, such as following a trajectory in space or tracking an object.

When individual UAVs are equipped with a controller, they can coordinate their movements to cooperate or go through space while maintaining a specific formation. The formation control layer supervises the behavior of each UAV to ensure a coordinated action of a group of UAVs towards an objective.

Similarly, collaborative control approaches for UAVs require an additional layer to define an overall task for the swarm. Subsequently, an appropriate architecture divides the task into sub-tasks for each agent. The UAVs interpret these sub-tasks as set points in their different control layers.

4.2.1 Single UAV controller design

Only 13 publications focused on designing UAV controllers, according to the inclusion criteria in

Section A.1. These inclusion criteria may leave out several relevant articles on the control of each UAV in isolation since some keywords like *swarm* may not appear in most relevant articles on UAV control. Isolate UAV control is the basis for generating collective behaviors among multiple UAVs. Thus, we have extended our inclusion criteria to cover state-of-the-art UAV controllers more reliably.

The control strategy for MAVs is generally a double-loop architecture, also known as cascade control. An inner loop for attitude stabilization and an outer loop for position control [104, 105]. Several different classes of controllers have been used to control MAVs. They can be broadly classified into three categories, as shown in Figure 5.

Linear controllers were the first controllers used to obtain a stable flight. The proportional Integral Derivative controller (PID) is one of the most popular controllers due to its simplicity. Other methods, such as Linear Quadratic Controllers (LQC), are control methods that use mathematical optimization to control the behavior of systems. There are two types of LQC: Linear Quadratic Regulator (LQR)[106] and Linear Quadratic Gaussian (LQG) controllers [107]:

- LQR controllers use linear control theory to optimize a cost function that balances the trade-off between control effort and system performance. The goal of an LQR controller is to find the optimal control inputs that minimize the cost function, which is a combination of the state of the system and control inputs. LQR controllers are widely used in control systems because of their simplicity, stability, and robustness.
- LQG controllers are an extension of LQR controllers that consider the presence of process noise and measurement noise. LQG controllers use Kalman filtering to estimate the system's state and optimize the control inputs based on this estimate. LQG controllers are commonly used in control systems with significant uncertainty in the system dynamics or measurement noise.

H-infinity control is another method mainly used for systems with external disturbances and model uncertainties. H-infinity control aims to minimize

the effect of external disturbances on the system by controlling the magnitude of the closed-loop transfer function. This method uses mathematical optimization to find control inputs that result in the best performance for the system, even in the presence of external disturbances. H-infinity control benefits control systems for its robustness, stability, and performance in the event of uncertainties in the model and external disturbances [108].

Since the quadrotor system has four inputs and six degrees of freedom, it can be considered a non-linear under-actuated system. Therefore, a non-linear (NL) controller is warranted to obtain a stable flight. Some commonly used non-linear controllers are feedback (FB) linearization, backstepping control, and sliding mode control (SMC). Intelligent control (I) covers a wide range of uncertainty compared to other controller categories. Model predictive control (MPC), fuzzy logic (FL), and neural network controllers are the types of intelligent controllers that are commonly used [109].

Romero et al. implement a model predictive contouring control (MPCC) for time-optimal quadrotor flight indoors. They address the problem of flying a UAV through multiple waypoints in minimum time by generating a path in real-time. Their approach is best suited for situations where UAVs are required to achieve high accelerations and aggressive attitude changes, such as in UAV racing. They can reach speeds of up to 60 km/h [110]. High-speed UAVs in industries could speed up industrial processes and save money. The University of Zurich has done substantial research on building high-speed UAVs that can beat professional human pilots in a UAV race [111–113]. However, more research is needed to make this technology safer and more viable for industries.

4.2.2 Collaborative control

Collaborative control, within the field of swarm intelligence, studies the ability of systems composed of multiple agents to execute a task in a coordinated manner. Over the years, several researchers have applied collaborative control techniques in mobile robotics (including UAVs) by imitating natural behaviors such as ant colonization, bird flocking, hunting packs, and others. Based on this, the control

Table 6: List of publication focused on control strategies deployed on UAVs.
FPID: Fuzzy PID, NMPC: Non-linear MPC

Pub.	[114]	[115]	[116]	[117]	[118]	[119]	[120]	[121]	[122]	[83]	[123]	[124]
Year	2014	2018	2019	2019	2019	2020	2020	2021	2021	2021	2021	2021
Category	L	I		I	I	I	NL	L	I	NL	I	I
Technique	LQR	FPID		Fuzzy	MPC	NMPC	SMC	H	NMPC	FB	MPC	NMPC
Swarm	H	-	H	H	H	NH	H	H	H	NH	H	-
Control	D	-	D	DC	D	C	DC	DC	C	D	C	-
Ease Rep.	N	N	N	N	N	Y	N	Y	N	N	N	N

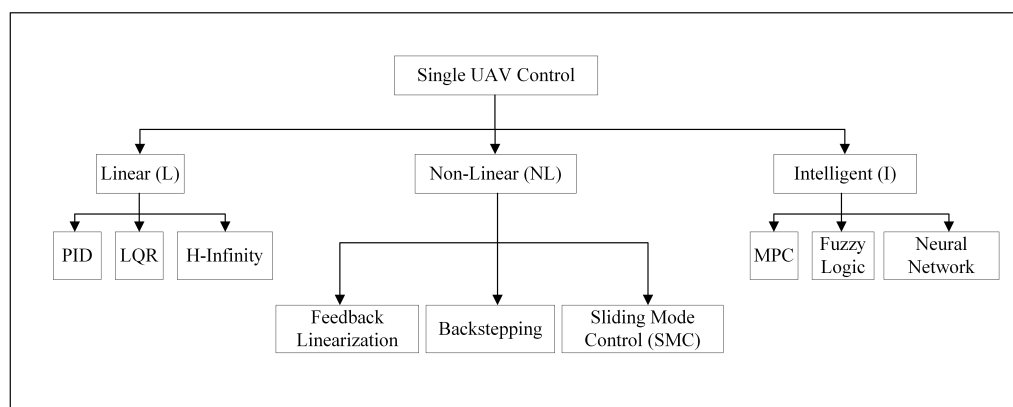


Fig. 5: Categorization of Controllers [109]

architecture is decisive in the coordination. Multiple works in the literature identify three types: centralized, decentralized, and distributed.

Therefore, in centralized architectures, task control depends on a central node; their main advantage is the simplicity of the agents in the swarm; however, their excessive dependence on the central system could be a problem. On the other hand, in the decentralized architecture, each agent performs its tasks autonomously or with a tiny intervention of the central node; its main disadvantage is the computational complexity of the hardware and software of each agent. Thus, distributed architectures leverage the advantages of both centralized and decentralized systems. For instance, Foerster et al. [125] use a centralized planning and distributed decision-making system to improve the limitations of single-agent observation; similarly, Luna et al. [126] propose a centralized task planning system with a distributed formation controller. In an indoor factory, collective perception of the environment can increase factory automation. Garcia et al. introduce two decentralized resource allocation schemes: 1. device sequential and 2. group scheduling. They evaluated the schemes in an industrial robotic swarm setting and applied them in a UAV swarming scenario [127]. In a recent approach of distributed control, where the authors propose a combination of locally centralized and distributed architecture to perform a cooperative navigation task, the centralized system estimates the positions of the UAVs in the first stage, and the corrections are calculated in a second stage with distributed collaborative estimations [128]. A similar approach using probabilistic estimation techniques can be found in [129].

In collaborative control proposals, the Multiple Travelling Salesman Problem (MTSP) is widely researched and has applications such as mapping, target tracking, and warehouse order-picking problems. Sathyan et al. follow the approach of minimizing the total time required to perform a task by the swarm to solve the MTSP problem. They propose a cluster-first approach that allocates each UAV to a subset of targets

[130]. On their side, Yazıcioglu et al. state a game theoretical solution to the distributed task execution problem, where a homogeneous team of robots plans their trajectories in a distributed manner to provide optimal service to cooperative tasks dispersed over space and time [131].

4.2.3 Formation Control

The swarm formation control has multiple applications and theoretical challenges that have attracted the attention of researchers in recent years. This technique organizes the robots in a global structure by modifying their locations to complete a defined task while considering their dynamic constraints [43]. According to [132], these systems face three main problems: formation generation, shape-retaining, and reconfiguration. In this context, the formation can be rigid (agents are moving to maintain relative positions), flexible (reconfiguration or splitting with detected obstacles), or both depending on the task [133, 134]. In the literature, several methods deal with the formation control problem. However, some authors [132, 135, 136] have grouped them into the following categories:

1. Leader-follower;
2. Virtual structure;
3. Behavior-based;
4. Consensus-based.

In this context, the leader-follower approach designates one or more agents in the formation to be the leaders and the others to be followers; in these cases, the trajectory path of the leader is the follower reference. The main advantage of this strategy is its simplicity and scalability; however, this configuration is highly dependent on the leader. For instance, the research presented by Rafifandi et al. [137] uses a pole-placement technique to develop proportional-derivative (PD) controllers for the follower in a real quadrotor scenario. Moreover, other researchers apply deep reinforcement learning techniques to perform this task [138–140]. In the case of a leader and follower failure, [103] propose a dynamic, collaborative navigation

Table 7: Classification of publications focused on formation control of UAV swarm.
C: Centralized, DC: De-centralized, D: Distributed, Y: Yes, N: No

Pub.	[114]	[87]	[157]	[116]	[137]	[56]	[69]	[158]	[65]	[159]	[144]	[160]	[161]	[145]	[162]
Year	2014	2017	2019	2019	2019	2019	2020	2020	2021	2021	2021	2021	2021	2021	2021
Category	4	1	-	3	1	4	4	1	3	3	3	4	1	3	4
Control	D	C	C	D	C	DC	C	D	DC	D	D	D	DC	D	D
Ease Rep	N	N	N	N	N	N	N	N	N	N	Y	N	N	N	N

model based on a hierarchical navigation structure to recover from the failure. Their approach improves the followers' positional accuracy and the swarm's navigation robustness.

In the virtual structure technique, UAVs should maintain a rigid geo-metrical relationship between them; its main challenge is to keep formation for collision avoidance tasks. Low and Ng [141] present a virtual structure approach based on curvilinear coordinates to get a flexible formation structure to avoid obstacles, and Cai et al. [142] combine the virtual structure technique with potential field to get a cooperative formation control.

On the other hand, in the behavior-based method, the control signal is obtained by the weighted combination of different behaviors, such as collision avoidance, moving to a goal, maintaining the formation, and others. For instance, Craig Reynolds developed the flocking behavior using three basic rules: cohesion rule, alignment rule, and separation rule [143]; other examples of flocking behavior can be found at [116, 118, 144–148]. Xinhua Wang et al. [149] uses the behavior-based strategy as an active fault-tolerant control method based on the principle of fault hiding to hide the failure.

Finally, the consensus strategy proposes cooperative control among swarm agents and is commonly used in decentralized systems. For example, in [150], Kuriki and Namerikawa propose a consensus-based control to keep the desired formation and decentralized MPC in each UAV to avoid obstacles. Furthermore, the research by Yan [151] shows cooperative guidance and control algorithms based on a second-order consensus algorithm. On the other hand, the authors in [152] propose a consensus control method using Riccati equations in discrete time.

The successful execution of a formation flight requires accurate location information. Accurate pattern formation of MAVs relies on either centralized or distributed control. Centralized control primarily relies on external tracking devices such as GPS or motion-capturing systems. Distributed control relies on onboard sensing, and MAV to MAV communication [153]. In this way, formation control could be a special case of collaborative control. The formation flying of UAVs is prone to failures or faults, often affecting the entire formation. The failures in UAVs generally include actuator and sensor failures. Therefore, fault-tolerant methods are required to ensure the error-free operation of the MAV swarm. Kalempa et al.

introduce an approach called Multi-Robot Preemptive Task Scheduling with Fault Recovery (MRPF) [154]. They evaluated the MRPF through experimentation on mobile robots in a small-scale physical warehouse called ARENA. In case a robot fails, MRPF ensures a replacement. MRPF is suitable for MAVs in logistics. Wubben et al. focus on resilience against losing any number of swarm elements and reconfiguring a swarm into any new desired formation [155]. Their approach can also handle swarm splitups so that a subset of the original swarm can still work together. Finally, Ramachandran et al. propose a method that enables a team of heterogeneous robots to reconfigure themselves to a new formation in case a robot's resource fails [156].

15 publications focused on formation control of UAV swarm and are listed in Table 7.

4.2.4 Discussion

In this chapter, we can observe different techniques used in the literature, starting with methods for the design of single UAV controllers up to the coordination of tasks and formation control. In this way, each control layer faces its own challenges.

When developing or using a controller, it is crucial to consider the angular stability based on IMU sensors; and the correction of accumulated errors in velocity and position, including the additional sensors used to correct them. Observing Table 6, it can be inferred that most publications use an intelligent controller, as it can manage the numerous uncertainties that occur during a UAV flight. However, no publications use AI-based techniques to develop a control strategy for an indoor UAV swarm. AI shows promising results in other fields and could help design a highly stable controller. The control methods are tested in a laboratory or a simulator. As the industrial environment is very different, experimentation in an industrial setting would give a clearer picture of the usability of the proposed controller for UAVs flying in an industry. Therefore, all publications in this category can be classified as belonging to TRL 4.

4.3 Guidance System

In this work, guidance systems include path planning and collision avoidance methods deployed on indoor UAV swarms.

Path planning uses sensor data and initial robot information to allow an autonomous robot to compute the best path from source to destination

without colliding with their environment [163], which constitutes an essential module for achieving safe autonomous flights. The computed path for the UAVs should be free from collisions such as inter-UAV and collisions with static and dynamic obstacles.

There are mainly two approaches, classic and probabilistic, in path planning algorithms. Classic approaches decompose the configuration space in a graph (cell decomposition, roadmaps or potential fields) and performs a search in the graph. The search algorithm computes the best path to overcoming challenges such as path length, obstacle avoidance, restricted areas, fault tolerance, completeness, UAV configuration, and other external factors [163, 164]. Some of the most used algorithms are Breadth-First Search (BFS), Depth-First Search (DFS), Dijkstra or A*.

The idea behind probabilistic approaches is to take random samples from the robot's configuration space, instead of decomposing it, and test them whether they are in free space or not. Then, one of the mentioned search algorithm computes the path to reach the goal through the graph. The most relevant probabilistic-based algorithms for planning are Rapidly-exploring Random Trees (RRT) and Probabilistic Roadmaps (PRM). Lu et al. propose a collision-free navigation system for UAVs to enable high-speed flights in cluttered environments like an industrial plant. First, they use a depth sensor to build a map of the environment. Subsequently, they develop a local planner using the RRT-based path generation algorithm and CHOMP objective function to select an optimal trajectory. Finally, the local planner combines localization, perception, trajectory optimization, and control to build a fully autonomous UAV system [165]. Punete et al. review AI-based approaches in path planning [163].

4.3.1 Collision Avoidance

Collision avoidance is one of the fundamental elements in an autonomous UAV to achieve a safe path. Sawalmeh et al. and Yasin et al. review the collision avoidance approaches for UAVs [166, 167]. Collision avoidance algorithms can be categorized into the following major methods:

- **Geometric Methods:** Geometric (Geo) methods compute the time to collision among UAVs and between a UAV and an obstacle. These methods utilize information such as velocities of both UAV and obstacle, the distance between UAVs and between a UAV and obstacles and the location of obstacles [166, 167]. These simple and computationally efficient methods can be used in simple environments. But, they might fail in cluttered environments.
- **Force Field Methods:** Force-field (FF) methods use a repulsive field to repel a robot from an obstacle or an attractive force field to pull it towards a goal. Different weights can be assigned to the forces when computing the UAV control commands [166].

FF methods are highly adaptable and perform well in dynamic and complex environments. On the other side, these methods need significant computing power and time, which makes this method unsuitable for small UAVs in real-life applications.

- **Optimization Based Methods:** Optimization (Opt) based methods aim to plan the most feasible collision-free trajectories for UAVs to reach the destination from current position. To address the high computational complexity of probabilistic search algorithms, several optimization methods such as ant-inspired algorithms, genetic algorithms, Bayesian optimization, gradient descent-based methods, particle swarm optimization, greedy methods, and local approximations are used [167]. Optimization methods provide high adaptability and accuracy in predicting obstacle locations and behaviours. However, their high computational cost and complexity can make these methods unsuitable for some MAVs applications.
- **Sense and Avoid Methods:** Sense and avoid (S&A) based methods react quickly to obstacles and are appropriate for dynamic environments. In this approach, a robot can be equipped with LiDAR, sonar, camera, and radar sensors. These methods focus on reducing the computational power by simplifying the process of collision avoidance to individual detection and avoidance of obstacles [167]. Lu et al. present a depth-based, robust, fast collision avoidance method for MAVs in a cluttered dynamic environment. They use only an onboard depth sensor and test their approach on a single MAV, but could be used for a swarm [168]. (S&A) approaches take advantage of various sensors that improve safety and are well-suited for dynamic environments. However, these algorithms can be rather complex and provide limited accuracy in predicting obstacles compared with other methods.

A total of 23 publications focused on computing a safe, collision-free path for a swarm of UAVs in an indoor environment. Work by Honig et al. is the only research focused on navigating a UAV swarm in a warehouse setting [169]. Ourari et al. simulate a virtual package delivery by UAVs using Deep RL [170]. Zhou et al. propose an algorithm suitable for a UAV swarm in an obstacle-rich environment and experiments in a forest [171]. The other works are motivated by something other than an application suitable for an indoor industrial setting. Table 8 compares 22 papers based on 5 categories. Jang et al. describe a 3D reference trajectory generation and tracking control method for a UAV without a clear method for collision avoidance; thus is not included in Table 8. Peterson et al. present an automaton-theoretic approach for generating collision-free paths for a multi-agent system such that each UAVs task is expressed as a Time-Window Temporal Logic (TWTL) [172]. Commonly used metrics by

the works listed in Table 8 include trajectory time, trajectory length, safety ratio, solver time, distance to an obstacle, computation time, total time required, goal completeness, distance traveled, and average episode reward.

4.3.2 Discussion

Environmental disturbances exist in the industries and significantly impact UAVs [167]. However, the publications must consider environmental effects while designing their methods. Analyzing Table 8, it is observed that publications mostly use optimization or force field methods for collision avoidance. Only one work uses Deep RL to ensure a collision-free path. Six publications use a decentralized approach, and four works are reproducible. None of the works uses a heterogeneous UAV swarm. All publications in Table 8 conducted testing and demonstrated their findings using simulations or in a laboratory setting. Therefore, all of these publications can be classified as belonging to TRL 4.

Based on the observations, more industry-focused research is necessary to deploy a UAV swarm in an industry. In addition, quickly reproducible methods help bring the technology faster to the industries. Moreover, AI-based techniques for guidance systems in an indoor UAV swarm could help create a safer environment for UAVs operating alongside humans in an industry. It is essential to consider environmental factors to deploy UAVs successfully in the industry. Moreover, experiments with UAV swarms around humans should be performed in a natural environment, as industries would feel safer deploying such swarms in reality. Therefore, works on ensuring a safe UAV flight indoors are discussed next.

4.4 Safety and Security

Safety is paramount when deploying UAVs indoors and around humans. In recent years the use of UAVs in industries has significantly increased, making the mitigation of risks due to onboard avionics malfunctions essential to ensure a sustainable and safe flight. Therefore, UAVs nowadays use a fault detection system to detect and mitigate the fault's effects on UAV performance.

Four key features are primarily present in a fault detection system [190]:

- Fast detection of abnormal situations;
- Identification of the fault and the faulty equipment;
- Robustness to noise and uncertainties;
- Low false alarm rate.

Faults can be divided into three categories [190]:

1. Sensor faults: a malfunction of the sensors on-board the UAV.
2. Actuator faults: a malfunction of actuators acting on system dynamics. For instance propeller loss, electrical or mechanical actuator failure.
3. Process faults: a strong change in system dynamics due to structural problems.

Amato et al. propose a fault detection and isolation algorithm for low-cost multi-rotor UAVs with duplex sensor architecture. The proposed procedure detects and isolates faults on inertial measurement units (IMUs) onboard a UAV. The hardware consists of two IMUs fitted on a tri-rotor UAV. A particle filtering approach deals with the attitude estimation problem [190]. Barbeau et al. use error tolerant path planning algorithm for MAV swarms to handle errors due to

Table 8: Classification of publications focused on guidance system for indoor UAV swarm. Publications test their method either with a Dynamic (D), Static(St) or without an obstacle. However, all methods implement inter UAV collision avoidance. S: Simulator, I: Indoor, C: Centralized, DC: Decentralized

Pub.	[173]	[169]	[174]	[175]	[176]	[177]	[178]	[179]	[180]	[181]	[172]
Year	2018	2018	2019	2019	2019	2020	2020	2020	2020	2020	2020
Method	Geo	Opt	Opt	FF	Opt	FF,Opt	Opt	Opt	Opt	Opt	-
Test Env.	I	S, I	S,I	I	S	I	S	S,I	S	S,I	S
Approach	C	C	C	C	C	C	C	C	C	DC	DC
Obstacle	D	St	-	St,D	-	-	St	St	St	D	St
Ease Rep.	N	N	N	N	N	N	Y	N	N	N	Y

Pub.	[182]	[183]	[89]	[171]	[170]	[184]	[185]	[186]	[187]	[188]	[189]
Year	2021	2021	2021	2021	2021	2021	2021	2021	2021	2021	2021
Method	FF	Opt	S&A	Opt	DRL	FF	Opt	FF,Opt	Geo	Geo	S&A
Test Env.	S	I,O	S,O	I	S,I	S,I	S,I	S,I	S	S	S
Approach	C	DC	DC	DC	DC	C	C	C	C	C	C
Obstacle	St	St	D	St	-	D	St	St,D	St	-	St
Ease Rep.	N	N	N	Y	N	N	Y	N	N	N	N

faulty sensors and errors due to weather conditions [191]. MAVs communicate and exchange information providing an adaptive error-tolerant navigation system.

Lanzon et al. solve the problem of controlling a quadrotor when one of the rotors can no longer supply thrust. They use a dual control loop architecture in which model-based techniques are adopted in both control loops to deal with a rotor fault [105]. In addition, they proposed a novel control strategy allowing the vehicle to use the remaining three functional rotors to enter a constant angular speed around its vertical axis, granting stability and representing an effective way to deal with rotor failure in quadrotor vehicles. Whereas, Lanzon et al. based their control strategy on external state estimation, Sun et al. proposed an algorithm that combines fault-tolerant control and onboard vision-based state estimation [192]. They achieved accurate control of the position of a quadrotor during a motor failure scenario without any external help.

Another important factor in security is data. The data captured by UAVs are precious and sensitive. Thus, it is essential to ensure secure data transfer between UAVs and UAVs to the ground station. Efficient techniques are required to protect UAVs from hackers and cyber-attacks. Syed et al. review three techniques, block-chain, ML, and watermarking, for securing data transmission of UAVs [193]. Jamming attacks are also a severe threat that causes a malfunction in UAV systems. Such attacks are even more dangerous for resource-constrained UAVs operating in a swarm. Jamming attacks can dramatically degrade the network performance by interfering transmitting of packets [194]. Mykytyn1 et al. propose a real-time Jamming detection mechanism for an IR-UWB ranging technology in an autonomous UAV swarm [195]. The mechanism utilizes the network parameters available to the system and some additional measures to distinguish between lousy transmission quality and Jamming to avoid false positive alarms.

4.4.1 Discussion

Safety and Security, seemed not to be a significant field of research today. There is also a lack of research regarding individual UAVs' safety while working collaboratively in a swarm. Moreover, none of the publications explicitly focus on UAV swarms or industry environments. Therefore, further research could increase UAV's industry deployment and robustness or reduce drone malfunctions. In addition, this would decrease the cost of automation in the industry using a MAV swarm. All publications conducted testing and demonstrated their findings using simulations or in a laboratory setting. Therefore, all of these publications can be classified as belonging to TRL 4.

4.5 MAV charging

Energy consumption is one of the biggest problems that MAVs face. MAVs mostly use lithium batteries to meet the energy requirements of onboard equipment, such as sensors, actuators, propellers, and controllers.

Unfortunately, the battery life for MAVs flying indoors generally varies between 10 min and 30 min [196], significantly limiting the applications a MAV can perform. In addition, batteries need to be charged or replaced to ensure continuous MAV flights. MAV batteries can be recharged via wired power transmission or wireless power transmission [42]. Ucgun et al. review the charging stations to charge the batteries of the rotary-wing UAVs [42].

A MAV swarm's energy requirement needs to be managed based on the task performed by individual MAVs. For instance, it would be wasteful to charge a MAV to maximum capacity if it is known that the task requires much less energy. Therefore, energy optimization algorithms are needed to reduce the wastage of unused energy. Moreover, exploiting environmental information gathered by swarm members would reduce the swarm energy costs. Efficient energy allocation would enable better and more prolonged cooperative operation of a MAV swarm. Chen et al. present an adaptive, energy-efficient, and energy-aware approach that minimizes a swarm's overall energy cost while maximizing swarm performance during foraging. Each robot stores energy thresholds and capacity variables to indicate the energy requirement and usage during foraging [197]. Mostaghim et al. introduce a PSO-based search mechanism called Energy Aware PSO, which considers each individual's energy consumption. Individuals estimate the required energy to move to the next position, then decide by considering the trade-off between profit in terms of the overall gain in the search process and the energy consumption cost [198]. Timothy and Dario compare three strategies suitable for UAV swarms, characterized by minimal computation, communication, and sensing requirements. They deployed the UAVs for a search task in an unknown environment. They used the Energy-Time-Product metric, measured in Joule-Seconds, to estimate the total energy consumption [199].

Charging stations can charge the batteries of single or multiple UAVs at a time. However, the charging stations are limited in number. Therefore, Hassija et al. propose an adequate, fair, and cost-optimal scheduling algorithm first to serve the most needed drone. A game-theoretic approach with constraints of optimizing criticality and task deadline is used to cost-effectively model the energy trading between the drones and charging stations. The energy system heavily constrains the overall flight duration of a MAV swarm [200]. Zhang et al. develop an autonomous mobile charging station for the UAV swarm system that automates the mission cycle, including taking off, complete area coverage, vision-based positioning, landing, and recharging. The authors propose charging scheduling algorithms and an area coverage policy to prolong the endurance of the UAV swarm [201].

4.5.1 Discussion

Environmental conditions such as wind, temperature and humidity could affect the energy consumption of a MAV swarm. However, there needs to be more research accounting for the above factors in optimization algorithms. Moreover, there need to be more AI algorithms to optimize the energy consumption of the MAV swarm. Furthermore, AI could predict future energy consumption based on various internal and external factors.

There is also a lack of research regarding individual UAVs' energy consumption and requirement while working collaboratively in a swarm. For instance, individual UAVs could have different energy requirements in a heterogeneous swarm. Therefore, further research could increase UAV's flight time, reduce idle time and optimize energy consumption. In addition, this would decrease the cost of automation in the industry using a MAV swarm. All publications conducted testing and demonstrated their findings using simulations or in a laboratory setting. Therefore, all of these publications can be classified as belonging to TRL 4.

Additionally, research by Stephen Baur highlights a significant decline in the cost of lithium-ion batteries, plummeting from \$ 917 per kw/h in 2011 to \$ 101 per kw/h in 2023. Concurrently, battery densities have demonstrated a yearly improvement of nearly 10% [24]. These trends collectively suggest that future MAVs will possess more powerful batteries, enabling them to accommodate larger payloads. This advancement would lead to many new use cases for MAVs, particularly in warehouse environments.

4.6 Communication

Communication plays a critical role in the performance of a swarm, as UAVs interact with each other to exchange knowledge about their environment. In general, multi mobile robot communication [202], and also UAV, can be divided into three categories;

- Explicit communication: UAVs directly and intentionally communicate with their teammates through some active means;
- Implicit communication: Uses the environment as a means of communication. Each UAV modifies the world to convey information to others that are captured using onboard sensors, i.e., stigmergy;
- Passive recognition of actions: UAVs use sensors to directly observe the behavior of their companions, decode it and interpret their actions.

Different approaches to multi-robot communication have their advantages and limitation. Stigmergy is simple and does not require explicit communication, but it is limited by the robot's perception of the environment. In [203], the authors proposed stigmergy to solve swarm communication for micro-UAV in an

unstructured environment. This approach leverages the modification of the environment to store information to solve the sparse payload available for complex onboard sensors. However, stigmergy is currently challenging to implement in real robots, so they proposed two approaches and tested them in a virtual environment. Since these approaches do not require global localization, they suit indoor environments. Passive action recognition is communication-free, but it depends on the robot's ability to interpret sensory information and analyze other robots' actions. In [204], the proposed system uses a passive action recognition technique that mimics the waggle dance of honey bees to form and recognize different patterns, which allows the robots to communicate with each other without the need for explicit communication channels.

Explicit communication is direct and effective but requires a reliable communication channel and mechanisms to handle communication failures. However, stigmergy and passive action recognition may be exciting fields of study but are mainly useful in changing environments with unreliable communication. In an indoor industrial environment, assuming that the infrastructure can enable fairly reliable channels to allow explicit communication is acceptable.

Explicit communication is performed between flying UAVs and the ground station (GS). UAVs can also be aerial user equipment or flying base stations (BSs).

There are already many surveys in the literature reviewing explicit communication. [205] states that satellite communication technology is preferred for drone communication when used for security, defense, or longer-range operations. In contrast, cellular communication technologies are preferred for civil and personal applications. However, for indoor communication, especially in the case of mesh networks and wireless sensor networks (WSN), communication using Bluetooth and other point-to-point (P2P) protocols has proven more efficient. This survey focuses on emerging communication technologies for unmanned aerial vehicles and their applications for next-generation wireless networks in an indoor environment.

[206] is a study of Unmanned Aerial Vehicle Communication Networks (UAVCN), defining it as a specific type of Mobile Adhoc Network (MANET) composed of a set of UAVs to build a network. This study describes the main issues affecting a UAVCN: high speed of mobile nodes and continuous change in the network's topology affect the routing mechanism and quality of service and optimize the limited power. It also provides a detailed taxonomy of wireless networks for next-generation UAV communication networks, their characteristics, design issues, routing, quality of service, power and energy consumption, and some applications in which UAVs will perform best.

UAV-based aerial networks and flying base stations enhance coverage and allow reliable, flexible, fast wireless connections. [207] tests the use of relay UAVs

within role-based connectivity management that extends a UAV's operational range while maintaining reliable communication between UAVs and GS.

[208] provides a comprehensive review of the potential applications of UAVs in conjunction with IoT and 5G technologies. In addition, it addresses the various technical, logistical, and security challenges that must be considered to ensure their safe and effective use. UAVs can also enhance wireless networks and 5G systems. Thus, they play a significant role in Internet of Drones (IoD) architecture.

In the Internet of Drones (IoD) [209] [210], UAVs are considered networked objects which can communicate among themselves and with several network entities deployed on the ground. An overview of the research activities on the IoD network architecture is provided in [211]. The authors also explain the communication technologies: Wi-Fi, mmWave, and machine-type communication and their application domain.

One exciting application of the UAV swarm network can be found in [212]. In this paper, the authors propose a method for detecting the coordinates of victims in emergencies using Wi-Fi signals generated from their phones and a flying network of UAVs. The method includes a new protocol for communication between UAVs and UAV swarms and a structure of UAV swarms to optimize search time.

Machine learning and AI-based techniques can also enhance the communication capabilities of multi-UAV systems. [213] presents an extensive overview of machine-learning applications in networks with UAVs. Based on the communication and network aspects implemented, these techniques are classified as follows:

- Physical Layer: including channel modeling, interference management, and transmission parameters configuration.
- Security and Safety: including physical layer security and public safety applications.
- Resource Management and Network Planning: including energy efficiency and power control, multiple access and routing protocols
- Position Related Aspects: detection, localization, placement, and trajectory design.

Finally, the authors conclude that deep learning-based solutions are useful for revealing correlations in large and heterogeneous datasets. However, they may not be practical in scenarios where UAVs have limited processing capabilities, energy constraints, and limited connectivity. In such cases, lower complexity solutions that involve local estimation and processing of parameters, such as reinforcement and regret-based learning, may be more appropriate.

One example of reinforcement learning applied to communication is proposed in [214]. The proposed framework considers multiple agents communicating over a noisy channel in a multi-agent reinforcement learning framework. As a result, the agents learn to collaborate and communicate effectively, resulting in a

superior joint policy. One of the real-world applications of this framework is drone swarm control.

[217] studies the possibility of using radio frequency identification (RFID) in communication inside a swarm of drones. The results show that this technology increased the protection against external interception and interference and decreased energy consumption.

Since there is a lack of dedicated spectrum for UAV communications, the large radio-frequency (RF) transmission footprint from a UAV can cause interference to cochannel ground communication links, significantly deteriorating their performance. As a result, it is necessary to design efficient spectrum-sharing policies for UAV communications to enhance spectral efficiency (SE) and control interference to ground communications. [218] analyze the implementation of spatial spectrum sensing (SSS), a technique for spectrum sharing that enables devices to sense spatial spectrum opportunities and reuse them aggressively and efficiently. [220] propose a centralized Cognitive Radio Network-based communication approach, using a Ground Control Station as a coordinator. Dynamic Time Division Multiple Access techniques share available frequencies between the UAVs. The proposed approach is evaluated in a surveillance context regarding data transfer time, packet count, and achieved throughput.

The radio frequency environment in some environments such as urban regions is complex, and meeting the latency thresholds of each receiver requires considering the propagation environment and selecting the best candidate nodes for transmission. Increasing SNR at the receiver is one way to ensure timely and correct packet delivery. [221] presents a novel distributed beam forming framework called SABRE for UAVs, which optimizes the selection of transmitters to achieve the best possible user-defined Quality of Service (QoS), considering factors such as the relative distances to receivers, traffic characteristics, the desired cumulative Signal-to-Noise Ratio (SNR) at the receiver, and the estimated individual SNR for each link. This work is flexible enough to be deployed on next-generation wireless protocols like WiFi 7, 5G/6G, and stand-alone aerial UAV networks.

IEEE 802.11ah is a promising technology for IoT applications due to its high data rates, flexibility, MIMO capabilities, and low power consumption. However, the performance of the communication links between UAVs and GCS in a UAV swarm can be affected by range and throughput requirements. To address these issues, [216] propose incorporating MultiCode MultiCarrier Code Division Multiple Access (MC-MC CDMA) in the physical layer of IEEE 802.11ah. The authors conclude that by incorporating MC-MC CDMA into IEEE 802.11ah, the overall performance aligns with the trade-off between data rate and throughput.

[219] explores the maximum sum rate performance for cellular-connected UAV swarm communications

Table 9: List of researches related to communication. SAR: Search and Rescue

Pub. Year	Problem Focus	Solution	Application
[207] 2014	Establish a reliable and continuous communication between an operator and the UAVs	Role-Based Connectivity Management to maintain reliable communication in UAV swarms	-
[204] 2016	Overcome limitations of implicit and explicit communication methods in adverse environments.	Proposes a novel multi-robot communication system, that uses a passive action recognition technique.	SAR
[215] 2019	Routing protocol have light fidelity.	Design a protocol referred to as the link velocity connectivity algorithm for indoor Flying Ad-hoc Network	Indoor UAV swarm
[216] 2020	Overcome differential requirements of range and throughput for UAV to UAV and UAV to Ground Control Station (GCS).	Incorporate MultiCode Multi-Carrier Code Division Multiple Access in the physical layer of IEEE 802.11ah.	goods delivery, real-time video surveillance
[217] 2020	Joint application of RFID and UAV to ensure secure communication and low power consumption.	Uses RFID to form control and traffic channels of a distributed self organizing UAV system.	-
[218] 2020	Designing efficient spectrum-sharing policies	Proposes spatial spectrum sensing to enable devices to sense spatial spectrum opportunities and reuse them efficiently by controlling the SSS radius.	-
[203] 2020	Development of tasks in difficult, unstructured environments, with signal availability and communication limitations.	Two types of swarm behavior (SLABE and SEPHT) that use stigmergy as an indirect communication are proposed.	Inspect unknown indoor environment.
[219] 2021	Cellular-connected UAV swarm communications	Proposes an iterative algorithm to solve the sum rate maximization problem.	UAV assisted IoT.
[212] 2021	Detecting the coordinates of subscribers with the Wi-Fi signals generated from victims' phone.	Designs a cluster-based Multichannel MAC IEEE 802.11p protocol.	SAR
[214] 2021	Multiple agents communicating over a noisy channel.	Propose a DRL technique employing DDPG, and actor-critic algorithm to significantly improve the block error probability of the resultant code.	-
[220] 2021	Overcome the spectrum scarcity issue faced by UAVs.	Propose a centralized cognitive radio network based communication approach for UAVs-GCS communication. Deploy two frequency sharing strategies based on dynamic TDMA.	Surveillance
[74] 2021	Robust drone localization.	Propose a localization system based on UWB-Ranging to fixed anchor nodes for autonomous quadcopters extendable to swarm localization.	Indoor and outdoor environments.
[221] 2022	Latency in a radio-frequency environment with a high density of users	Propose a framework called SABRE that synchronizes airborne transmitters for data communication with target receivers based on user-defined QoS.	-

for IoT applications. The problem is formulated as a non-convex optimization problem and solved using an iterative algorithm that converges to a global solution. Simulation results indicate that the algorithm proposed can find an optimal antenna beamwidth to maximize the sum rate. Furthermore, an increase in the maximum transmit power of the UAV leads to an increase in the sum rate.

Microwave bands are widely used in terrestrial communication networks, but they may not be ideal for UAV communications due to the crowded frequency spectrum and high interference levels. Furthermore, with the increasing demand for wireless communication services, these bands are facing severe spectrum

scarcity, which can limit their availability and bandwidth for UAVs. In [222], the authors study the application of mmWave beamforming in UAV communication. In contrast to traditional lower frequency bands, mmWave bands have wider bandwidths, allowing for the transmission of larger amounts of data in a shorter time. This is especially useful for high-speed data transfer applications, such as high-resolution video streaming. mmWave communication has been successfully used in satellite communications and indoor short-range communications.

Reducing traffic loads for central cloud servers and decreasing latency and high throughput is essential to enhancing intra-UAV and UAV-to-GCS

communication. For UAVs, mobile edge computing (MEC) offers a solution to improve the quality of service. MEC computations are performed on edge devices such as UAVs, reducing network traffic and load on central servers. MEC is one of the central building blocks for 5G networks [223].

Generally, MAVs are constrained in energy and processing power, making long-term handling of large data volumes impossible for standalone MAVs. Mukherjee et al. propose load mitigation by offloading data from a source UAV to other swarm members with sufficient energy and processing requirements. They formulate a multi-armed bandit-based offload path selection scheme, which selects the most resource-optimized multi-hop path between a source and a target UAV in a decentralized edge UAV swarm [224].

Steup et al. propose a single-copter localization system using UWB transceiver modules for communication and distance measurement [74]. This system has been designed to be easily extendable to drone swarms and used in indoor and outdoor scenarios. Furthermore, the authors aim to create a scalable multi-hop drone swarm localization system where drones can switch roles between active members and anchor nodes.

In recent years new technologies are under study. Terahertz band communication and unmanned aerial vehicles (UAVs) are potential 6G technologies that can provide ultra-high rate and reliable wireless connectivity for critical scenarios. THz-UAV communication has several open issues and challenges, and since THz communication is highly affected by meteorological conditions, it is suited for indoor applications. [225] explores recent works and physical layer-related challenges and opportunities to inspire research breakthroughs.

4.6.1 Discussion

A total of 11 publications reached this stage, listed in table 9. Analyzing the table, one can infer there has been a steady increase in publications per year over the past decade. Moreover, none of the publications explicitly focus on establishing communication for UAV swarms in an industry. However, few works focus on devising communication strategies specifically for the indoor environment, which could be used in industries. There are also many surveys about communication techniques and applications on UAVs and swarms. Based on the papers reviewed, explicit communication is mostly preferred to establish communication among UAVs in a swarm indoors.

The commonly used metrics to validate the method are: packets received, bit error rate, data rate, spectral efficiency, re-transmission attempts, average throughput, average delay, number of collisions, energy consumption, and total flight time. All publications conducted testing and demonstrated their findings using simulations or in a laboratory setting. Therefore, all of these publications can be classified as belonging to TRL 4.

4.7 Artificial Intelligence

Incorporating AI on UAVs would enable them to perform complex tasks accurately, speedily, and intelligently in a complex and dynamic environment, similar to how a human would do [213, 226, 227]. 12 publications focus on using AI on a multi-UAV system, according to the inclusion criteria A.1. None of the works focus on deploying UAVs for automating tasks in the industry. Akhloufi et al. [228], and Sen et al. [229] test their method on a single UAV but is transferable to a swarm. Most works validate their approach using a simulator (S) or just a dataset (D).

Although AI encompasses many more fields, nowadays, we mainly refer to Deep Learning (DL) when we talk about AI applied to robotics. The main advantage of deep learning techniques is that it is unnecessary to code the solution for each case it faces. Instead, it is only necessary to acquire sufficient information so the neural network can learn the main features to obtain the desired answer, facilitating the realization of more robust behaviors. However, neural networks require high computational resources, which may limit their use in specific configurations, such as onboard computing.

Most DL techniques applied to drones focus on environment perception and control strategies. In terms of perception, convolutional neural networks (CNNs) were a breakthrough in image processing. Techniques based on this type of neural network are used in the industry mainly for object detection and classification. Some examples in swarm application are landmark recognition [229], segmentation of object instances [230], exploration of unknown environments [231], or detection of other drones for formation control [83].

Reinforcement learning (RL) and deep reinforcement learning (DRL) are generally used for designing controllers [123, 146], generation of a collision-free trajectory [232] or the addition of imitation learning for cooperation between UGV and UAV [233]. Obtaining actual data to train DL models is feasible, but this is quite difficult for RL. Since RL obtains data during training, improving its performance with each failure, training an aerial robot in a natural environment is risky. Therefore, most RL training is done on simulators. Some research focuses on creating accurate simulation environments for RL training [145] and transferring the models trained in simulation to the real world [234].

Moreover, both DL and RL techniques can be combined for pursuit-evasion, as shown in [228]. The authors trained policies parameterized by neural networks capable of controlling individual drones in a swarm in a fully decentralized manner. They have shown the successful deployment of the model learned in simulation to highly resource-constrained physical quadrotors performing station-keeping and goal-swapping behaviors.

Table 10: List of publication focused on using AI on multi UAV systems. AI: AI technique used, Test: Test environment, Rep: Reproducible, IL: Incremental Learning, OR: Object Recognition, RL: Reinforcement Learning, S: Simulator, D: Dataset, O: Outdoor, I: Indoor, Y: Yes, N: No

Pub	Year	AI	Test	Rep.	Focus and Findings	Application
[146]	2018	RL	S	N	Consists of modular state-action-reward-state-action (SARSA) controller that learn multiple Q tables.	Swarm control
[228]	2019	RL, DL	O	N	Employs a vision-based deep learning object detection and reinforcement learning for detecting and tracking a UAV by another UAV. Deploy YOLO v2 for object detection and first layers of VGG-M network in Deep RL architecture.	pursuit-evasion
[232]	2019	RL	S	N	Deep Q-learning and Hungarian algorithm is used for implementing obstacle avoidance in multi-UAV swarm environment.	collision free trajectory
[230]	2019	DL, OR	D	N	Mask R-CNN is experimentally evaluated and compared with Faster R-CNN for object instance segmentation.	SAR
[229]	2020	IL	D	N	propose an incremental learning-based network architectures, which combines the advantages of deep learning and broad learning system.	landmark recognition
[233]	2020	DRL	S	N	Propose an Imitation Augmented Deep Reinforcement Learning model that enables a UGV and UAV to perform tasks cooperatively.	Tasking in dynamic environment
[231]	2020	DL	S,I, O	N	Aims to understand items in an unknown environment. The authors combine ML and YOLO object detection to understand unknown environment better. The proposed architecture is generalizable, transportable and scalable for UAV flocks.	Exploration
[234]	2021	DRL	S,I	Y	Propose a model agnostic method for learning drone swarm controllers that are zero-shot transferable to real UAVs via large-scale multi-agent end-to-end reinforcement learning.	Swarm control
[83]	2021	DL	S,I	N	Drone detection using YOLO v3 tiny.	Formation Control
[123]	2021	RL	S	N	Present an approach for tuning MPC parameters through cooperative reinforcement learning. The UAVs coordinate their learning strategies in real time.	MPC
[145]	2021	DRL	S	N	A digital twin (DT) enabled DRL training framework is proposed. DT enables the DRL model to be deployed faster on real world multi-UAV system.	Flocking
[235]	2021	IL	I,O	Y	Present an approach to fly a UAV at high speeds in environments with complex obstacle geometry using only onboard sensing and computation. The authors present a zero-shot transfer from simulation to challenging unseen real-world environments. In addition, they train the navigation policy via privileged learning.	High-speed flight in wild

4.7.1 Discussion

AI, and specifically DL, constitute a significant field of research today. Table 10 categorizes the publications from the last 10 years. Since both DL and drone swarms are relatively recent research fields, few publications combine both. As can be seen in the table, most publications are from the years 2018-2021. Nevertheless, much of the research being done in AI applies to fields that affect swarms, such as localization, perception, or control. None of the publications focuses on the application in an industrial environment. All publications conducted testing and demonstrated their findings using simulations or in a laboratory setting. Therefore, all of these publications can be classified as belonging to TRL 4.

4.8 Application

MAVs have a wide range of applications in various fields, from agriculture to emergency response or environmental monitoring. The most noteworthy application are the ones that take place in areas that are not easily accessible or are dangerous for humans and can easily navigate through narrow and cluttered spaces with high agility due to their small dimensions [19]. Therefore, they are suitable for applications such as inventory management, exploration [236] of unknown indoor spaces, gas leak localization, and search and rescue (SAR). Table 11 lists the 16 publications focused on using UAVs in an indoor industrial setting, as per the inclusion criteria in Section A.1. Hartman et al. [237], and Almesha et al. [238] use a single UAV to complete their missions. However, the methods they deploy are transferable to a swarm of UAVs. The remaining 14 publications deploy a swarm in an indoor testbed or

Table 11: List of application focused researches. SA: Swarming Approach, Rep:Reproducible, Test: Test environment, S: Simulator, O: Outdoor, I:Indoor, C:Centralized, DC: Decentralized, D: Distributed, HPE: Human pose estimation, SAR: Search and Rescue, Y: Yes, N: No

Pub.	Year	Application	Test	SA	Rep	Focus Points
[98]	2013	Exploration	S,I	C	N	Resource constrained MAVs achieve efficient sensing coverage.
[237]	2016	Radiation detection	I	-	N	Remote sensing of neutron and gamma radiations
[239]	2018	HPE	I,O	C	N	A swarm of camera-equipped MAVs jointly optimizes swarm's and skeletal states (3D joint positions) in real time.
[238]	2018	SAR	S,I	-	N	A vision-based neural network controller is designed for autonomous landing of a UAV on fixed and moving targets.
[240]	2019	Target search	I	C	N	- UAVs perform search, track, return, and deploy operations using on-board sensor and battery measurements. - Autonomous recharging of UAVs ensures continuous operation of the swarm.
[241]	2019	Gas tracking	S	C	N	The swarm of UAVs determine the location of a gas dispersion in a production area.
[242]	2020	Inventory management	I	DC	N	- Implements UAV swarm management, wireless charging, inventorying, inventory data storage using low cost UAVs. - Simulated the operations of a food warehouse. - UAVs autonomously recharge at the ground recharge station to enable 24/7 operation.
[243]	2021	Gas tracking	S	D	Y	- A swarm of UAVs is equipped with gas sensors for industrial remote gas-plume sensing. - The swarm dynamically adjusts the formation to maximize the perception of the dynamic plume-cloud. - A simulator simulates an indoor industrial environment for testing.
[244]	2021	Gas tracking	S,I	C	Y	- Fully autonomous swarm of gas-seeking nano UAVs. - Parameters are evolved in simulation and successfully transferred to real-world environment.
[245]	2021	Target search	S	DC	Y	- A team of UAVs cooperatively explores and finds a target in a complex indoor environment with obstacles. - Use laser sensors and known map for localization. - The UAVs share their observations and location with other UAVs.
[246]	2021	Target search	S	C	N	Focuses on detection of targets which can only be detected within specific angles.
[247]	2021	Target Search	S	C	N	- The task consists of coordinated motion of a UAV swarm to locate a target zone. - Uses a multi-objective optimization algorithm on a UAV swarm without and with the presence of obstacles.
[96]	2021	Transportation	S	C	N	- Focuses on UAVs picking up goods in a logistic industry. - The Multi-UAV pickup theory combines the idea of green scheduling and the theory of secondary task assignment. - Improves the utilization rate of UAVs to complete a pickup task and reduces energy consumption.
[248]	2021	Inspection	S	C	N	- Low-cost UAVs are used for visual inspection of oil and gas pressure vessel. - ORB-SLAM3 is used for localizing the UAV. - Simulated pressure vessel is created for testing.
[249]	2021	Exploration	S	C	N	Proposes an exploration strategy in unknown environments for a team of UAVs
[250]	2021	Aerial manipulator	I	DC	N	- Proposes a method to control multiple UAVs connected to an end-effector by passive kinematic chains. - Use onboard monocular vision and internal configuration control of UAVs without extroceptive measurements.

a simulation. Therefore, all the 16 publications in this category can be classified as belonging to TRL 4. The works predominantly still use a centralized approach, even though a decentralized or distributed one holds greater advantages for a swarm [22].

In recent years, some MAVs have been deployed in warehouses for inventorying tasks [251–253]. However, these works only use a single MAV to perform simple tasks like detecting a fiducial marker or identifying tags. Deploying a swarm of MAVs in industries capable of performing complex tasks is still an open challenge. Awasthi et al. deploy a swarm of MAVs alongside humans to automate picking up multiple virtual packages from various locations and delivering them to the specified destination. The task is performed in a warehouse-like environment [254]. Only two of the 16 publications deploy a MAV swarm in a warehouse for inventory management [242] and transportation [96]. Thus, the use of UAVs in the manufacturing and supply chain is still in its infancy. The size and sensor capabilities onboard a UAV open new perspectives under the industry 4.0 framework. UAVs are used for industrial tasks such as manufacturing, maintenance, monitoring, material handling, asset management, and smart factory [6, 255]. Mourtzis et al. propose an intelligent framework based on the Industrial Internet of Things (IIoT) for real-time machine shop monitoring and data acquisition in strategic production points [255]. A scheduler schedules the execution of tasks and monitors the UAV operations according to a given schedule, and it is essential to achieve efficient UAV operations in an indoor environment. Khosiawan and Nielsen present a detailed study of existing UAV systems focused on UAV scheduling systems [256].

The Internet of Drones recently gained momentum due to their adaptability to various complex scenarios [211]. Low-altitude UAVs-enabled wireless networks can be quickly deployed and flexibly reconfigured to enhance network coverage and capacity. Liu et al. review the opportunities and challenges of UAVs for the Internet of Everything (IoE) [95].

Some works deploy a single medium or large-sized UAV for industrial tasks performed indoors or in GPS-denied environments. For example, Novak et al. propose a smart hangar system that uses UAVs for aircraft maintenance. They use digital technologies to record data which can be a part of industry 4.0 [257]. Rozas et al. propose a framework for fire extinguishing in an urban scenario by a team of aerial and ground robots [258]. They designed a 3D LIDAR-based mapping and localization module to work in GPS-denied scenarios and performed tests on UAVs weighing more than 6 kg. Lu et al. propose an autonomous exploration algorithm for aerial robots suitable for SAR tasks. However, they only tested the algorithm on a single UAV [236].

High-level tasks, such as automatic target detection, inspection, and autonomous exploration in an indoor environment using a UAV, are challenging. A flexible

architecture composed of various modules such as localization, path planner, obstacle avoidance, controller, communication, and safety is essential to overcome the challenges. It is beneficial to have such an architecture for a UAV swarm operating in a complex industrial environment, where time, safety, and accuracy are critical constraints. Software architectures like the Aerostack framework [259], eases the development of these tasks, providing an ecosystem of modules ready to be used. Moreover, Sampedro et al. present a scalable, robust, and flexible architecture for dynamic agent-to-task assignment and real-time mission planning for a swarm of UAVs [260] integrated in this framework.

5 OBSERVATIONS

In this section, we delve into an analysis of prevailing patterns and trends across publications that have successfully navigated through the review process to its final stage. Given the constrained nature of MAVs due to their weight limitations, we further stratify these publications based on weight. Subsequently, the observations from Section 4 to Section 4.8 are summarized.

Figure 6 shows the distribution of the publications over the past ten years that reached the final stage of the review process. Considering the 148 publications (excluding reviews), 108 publications use more than two UAVs for testing their method indoors or on a simulator. 20 publications test their method on a single UAV but are transferable to a swarm. 20 works either do not mention the number of UAVs, use a mobile robot for experimentation, or use a dataset to test their approach. Nevertheless, these approaches are adaptable for application in UAV swarms. Remarkably, none of the publications ventured into field-testing their methods in industrial or warehouse environments. In this work, the majority of publications centered around the use of homogeneous swarms. Over the past decade, there hasn't been any discernible inclination or preference for centralized or decentralized control or decision-making strategies within the Micro Aerial Vehicle (MAV) swarm research community. Furthermore, it's worth noting that the bulk of experiments took place in simulated environments or controlled indoor laboratory settings.

Among the 148 publications surveyed, 86 of them conducted experiments using Micro Aerial Vehicles (MAVs). An additional eight studies utilized various DJI drone variants, while a few others opted for Sensorfly, Parrot, F450, and Intel Aero MAVs. It's important to highlight that several publications did not specify the type of MAV used or its weight, leading us to categorize them as custom-designed MAVs, although determining their exact weight remains challenging.

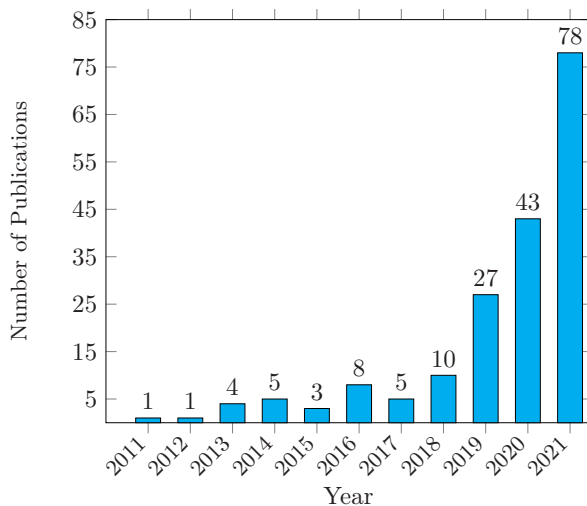


Fig. 6: Distribution of the 185 publications over the last ten years.

Out of the total, 35 publications either mentioned the complete weight of the MAV, inclusive of onboard equipment, or provided enough information to estimate the approximate total weight. Notably, 28 of these studies employed Crazyflie MAVs, which have a compact design with a weight of 27 grams and a maximum take-off capacity of 42 grams. In 15 publications, the authors indicated the type of MAV used but omitted details regarding its total weight. In these cases, we considered the base weight of the MAV. It's noteworthy that the MAVs in these 50 publications all weighed less than 2 kilograms. The distribution of publications based on weight categories is presented in Table 12.

Table 12: Number of publications distributed by weight.

Number of publications	Weight of MAV (grams)
28	<50
12	50 - 1000
10	1000 - 2000

Summarizing the observations in this work, a fusion of UWB, INS, and Optical-based methods emerges as the most prevalent approach to achieve indoor localization. Attaining stable control is frequently accomplished through the adoption of intelligent controllers, as it can manage the numerous uncertainties intrinsic to a MAV flight. However, it's noteworthy that AI-based techniques have yet to find widespread application in the formulation of control strategies for indoor MAV swarms. Majority of the works use optimization or force field methods for collision avoidance, while path planning is achieved using classic and probabilistic approaches. Research pertaining to

safety and security of MAV swarms is scarce at present. However, safety becomes acutely pronounced if MAV swarms are to be deployed in industries replete with both static and dynamic obstacles. The battery life of MAVs significantly influences their flight duration and payload capacity. However there is a scarcity of research addressing the energy demands of individual MAVs within a swarm context. Intra-swarm communication is chiefly executed through explicit communication-based methodologies. Meanwhile, there has been a surge in research applying artificial intelligence to MAV operations. Nevertheless, this surge of research has yet to be effectively channeled into industrial applications. While a few publications do strive to offer solutions tailored to industrial tasks, the validation of their findings predominantly occurs through simulations or controlled laboratory environments. Consequently, all the publications encompassed within this study can be classified under Technology Readiness Level (TRL) 4. The progression of research toward TRL 9 necessitates a concerted endeavor to bridge the existing gap.

6 CONCLUSION

This systematic literature review aims to identify the gaps that capture the state-of-the-art and the trends for Micro UAV swarms operating in an indoor industrial setting. 186 contributions are selected from an initial list of 1997 publications according to predefined Inclusion Criteria. The relevant literature is categorized and analyzed by domain experts in robotics. Every category has a discussion section that discusses the findings and identifies the gaps in that category. Based on the findings from each category, the guiding questions from Section 1 are answered:

1. Which localization technologies are preferred, and how accurate and costeffective are they?

As discussed in Section 4.1, sensor fusion is primarily used. Most research is done by fusing UWB, IMU, and vision sensors. These sensors weigh less than 15 grams and can be as small as 11 x 9 x 2 mm. Sensor fusion increases the accuracy up to 10 – 15 cm. However, many works prefer to use only UWB or vision sensors. Setting up IMUs, Cameras, and UWB indoors is cheaper than setting up an external localization system such as a motion capturing system. Even though motion capturing systems have accuracy in mm, they are still not preferred by industries due to their high cost.

2. What type of guidance, navigation, and control (GNC) methods are used in MAV swarms, and how does each contribute to system autonomy?

Section 4.2 presents two main trends to control UAV swarms: collaborative and formation control. In collaborative approaches, each UAV has a subtask assigned to it as part of a global task, while in formation control methods, the coordinated flight of all agents is

required. Furthermore, these swarms can be controlled in a centralized or distributed manner. Thus, in distributed systems, UAVs have greater autonomy than centralized ones because they do not depend totally on the central node; however, these approaches require aircraft with more complex guidance and navigation systems. In this context, Section 4.3 presents the techniques of guidance and navigation where collision-free path planning and onboard sensor-based obstacle avoidance approaches predominate.

3. *MAVs are considered suitable for indoors. What are the safety concerns regarding deploying MAVs in industries?*

Major safety concerns are collisions, failure of sensors onboard a MAV, and failure of MAV actuators. Out of these, most works focus on collision avoidance based methods to ensure MAV safety. However, if MAVs are to be deployed in industries, other safety concerns should also be focused upon and incorporated into each MAV. Multiple methods for collision avoidance are listed in Section 4.3.1. Methods to tackle the failure of UAV components and sensors are listed in Section 4.4.

4. *What are problems faced to achieve 24/7 operation of the MAV swarm in industries, and what approaches are discussed to resolve them?*

The MAVs have a limited battery capacity, which is the major constraint in achieving 24/7 operation of the MAV swarm in industries. Therefore, researching ways to frequently charge the MAVs, such as using charging stations, is essential. However, more research is needed on charging stations for MAVs. As a result, it is yet to be feasible to deploy them in real-world scenarios. Methods for battery management, scheduling, and charging stations are discussed in Section 4.5. However, further research is required regarding the flexibility of deploying charging stations, their deployment feasibility, and cost-benefit analysis for industries.

5. *What are the most suitable swarm communication systems for an indoor industrial application?*

As discussed earlier in the section on section 4.6, although even perception-based techniques like stigmergy and passive recognition are being studied, in an indoor industrial environment, it is reasonable to assume that the infrastructure can support reliable channels for explicit communication, which is direct and effective. Next-generation wireless networks such as IEEE 802.11be (WiFi 7) are exploring new technologies like multi-Access Point coordination and coordinated beamforming to support high-throughput and low-latency applications in dense user deployments while minimizing interference. Industries like automotive, transport, logistics, and IoT have specified their service requirements in standard specifications, such as the 3GPP technical specification for 5G. Different applications have varying latency

thresholds, such as 20ms for sensor data sharing between users and 10ms for coordinated control of equipment. While WiFi and mmWave can be used for UAV communication in indoor environments, mmWave offers some additional advantages. It can provide higher data rates and bandwidth and better network reliability through multi-path routing. Additionally, mmWave is well-suited for mission-critical applications such as UAV communication.

6. *What is current trend seen for MAV swarms in industries with regards to AI?*

There has been a substantial increase in publications using AI for MAV swarm localization, security and communication over the past years, with a particular interest in control and perception. Several publications have reviewed the use of AI algorithms in localization, communication, and control. As seen in Section 4.2, intelligent controllers are the preferred controllers among many.

Section 4.7 explained primary AI research fields currently, mainly Deep Learning and Reinforcement Learning, applied in control and perception. However, as AI has been successfully adopted in other domains, we believe there will be an increase in implementing AI algorithms for other topics like collision avoidance or path planning for a MAV swarm indoors.

7. *What are the tasks that are being or could potentially be performed using MAVs in industries?*

Manually and semi-autonomous operated MAVs have been deployed in inventory management and inspection in industries. Numerous researchers use autonomous MAV swarms in the laboratory environment to perform tasks such as exploration, inspection, surveillance, and inventory management. Such research could potentially be used in industries to automate various tasks. However, testing in industries would give a better picture. Transportation of goods in an industry is an essential task primarily performed manually or using mobile robots. However, there needs to be more research on using MAV swarms to transport lightweight goods in an industrial setting safely.

8. *What is the research gap to deploy MAV swarms in industries? What should be the future scope?*

From the reviewer's perspective, further research on MAV swarms for industries should focus on the following issues:

- (a) Research on a dynamic swarm that allows joining and leaving MAVs in real-time without affecting swarm operations is missing. This feature could make the swarm flexible, robust, scalable, economical, and safer to deploy in industries.
- (b) Only 16 out of the 148 publications are reproducible. This makes it difficult for industries to verify the proposed method and

integrate them into the supply chain. Thus, there needs to be more easily reproducible research.

- (c) Incorporating methods from the Sections 4.1 – 4.6 on a MAV swarm and testing the swarm in a real industry would give a better understanding of the shortcomings and feasibility of deploying a fully autonomous MAV swarm.
- (d) Dynamic environment conditions, dynamic obstacle, human behavior, and their effect on MAVs in real-time are challenging to recreate in a laboratory or simulator. Further research in creating a digital twin, replicating the exact industrial environment, or experimenting in an industry would give more realistic results.
- (e) It is challenging to estimate the battery consumption of a MAV when testing on a simulator or laboratory. The reason is that environmental effects such as wind, temperature, and humidity could affect the UAV dynamics, affecting battery consumption.

7 ACKNOWLEDGMENT

This work is a part of the project 45KI02B021 “Silicon Economy Logistics Ecosystem” funded by the German Federal Ministry of Transport and Digital Infrastructure.

The work in this publication was supported the German Federal Ministry of Education and Research (BMBF) in the context of the project “LAMARR Institute for Machine Learning and Artificial Intelligence” (Funding Code: LAMARR22B)

This work has been supported by the project COPILOT ref. Y2020\EMT6368 “Control, Monitoring and Operation of Photovoltaic Solar Power Plants by means of synergic integration of Drones, IoT and advanced communication technologies”, funded by Madrid Government under the R&D Synergic Projects Program.

This work has also been supported by the project INSERTION ref. ID2021-127648OBC32, “UAV Perception, Control and Operation in Harsh Environments”, funded by the Spanish Ministry of Science and Innovation under the program “Projects for Knowledge Generating”. The work of the fourth author is supported by the Grant FPU20/07198 of the Spanish Ministry for Universities. The work of the sixth author is supported by the Spanish Ministry of Science and Innovation under its Program for Technical Assistants PTA2021-020671.

8 DECLARATIONS

8.1 Funding

This work is a part of the project 45KI02B021 “Silicon Economy Logistics Ecosystem” funded by the German Federal Ministry of Transport and Digital Infrastructure.

The work in this publication was supported the German Federal Ministry of Education and Research (BMBF) in the context of the project “LAMARR Institute for Machine Learning and Artificial Intelligence” (Funding Code: LAMARR22B)

This work has been supported by the project COPILOT ref. Y2020\EMT6368 “Control, Monitoring and Operation of Photovoltaic Solar Power Plants by means of synergic integration of Drones, IoT and advanced communication technologies”, funded by Madrid Government under the R&D Synergic Projects Program.

This work has also been supported by the project INSERTION ref. ID2021-127648OBC32, “UAV Perception, Control and Operation in Harsh Environments”, funded by the Spanish Ministry of Science and Innovation under the program “Projects for Knowledge Generating”. The work of the fourth author is supported by the Grant FPU20/07198 of the Spanish Ministry for Universities. The work of the sixth author is supported by the Spanish Ministry of Science and Innovation under its Program for Technical Assistants PTA2021-020671.

8.2 Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

9 FUTURE WORK

While conducting this review, it became evident that the researches did not prioritize the crucial aspect of sustainability. Recognizing its significance, we intend to undertake a study that specifically examines the sustainability implications of diverse technologies associated with MAVs. This study would shed light on how these technologies can align with environmental considerations and long-term viability. Furthermore, we would want to delve deeper into the realm of human-drone interaction. This aspect deserves heightened attention, as seamless collaboration between humans and drones becomes increasingly integral across various applications in industries.

REFERENCES

- [1] Barreto, L., Amaral, A., Pereira, T.: Industry 4.0 implications in logistics: an overview. *Procedia manufacturing* **13**, 1245–1252 (2017)
- [2] Öztuna, B.: Logistics 4.0 and technologic applications. *Logistics 4.0 and Future of Supply Chains*, 9–27 (2022)
- [3] Dördüncü, H.: *Logistics, Supply Chains and Smart Factories*, Springer, 2021, pp. 137–152
- [4] EU Science Hub Transport sector economic analysis. <https://ec.europa.eu/jrc/en/research-topic/transport-sector-economic-analysis>. Accessed: 2021-02-01
- [5] Bamburly, D.: Drones: Designed for product delivery. *Design Management Review* **26**(1), 40–48 (2015)
- [6] Amza, C.G., Cantemir, D., Cantemir, I., Oikonomoula, A., Poterucha, P., Salucci, G., Spanu, P., Tarantino, F., Triantafyllou, M.: Guidelines on industry 4.0 and drone entrepreneurship for vet students. *Danmar Computers, Drone technology training to boost EU entrepreneurship and Industry* **4**, 1–45 (2018)
- [7] Companik, E., Gravier, M.J., Farris II, M.T.: Feasibility of warehouse drone adoption and implementation. *Journal of Transportation Management* **28**(2), 5 (2018)
- [8] Rejeb, A., Rejeb, K., Simske, S.J., Treiblmaier, H.: Drones for supply chain management and logistics: a review and research agenda. *International Journal of Logistics Research and Applications*, 1–24 (2021)
- [9] Polaris: Drone logistics and transportation market share, size, trends, industry analysis report, by application (logistics, and transportation); user; by product; by range; by region; segment forecast, 2022 – 2030. Technical report, Polaris (2022)
- [10] Wawrla, L., Maghazei, O., Netland, T.: Applications of drones in warehouse operations. Whitepaper. ETH Zurich, D-MTEC (2019)
- [11] Tang, C.S., Veelenturf, L.P.: The strategic role of logistics in the industry 4.0 era. *Transportation Research Part E: Logistics and Transportation Review* **129**, 1–11 (2019)
- [12] Beke, É., Bódi, A., Katalin, T.G., Kovács, T., Maros, D., Gáspár, L.: The role of drones in linking industry 4.0 and its ecosystems. In: 2018 IEEE 18th International Symposium on Computational Intelligence and Informatics (CINTI), pp. 000191–000198 (2018). IEEE
- [13] Singhal, G., Bansod, B., Mathew, L.: Unmanned aerial vehicle classification, applications and challenges: A review (2018)
- [14] Elmeseiry, N., Alshaer, N., Ismail, T.: A detailed survey and future directions of unmanned aerial vehicles (uavs) with potential applications. *Aerospace* **8**(12), 363 (2021)
- [15] Alghamdi, Y., Munir, A., La, H.M.: Architecture, classification, and applications of contemporary unmanned aerial vehicles. *IEEE Consumer Electronics Magazine* **10**(6), 9–20 (2021). <https://doi.org/10.1109/MCE.2021.3063945>
- [16] Chamola, V., Kotesch, P., Agarwal, A., Gupta, N., Guizani, M., *et al.*: A comprehensive review of unmanned aerial vehicle attacks and neutralization techniques. *Ad hoc networks* **111**, 102324 (2021)
- [17] Stöcker, C., Bennett, R., Nex, F., Gerke, M., Zevenbergen, J.: Review of the current state of uav regulations. *Remote sensing* **9**(5), 459 (2017)
- [18] Tahir, A., Böling, J., Haghbayan, M.-H., Toivonen, H.T., Plosila, J.: Swarms of unmanned aerial vehicles – a survey. *Journal of Industrial Information Integration* **16**, 100106 (2019)
- [19] Coppola, M., McGuire, K.N., De Wagter, C., De Croon, G.C.: A survey on swarming with micro air vehicles: Fundamental challenges and constraints. *Frontiers in Robotics and AI* **7**, 18 (2020)
- [20] Hassanalian, M., Mirzaeinia, A., Bawana, N., Heppner, F.: Energy management of echelon flying northern bald ibises with different wingspans and variable wingtip spacing. *Journal of Bionic Engineering*, 1–18 (2021)
- [21] Yang, G.-Z., Bellingham, J., Dupont, P.E., Fischer, P., Floridi, L., Full, R., Jacobstein, N., Kumar, V., McNutt, M., Merrifield, R., *et al.*: The grand challenges of science robotics. *Science robotics* **3**(14), 7650 (2018)
- [22] Tan, Y., Zheng, Z.-y.: Research advance in swarm robotics. *Defence Technology* **9**(1), 18–39 (2013)
- [23] Jamshidpey, A., Wahby, M., Heinrich, M., Allwright, M., Zhu, W., Dorigo, M.: Centralization vs. decentralization in multi-robot coverage: Ground robots under uav supervision (2021)
- [24] Cargo drones: A potential gamechanger in the logistics industry (2022)
- [25] Innovation, D.: The Autonomous Solution for your Intralogistics (2017). <https://doi.org/10.6084/m9.figshare.853801>
- [26] Kft., A.S.S.: How Drones are Reshaping Warehouse Inventory Checks (2021). <https://www.aeriu.co/news/>
- [27] corvus Drones: DIGITALEYES EVERY PLANT (2022). <https://www.corvusdrones.com/en/in-development/>

- [28] Amazon: How Amazon is building its drone delivery system (2022). <https://www.aboutamazon.com/news/transportation/how-amazon-is-building-its-drone-delivery-system>
- [29] FedEx: Wing drone deliveries take flight with FedEx (2019). <https://www.fedex.com/en-us/sustainability/wing-drones-transport-fedex-deliveries-directly-to-homes.html>
- [30] Walmart: We're Bringing the Convenience of Drone Delivery to 4 Million U.S. Households in Partnership with DroneUp (2019). <https://corporate.walmart.com/newsroom/2022/05/24/were-bringing-the-convenience-of-drone-delivery-to-4-million-u-s-households-in-partnership-with-droneup>
- [31] Ikea: Ikea adds stock-counting drones to more of its stores (2023). <https://www.theverge.com/2023/3/20/23648156/ikea-verity-drones-stock-counting-stores>
- [32] DSV: DSV improves warehouse operations with drone system (2020). <https://www.dsv.com/en/about-dsv/press/news/com/2020/11/dsv-improves-warehouse-operations-with-drone-system>
- [33] Logistics, C.: CEVA Logistics supports innovation and the use of robots within our business and encourages start-ups. (2020). <https://www.cevalogistics.com/en/what-we-do/contract-logistics/innovation>
- [34] Group, H.: A COMPREHENSIVE DRONE INVENTORY SOLUTION (2020). <https://www.hardis-group.com/en/services-solutions/solutions/eyesee-drone-allowing-automate-inventory-warehouses>
- [35] Solution, A.R.: InWareDrones, inventory by using drones and RFID (2020). <https://www.aucxis.com/en/rfid/news/inwardrones-inventory-by-using-drones-and-rfid/rfids>
- [36] Mankins, J.C.: Technology readiness levels: A white paper. <http://www.hq.nasa.gov/office/codeq/trl/trl.pdf> (1995)
- [37] Kitchenham, B., Brereton, P.: A systematic review of systematic review process research in software engineering. *Information and software technology* **55**(12), 2049–2075 (2013)
- [38] Reining, C., Niemann, F., Moya Rueda, F., Fink, G.A., ten Hompel, M.: Human activity recognition for production and logistics – a systematic literature review. *Information* **10**(8), 245 (2019)
- [39] Delgado López-Cózar, E., Orduña-Malea, E., Martín-Martín, A.: Google scholar as a data source for research assessment. *Springer handbook of science and technology indicators*, 95–127 (2019)
- [40] Martín-Martín, A., Thelwall, M., Orduna-Malea, E., Delgado López-Cózar, E.: Google scholar, microsoft academic, scopus, dimensions, web of science, and opencitations' coci: a multidisciplinary comparison of coverage via citations. *Scientometrics* **126**(1), 871–906 (2021)
- [41] Obeidat, H., Shuaieb, W., Obeidat, O., Abd-Alhameed, R.: A review of indoor localization techniques and wireless technologies. *Wireless Personal Communications* **119**(1), 289–327 (2021)
- [42] Uçgun, H., Yuzgeç, U., Bayilmis, C.: A review on applications of rotary-wing unmanned aerial vehicle charging stations. *International Journal of Advanced Robotic Systems* **18**(3), 17298814211015863 (2021)
- [43] Dias, P.G.F., Silva, M.C., Rocha Filho, G.P., Vargas, P.A., Cota, L.P., Pessin, G.: Swarm robotics: A perspective on the latest reviewed concepts and applications. *Sensors* **21**(6), 2062 (2021)
- [44] Škrinjar, J.P., Škorput, P., Furdić, M.: Application of unmanned aerial vehicles in logistic processes. In: *International Conference "New Technologies, Development and Applications"*, pp. 359–366 (2018). Springer
- [45] Suzuki, S.: Recent researches on innovative drone technologies in robotics field. *Advanced Robotics* **32**(19), 1008–1022 (2018)
- [46] Khullar, R., Dong, Z.: Indoor localization framework with wifi fingerprinting. In: *2017 26th Wireless and Optical Communication Conference (WOCC)*, pp. 1–6 (2017). IEEE
- [47] Basiri, M., Schill, F., Floreano, D., Lima, P.U.: Audio-based localization for swarms of micro air vehicles. In: *2014 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 4729–4734 (2014). IEEE
- [48] Dimakos, A., Woodhall, D., Asif, S.: A study on centralised and decentralised swarm robotics architecture for part delivery system. *Acad. J. Eng. Stud* **2**(3) (2021)
- [49] Alrajeh, N.A., Bashir, M., Shams, B.: Localization techniques in wireless sensor networks. *International journal of distributed sensor networks* **9**(6), 304628 (2013)
- [50] Kang, J.-H., Park, K.-J., Kim, H.: Analysis of localization for drone-fleet. In: *2015 International Conference on Information and Communication Technology Convergence (ICTC)*, pp. 533–538 (2015). IEEE
- [51] Shakra, E.Q., Sheltami, T.R., Shakshuki, E.M.: A comparative study of range-free and range-based localization protocols for wireless sensor network: Using cooja simulator. In: *Sensor Technology: Concepts, Methodologies, Tools, and Applications*, pp. 1522–1537. IGI Global (2020)

- [52] Shi, Z., Li, H., Lin, H., Huang, L.: A nano-quadcopter formation flight system based on uwb indoor positioning technology. In: 2018 13th International Conference on Computer Science & Education (ICCSE), pp. 1–4 (2018). IEEE
- [53] Stirling, T., Roberts, J., Zufferey, J.-C., Floreano, D.: Indoor navigation with a swarm of flying robots. In: 2012 IEEE International Conference on Robotics and Automation, pp. 4641–4647 (2012). IEEE
- [54] Li, J., Bi, Y., Li, K., Wang, K., Lin, F., Chen, B.M.: Accurate 3d localization for mav swarms by uwb and imu fusion. In: 2018 IEEE 14th International Conference on Control and Automation (ICCA), pp. 100–105 (2018). IEEE
- [55] Li, S., Coppola, M., De Wagter, C., de Croon, G.C.: An autonomous swarm of micro flying robots with range-based relative localization. arXiv preprint arXiv:2003.05853 (2020)
- [56] Guo, K., Li, X., Xie, L.: Ultra-wideband and odometry-based cooperative relative localization with application to multi-uav formation control. IEEE transactions on cybernetics **50**(6), 2590–2603 (2019)
- [57] Cao, Y., Beltrame, G.: Vir-slam: Visual, inertial, and ranging slam for single and multi-robot systems. Autonomous Robots **45**(6), 905–917 (2021)
- [58] Zhang, S., Tang, S., Wang, W., Jiang, T., Zhang, Q.: Conquering textureless with rf-referenced monocular vision for mav state estimation. In: 2021 IEEE International Conference on Robotics and Automation (ICRA), pp. 146–152 (2021). IEEE
- [59] Maghdid, S.M., *et al.*: A comprehensive review of indoor/outdoor localization solutions in iot era: Research challenges and future perspectives (2021)
- [60] Yousif, K., Bab-Hadiashar, A., Hoseinnezhad, R.: An overview to visual odometry and visual slam: Applications to mobile robotics. Intelligent Industrial Systems **1**(4), 289–311 (2015)
- [61] Roozing, W., Göktoğan, A.H.: Low-cost vision-based 6-dof mav localization using ir beacons. In: 2013 IEEE/ASME International Conference on Advanced Intelligent Mechatronics, pp. 1003–1009 (2013). IEEE
- [62] Suwansrikham, P., Singkhamfu, P.: Indoor vision based guidance system for autonomous drone and control application. In: 2017 International Conference on Digital Arts, Media and Technology (ICDAMT), pp. 110–114 (2017). <https://doi.org/10.1109/ICDAMT.2017.7904945>
- [63] Chen, K.-W., Wang, C.-H., Wei, X., Liang, Q., Chen, C.-S., Yang, M.-H., Hung, Y.-P.: Vision-based positioning for internet-of-vehicles. IEEE Transactions on Intelligent Transportation Systems **18**(2), 364–376 (2016)
- [64] Li, S., De Wagter, C., de Croon, G.C.: Self-supervised monocular multi-robot relative localization with efficient deep neural networks. arXiv preprint arXiv:2105.12797 (2021)
- [65] Zhang, P., Chen, G., Dong, W.: Agile formation control of drone flocking enhanced with active vision-based relative localization. arXiv preprint arXiv:2108.05505 (2021)
- [66] Pavliv, M., Schiano, F., Reardon, C., Floreano, D., Loianno, G.: Tracking and relative localization of drone swarms with a vision-based headset. IEEE Robotics and Automation Letters **6**(2), 1455–1462 (2021)
- [67] Holter, S., Tsoukalas, A., Evangeliou, N., Giakoumidis, N., Tzes, A.: Relative visual localization for unmanned aerial systems. arXiv preprint arXiv:2003.01954 (2020)
- [68] Nadler, N., Cohen, E., Medina, O., Hacohen, S.: Bearing sensor for 3d localization and swarm centroid detection. IEEE Sensors Journal **21**(23), 26716–26723 (2021)
- [69] Chen, S., Jin, X., Zhang, W., Tang, Y.: Vision-based formation control of multiple uavs with event-triggered integral sliding mode control. Cyber-Physical Systems **6**(4), 231–251 (2020)
- [70] Barranco, F., Fermuller, C., Ros, E.: Real-time clustering and multitarget tracking using event-based sensors. In: 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 5764–5769 (2018). <https://doi.org/10.1109/IROS.2018.8593380>
- [71] Gallego, G., Delbrück, T., Orchard, G., Bartolozzi, C., Taba, B., Censi, A., Leutenegger, S., Davison, A.J., Conradt, J., Daniilidis, K., *et al.*: Event-based vision: A survey. IEEE transactions on pattern analysis and machine intelligence **44**(1), 154–180 (2020)
- [72] Bajestani, S.E.M., Beltrame, G.: Event-based rgb sensing with structured light. In: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pp. 5458–5467 (2023)
- [73] Event-based Vision Resources. https://github.com/uzh-rpg/event-based_vision_resources#slam. Accessed: 2023-02-18
- [74] Steup, C., Beckhaus, J., Mostaghim, S.: A single-copter uwb-ranging-based localization system extendable to a swarm of drones. Drones **5**(3), 85 (2021)
- [75] Lee, S., Yoo, S., Lee, J.Y., Park, S., Kim, H.: Drone positioning system using uwb sensing and out-of-band control. IEEE Sensors Journal **22**(6), 5329–5343 (2021)

- [76] Sun, W.: Enabling relative localization for nanodrone swarm platooning. arXiv preprint arXiv:2204.07865 (2022)
- [77] Natter, D., Ening, K., Paliotta, C.: An incrementally deployed swarm of mavs for localization using ultra-wideband. In: 2022 International Conference on Unmanned Aircraft Systems (ICUAS), pp. 497–505 (2022). <https://doi.org/10.1109/ICUAS54217.2022.9836178>
- [78] Cossette, C.C., Shalaby, M., Saussié, D., Forbes, J.R., Le Ny, J.: Relative position estimation between two uwb devices with imus. *IEEE Robotics and Automation Letters* **6**(3), 4313–4320 (2021)
- [79] Liu, X., Zhou, B., Wu, Z., Liang, A., Li, Q.: An indoor 3-d quadrotor localization algorithm based on wifi rtt and mems sensors. *IEEE Internet of Things Journal* **9**(21), 20879–20888 (2022)
- [80] Bavle, H., Sanchez-Lopez, J.L., Rodriguez-Ramos, A., Sampedro, C., Campoy, P.: A flight altitude estimator for multirotor uavs in dynamic and unstructured indoor environments. In: 2017 International Conference on Unmanned Aircraft Systems (ICUAS), pp. 1044–1051 (2017). IEEE
- [81] Xu, H., Zhang, Y., Zhou, B., Wang, L., Yao, X., Meng, G., Shen, S.: Omni-swarm: A decentralized omnidirectional visual–inertial–uwb state estimation system for aerial swarms. *IEEE Transactions on Robotics* (2022)
- [82] Zhang, P., Chen, G., Li, Y., Dong, W.: Agile formation control of drone flocking enhanced with active vision-based relative localization. *IEEE Robotics and Automation Letters* **7**(3), 6359–6366 (2022)
- [83] Kabore, K.M., Güler, S.: Distributed formation control of drones with onboard perception. *IEEE/ASME Transactions on Mechatronics* (2021)
- [84] Zhang, Y., Tian, B., Chen, H.: Ultra-wideband and visual odometry based relative localization for multi-uav system. In: 2020 39th Chinese Control Conference (CCC), pp. 4665–4670 (2020). IEEE
- [85] Choi, H.-B., Lim, K.-W., Ko, Y.-B.: Luvi: Lightweight uwb-vio based relative positioning for ar-iot applications. Available at SSRN 4243419
- [86] Chen, X., Ruiz, C., Zeng, S., Gao, L., Purohit, A., Carpin, S., Zhang, P.: H-drunkwalk: Collaborative and adaptive navigation for heterogeneous mav swarm. *ACM Transactions on Sensor Networks (TOSN)* **16**(2), 1–27 (2020)
- [87] Saska, M., Baca, T., Thomas, J., Chudoba, J., Preucil, L., Krajnik, T., Faigl, J., Loianno, G., Kumar, V.: System for deployment of groups of unmanned micro aerial vehicles in gps-denied environments using onboard visual relative localization. *Autonomous Robots* **41**(4), 919–944 (2017)
- [88] Vemprala, S.H., Saripalli, S.: Collaborative localization for micro aerial vehicles. *IEEE Access* **9**, 63043–63058 (2021)
- [89] Novák, F., Walter, V., Petráček, P., Báča, T., Saska, M.: Fast collective evasion in self-localized swarms of unmanned aerial vehicles. *Bioinspiration & biomimetics* **16**(6), 066025 (2021)
- [90] Poullose, A., Han, D.S.: Uwb indoor localization using deep learning lstm networks. *Applied Sciences* **10**(18), 6290 (2020)
- [91] Maali, A., Ouldali, A., Mimoun, H., Baudoin, G.: An evaluation of uwb localization under non line-of-sight (nlos) propagation. In: 2008 3rd International Symposium on Wireless Pervasive Computing, pp. 379–382 (2008). IEEE
- [92] Shan, F., Zeng, J., Li, Z., Luo, J., Wu, W.: Ultra-wideband swarm ranging. In: IEEE INFOCOM 2021-IEEE Conference on Computer Communications, pp. 1–10 (2021). IEEE
- [93] Xianjia, Y., Qingqing, L., Queraltá, J.P., Heikkonen, J., Westerlund, T.: Applications of uwb networks and positioning to autonomous robots and industrial systems. In: 2021 10th Mediterranean Conference on Embedded Computing (MECO), pp. 1–6 (2021). IEEE
- [94] Orgeira-Crespo, P., Ulloa, C., Rey-Gonzalez, G., Pérez García, J.A.: Methodology for indoor positioning and landing of an unmanned aerial vehicle in a smart manufacturing plant for light part delivery. *Electronics* **9**(10), 1680 (2020)
- [95] Liu, Y., Dai, H.-N., Wang, Q., Shukla, M.K., Imran, M.: Unmanned aerial vehicle for internet of everything: Opportunities and challenges. *Computer communications* **155**, 66–83 (2020)
- [96] Liu, S., Fang, X., Guo, Y., Liu, C., Yang, J.: Theory and realization of secondary task assignment for multi-uav pickup based on green scheduling. *Complexity* **2021** (2021)
- [97] Dimitriou, A.G., Siachalou, S., Tsardoulías, E., Petrou, L.: Robotics meets rfid for simultaneous localization (of robots and objects) and mapping (slam)—a joined problem. *Wireless Power Transmission for Sustainable Electronics*, 175–222 (2020)
- [98] Purohit, A., Sun, Z., Zhang, P.: Sugarmap: Location-less coverage for micro-aerial sensing swarms. In: Proceedings of the 12th International Conference on Information Processing in Sensor Networks, pp. 253–264 (2013)

- [99] Xiao, J., Zhou, Z., Yi, Y., Ni, L.M.: A survey on wireless indoor localization from the device perspective. *ACM Computing Surveys (CSUR)* **49**(2), 1–31 (2016)
- [100] Bao, H., Wong, W.-C.: A novel map-based dead-reckoning algorithm for indoor localization. *Journal of Sensor and Actuator Networks* **3**(1), 44–63 (2014)
- [101] Liu, M., Cheng, L., Qian, K., Wang, J., Wang, J., Liu, Y.: Indoor acoustic localization: a survey. *Human-centric Computing and Information Sciences* **10**(1), 1–24 (2020)
- [102] Xu, H., Zhang, Y., Zhou, B., Wang, L., Yao, X., Meng, G., Shen, S.: Omni-swarm: A decentralized omnidirectional visual-inertial-uwB state estimation system for aerial swarm. *arXiv preprint arXiv:2103.04131* (2021)
- [103] Wang, R., Du, J., Xiong, Z., Chen, X., Liu, J.: Hierarchical collaborative navigation method for uav swarm. *Journal of Aerospace Engineering* **34**(1), 04020097 (2021)
- [104] Nascimento, T.P., Saska, M.: Position and attitude control of multi-rotor aerial vehicles: A survey. *Annual Reviews in Control* **48**, 129–146 (2019)
- [105] Lanzon, A., Freddi, A., Longhi, S.: Flight control of a quadrotor vehicle subsequent to a rotor failure. *Journal of Guidance, Control, and Dynamics* **37**(2), 580–591 (2014)
- [106] Priyambodo, T.K., Dhewa, O.A., Susanto, T.: Model of linear quadratic regulator (lqr) control system in waypoint flight mission of flying wing uav. *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)* **12**(4), 43–49 (2020)
- [107] Fessi, R., Bouallègue, S.: Lqg controller design for a quadrotor uav based on particle swarm optimisation. *International Journal of Automation and Control* **13**(5), 569–594 (2019)
- [108] Azar, A.T., Serrano, F.E., Koubaa, A., Kamal, N.A.: Backstepping h-infinity control of unmanned aerial vehicles with time varying disturbances. In: 2020 First International Conference of Smart Systems and Emerging Technologies (SMARTTECH), pp. 243–248 (2020). IEEE
- [109] Kim, J., Gadsden, S.A., Wilkerson, S.A.: A comprehensive survey of control strategies for autonomous quadrotors. *Canadian Journal of Electrical and Computer Engineering* **43**(1), 3–16 (2019)
- [110] Romero, A., Sun, S., Foehn, P., Scaramuzza, D.: Model predictive contouring control for time-optimal quadrotor flight. *IEEE Transactions on Robotics* (2022)
- [111] Pfeiffer, C., Scaramuzza, D.: Expertise affects drone racing performance. *arXiv preprint arXiv:2109.07307* (2021)
- [112] Pfeiffer, C., Scaramuzza, D.: Human-piloted drone racing: Visual processing and control. *IEEE Robotics and Automation Letters* **6**(2), 3467–3474 (2021)
- [113] Foehn, P., Romero, A., Scaramuzza, D.: Time-optimal planning for quadrotor waypoint flight. *Science Robotics* **6**(56), 1221 (2021)
- [114] Nägeli, T., Conte, C., Domahidi, A., Morari, M., Hilliges, O.: Environment-independent formation flight for micro aerial vehicles. In: 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 1141–1146 (2014). IEEE
- [115] Candan, F., Beke, A., Kumbasar, T.: Design and deployment of fuzzy pid controllers to the nano quadcopter crazyflie 2.0. In: 2018 Innovations in Intelligent Systems and Applications (INISTA), pp. 1–6 (2018). IEEE
- [116] Liu, X., Qiu, L.: Bird flocking inspired control strategy for multi-uav collective motion. *arXiv preprint arXiv:1912.00168* (2019)
- [117] Sathyan, A., Ma, O.: Collaborative control of multiple robots using genetic fuzzy systems. *Robotica* **37**(11), 1922–1936 (2019)
- [118] Lyu, Y., Hu, J., Chen, B.M., Zhao, C., Pan, Q.: Multivehicle flocking with collision avoidance via distributed model predictive control. *IEEE transactions on cybernetics* **51**(5), 2651–2662 (2019)
- [119] Bicego, D., Mazzetto, J., Carli, R., Farina, M., Franchi, A.: Nonlinear model predictive control with enhanced actuator model for multi-rotor aerial vehicles with generic designs. *Journal of Intelligent & Robotic Systems* **100**(3), 1213–1247 (2020)
- [120] Parrany, A.M., Alasty, A.: Decentralized aggregation and leader-following control of a swarm of quadcopters with nonlinear underactuated dynamics. *Aerospace Science and Technology* **107**, 106317 (2020)
- [121] Jansch-Porto, J.P., Dullerud, G.E.: Robust decentralized switching control of uavs using uwB-based localization and cooperation. *IFAC-PapersOnLine* **53**(2), 7418–7423 (2020)
- [122] Soria, E., Schiano, F., Floreano, D.: Predictive control of aerial swarms in cluttered environments. *Nature Machine Intelligence* **3**(6), 545–554 (2021)
- [123] Jardine, P.T., Givigi, S.: Improving control performance of unmanned aerial vehicles through shared experience. *Journal of Intelligent & Robotic Systems* **102**(3), 1–11 (2021)
- [124] Shawky, D., Yao, C., Janschek, K.: Nonlinear model predictive control for trajectory tracking of a hexarotor with actively tilttable propellers. In: 2021 7th International Conference on Automation, Robotics and Applications (ICARA), pp. 128–134 (2021). IEEE

- [125] Foerster, J., Assael, I.A., De Freitas, N., Whiteson, S.: Learning to communicate with deep multi-agent reinforcement learning. *Advances in neural information processing systems* **29** (2016)
- [126] Luna, M.A., Ragab, A.R., Isac, M.S.A., Peña, P.F., Cervera, P.C.: A new algorithm using hybrid uav swarm control system for firefighting dynamical task allocation. In: 2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 655–660 (2021). IEEE
- [127] García, C.S.M., Bruun, R.L., Sørensen, T.B., Pratas, N.K., Madsen, T.K., Lianghai, J., Mogensen, P.: Cooperative resource allocation for proximity communication in robotic swarms in an indoor factory. In: 2021 IEEE Wireless Communications and Networking Conference (WCNC), pp. 1–6 (2021). IEEE
- [128] Shen, J., Wang, S., Zhan, X.: Multi-uav cluster-based cooperative navigation with fault detection and exclusion capability. *Aerospace Science and Technology* **124**, 107570 (2022)
- [129] Wang, D., Lian, B., Liu, Y., Gao, B.: A cooperative uav swarm localization algorithm based on probabilistic data association for visual measurement. *IEEE Sensors Journal* **22**(20), 19635–19644 (2022)
- [130] Sathyan, A., Boone, N., Cohen, K.: Comparison of approximate approaches to solving the travelling salesman problem and its application to uav swarming. *International Journal of Unmanned Systems Engineering*. **3**(1), 1 (2015)
- [131] Yazıcıoğlu, Y., Bhat, R., Aksaray, D.: Distributed planning for serving cooperative tasks with time windows: A game theoretic approach. *Journal of Intelligent & Robotic Systems* **103**(2), 1–19 (2021)
- [132] Do, H.T., Hua, H.T., Nguyen, M.T., Nguyen, C.V., Nguyen, H.T., Nguyen, H.T., Nguyen, N.T.: Formation control algorithms for multipleuavs: a comprehensive survey. *EAI Endorsed Transactions on Industrial Networks and Intelligent Systems* **8**(27), 3–3 (2021)
- [133] Anderson, B.D., Fidan, B., Yu, C., Walle, D.: Uav formation control: Theory and application. In: *Recent Advances in Learning and Control*, pp. 15–33 (2008). Springer
- [134] Hou, Z., Wang, W., Zhang, G., Han, C.: A survey on the formation control of multiple quadrotors. In: 2017 14th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI), pp. 219–225 (2017). IEEE
- [135] Liu, Y., Bucknall, R.: A survey of formation control and motion planning of multiple unmanned vehicles. *Robotica* **36**(7), 1019–1047 (2018)
- [136] Zhou, Y., Rao, B., Wang, W.: Uav swarm intelligence: Recent advances and future trends. *IEEE Access* **8**, 183856–183878 (2020)
- [137] Rafifandi, R., Asri, D.L., Ekawati, E., Budi, E.M.: Leader–follower formation control of two quadrotor uavs. *SN Applied Sciences* **1**(6), 1–12 (2019)
- [138] Raja, G., Essaky, S., Ganapathisubramanian, A., Baskar, Y.: Nexus of deep reinforcement learning and leader-follower approach for aiot enabled aerial networks. *IEEE Transactions on Industrial Informatics* (2022)
- [139] Selje, R.A., Al-Radaideh, A., Dutta, R., Sun, L.: Gps-denied three dimensional leader-follower formation control using deep reinforcement learning. In: *AIAA SciTech 2022 Forum*, p. 2237 (2022)
- [140] Shi, Y., Song, J., Hua, Y., Yu, J., Dong, X., Ren, Z.: Leader-follower formation control for fixed-wing uavs using deep reinforcement learning. In: 2022 41st Chinese Control Conference (CCC), pp. 3456–3461 (2022). IEEE
- [141] Low, C.B., San Ng, Q.: A flexible virtual structure formation keeping control for fixed-wing uavs. In: 2011 9th IEEE International Conference on Control and Automation (ICCA), pp. 621–626 (2011). IEEE
- [142] Cai, Z., Liu, Y., Zhao, J., Wang, Y.: Virtual structure and artificial potential field-based cooperative control for uav formation. In: *Advances in Guidance, Navigation and Control: Proceedings of 2022 International Conference on Guidance, Navigation and Control*, pp. 366–375 (2023). Springer
- [143] Reynolds, C.W.: Flocks, herds and schools: A distributed behavioral model. In: *Proceedings of the 14th Annual Conference on Computer Graphics and Interactive Techniques*, pp. 25–34 (1987)
- [144] Fernando, M.: Online flocking control of uavs with mean-field approximation. In: 2021 IEEE International Conference on Robotics and Automation (ICRA), pp. 8977–8983 (2021). IEEE
- [145] Shen, G., Lei, L., Li, Z., Cai, S., Zhang, L., Cao, P., Liu, X.: Deep reinforcement learning for flocking motion of multi-uav systems: Learn from a digital twin. *IEEE Internet of Things Journal* (2021)
- [146] Speck, C., Bucci, D.J.: Distributed uav swarm formation control via object-focused, multi-objective sarsa. In: 2018 Annual American Control Conference (ACC), pp. 6596–6601 (2018). IEEE
- [147] Guinand, F., Guérin, F., Petitprez, E.: Uav-ugv multi-robot system for warehouse inventory: Scheduling issues. In: *International Conference on Computational Collective Intelligence*, pp. 241–254 (2021). Springer

- [148] Elmokadem, T., Savkin, A.V.: Computationally-efficient distributed algorithms of navigation of teams of autonomous uavs for 3d coverage and flocking. *Drones* **5**(4), 124 (2021)
- [149] Wang, X., Chen, G., Gong, H., Jiang, J.: Uav swarm autonomous control based on internet of things and artificial intelligence algorithms. *Journal of Intelligent & Fuzzy Systems* **40**(4), 7121–7133 (2021)
- [150] Kuriki, Y., Namerikawa, T.: Formation control with collision avoidance for a multi-uav system using decentralized mpc and consensus-based control. *SICE Journal of Control, Measurement, and System Integration* **8**(4), 285–294 (2015)
- [151] Yan, M.-d., Zhu, X., Zhang, X.-x., Qu, Y.-h.: Consensus-based three-dimensional multi-uav formation control strategy with high precision. *Frontiers of Information Technology & Electronic Engineering* **18**(7), 968–977 (2017)
- [152] Steinleitner, A., Ballam, R., McFadyen, A.: Practical consensus-based formation control for quadrotor systems. In: *2022 International Conference on Unmanned Aircraft Systems (ICUAS)*, pp. 1510–1519 (2022). IEEE
- [153] Nägeli, T., Conte, C., Domahidi, A., Morari, M., Hilliges, O.: Environment-independent formation flight for micro aerial vehicles. In: *2014 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 1141–1146 (2014). <https://doi.org/10.1109/IROS.2014.6942701>
- [154] Kalempa, V.C., Piardi, L., Limeira, M., de Oliveira, A.S.: Multi-robot preemptive task scheduling with fault recovery: A novel approach to automatic logistics of smart factories. *Sensors* **21**(19), 6536 (2021)
- [155] Wubben, J., Fabra, F., Calafate, C.T., Cano, J.-C., Manzoni, P.: A novel resilient and reconfigurable swarm management scheme. *Computer Networks* **194**, 108119 (2021)
- [156] Ramachandran, R.K., Preiss, J.A., Sukhatme, G.S.: Resilience by reconfiguration: Exploiting heterogeneity in robot teams. In: *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 6518–6525 (2019). IEEE
- [157] Punpikul, N., Thammawichai, M.: A flight formation control of a micro aerial vehicle swarm using a motion capture. In: *2019 16th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*, pp. 128–131 (2019). IEEE
- [158] Liu, H., Lyu, Y., Zhao, W.: Robust visual servoing formation tracking control for quadrotor uav team. *Aerospace Science and Technology* **106**, 106061 (2020)
- [159] Bai, T., Wang, D., Masood, R.J.: Formation control of quad-rotor uav via pio. *Science China Technological Sciences*, 1–8 (2021)
- [160] Ziegler, T., Karrer, M., Schmuck, P., Chli, M.: Distributed formation estimation via pairwise distance measurements. *IEEE Robotics and Automation Letters* **6**(2), 3017–3024 (2021)
- [161] Ambroziak, L., Ciężkowski, M.: Virtual electric dipole field applied to autonomous formation flight control of unmanned aerial vehicles. *Sensors* **21**(13), 4540 (2021)
- [162] Panpan, Z., *et al.*: Semi-global leader-following consensus-based formation flight of unmanned aerial vehicles. *Chinese Journal of Aeronautics* **35**(1), 31–43 (2022)
- [163] Puente-Castro, A., Rivero, D., Pazos, A., Fernandez-Blanco, E.: A review of artificial intelligence applied to path planning in uav swarms. *Neural Computing and Applications*, 1–18 (2021)
- [164] Khan, M.T.R., Muhammad Saad, M., Ru, Y., Seo, J., Kim, D.: Aspects of unmanned aerial vehicles path planning: Overview and applications. *International Journal of Communication Systems* **34**(10), 4827 (2021)
- [165] Lu, L., Yunda, A., Carrio, A., Campoy, P.: Robust autonomous flight in cluttered environment using a depth sensor. *International Journal of Micro Air Vehicles* **12**, 1756829320924528 (2020)
- [166] Sawalmeh, A.H., Othman, N.S.: An overview of collision avoidance approaches and network architecture of unmanned aerial vehicles (uavs). *arXiv preprint arXiv:2103.14497* (2021)
- [167] Yasin, J.N., Mohamed, S.A., Haghbayan, M.-H., Heikkonen, J., Tenhunen, H., Plosila, J.: Unmanned aerial vehicles (uavs): Collision avoidance systems and approaches. *IEEE access* **8**, 105139–105155 (2020)
- [168] Lu, L., Carrio, A., Sampedro, C., Campoy, P.: A robust and fast collision avoidance approach for micro aerial vehicles using a depth sensor. *Remote Sensing* **13**(9), 1796 (2021)
- [169] Hönig, W., Preiss, J.A., Kumar, T.S., Sukhatme, G.S., Ayanian, N.: Trajectory planning for quadrotor swarms. *IEEE Transactions on Robotics* **34**(4), 856–869 (2018)
- [170] Ourari, R., Cui, K., Koepl, H.: Decentralized swarm collision avoidance for quadrotors via end-to-end reinforcement learning. *arXiv preprint arXiv:2104.14912* (2021)
- [171] Zhou, X., Zhu, J., Zhou, H., Xu, C., Gao, F.: Ego-swarm: A fully autonomous and decentralized quadrotor swarm system in cluttered environments. In: *2021 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 4101–4107 (2021). IEEE

- [172] Peterson, R., Buyukkocak, A.T., Aksaray, D., Yazıcıoğlu, Y.: Decentralized safe reactive planning under twtl specifications. In: 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 6599–6604 (2020). IEEE
- [173] Majd, A., Ashraf, A., Troubitsyna, E., Daneshmand, M.: Integrating learning, optimization, and prediction for efficient navigation of swarms of drones. In: 2018 26th Euromicro International Conference on Parallel, Distributed and Network-based Processing (PDP), pp. 101–108 (2018). IEEE
- [174] Parker, L., Butterworth, J., Luo, S.: Fly safe: Aerial swarm robotics using force field particle swarm optimisation. arXiv preprint arXiv:1907.07647 (2019)
- [175] Sanchez-Lopez, J.L., Wang, M., Olivares-Mendez, M.A., Molina, M., Voos, H.: A real-time 3d path planning solution for collision-free navigation of multirotor aerial robots in dynamic environments. *Journal of Intelligent & Robotic Systems* **93**(1), 33–53 (2019)
- [176] Behjat, A., Paul, S., Chowdhury, S.: Learning reciprocal actions for cooperative collision avoidance in quadrotor unmanned aerial vehicles. *Robotics and Autonomous Systems* **121**, 103270 (2019)
- [177] Datar, A., Paulsen, P., Werner, H.: Flocking towards the source: Indoor experiments with quadrotors. In: 2020 European Control Conference (ECC), pp. 1638–1643 (2020). IEEE
- [178] Bojeri, A., Iacca, G.: Evolutionary optimization of drone trajectories based on optimal reciprocal collision avoidance. In: 2020 27th Conference of Open Innovations Association (FRUCT), pp. 18–26 (2020). IEEE
- [179] Luis, C.E., Vukosavljev, M., Schoellig, A.P.: Online trajectory generation with distributed model predictive control for multi-robot motion planning. *IEEE Robotics and Automation Letters* **5**(2), 604–611 (2020)
- [180] Abhishek, B., Ranjit, S., Shankar, T., Eappen, G., Sivasankar, P., Rajesh, A.: Hybrid pso-hsa and pso-ga algorithm for 3d path planning in autonomous uavs. *SN Applied Sciences* **2**(11), 1–16 (2020)
- [181] Park, J., Kim, H.J.: Online trajectory planning for multiple quadrotors in dynamic environments using relative safe flight corridor. *IEEE Robotics and Automation Letters* **6**(2), 659–666 (2020)
- [182] Xu, W., Xiang, L., Zhang, T., Pan, M., Han, Z.: Cooperative control of physical collision and transmission power for uav swarm: A dual-fields enabled approach. *IEEE Internet of Things Journal* (2021)
- [183] Zhou, X., Wang, Z., Wen, X., Zhu, J., Xu, C., Gao, F.: Decentralized spatial-temporal trajectory planning for multicopter swarms. arXiv preprint arXiv:2106.12481 (2021)
- [184] Quan, Q., Fu, R., Cai, K.-Y.: Practical control for multicopters to avoid non-cooperative moving obstacles. *IEEE Transactions on Intelligent Transportation Systems* (2021)
- [185] Park, J., Kim, D., Kim, G.C., Oh, D., Kim, H.J.: Online distributed trajectory planning for quadrotor swarm with feasibility guarantee using linear safe corridor. *IEEE Robotics and Automation Letters* **7**(2), 4869–4876 (2022)
- [186] Huang, S., Zhang, H., Huang, Z.: E2coop: Energy efficient and cooperative obstacle detection and avoidance for uav swarms. In: *Proceedings of the International Conference on Automated Planning and Scheduling*, vol. 31, pp. 634–642 (2021)
- [187] Yasin, J.N., Haghbayan, M.-H., Yasin, M.M., Plosila, J.: Swarm formation morphing for congestion-aware collision avoidance. *Heliyon* **7**(8), 07840 (2021)
- [188] Li, R., Yang, Q., Zhao, W., Fang, H.: Collision-free trajectory generation for multiple uavs with sensing constraints. In: 2021 40th Chinese Control Conference (CCC), pp. 5592–5597 (2021). IEEE
- [189] Toumeh, C., Lambert, A.: High-speed planning in unknown environments for multirotors considering drag. In: 2021 IEEE International Conference on Robotics and Automation (ICRA), pp. 7844–7850 (2021). IEEE
- [190] D’Amato, E., Nardi, V.A., Notaro, I., Scordamaglia, V.: A particle filtering approach for fault detection and isolation of uav imu sensors: Design, implementation and sensitivity analysis. *Sensors* **21**(9), 3066 (2021)
- [191] Barbeau, M., Garcia-Alfaro, J., Kranakis, E., Santos, F.: Quality amplification of error prone navigation for swarms of micro aerial vehicles (with detailed simulations). arXiv e-prints, 1906 (2019)
- [192] Sun, S., Cioffi, G., De Visser, C., Scaramuzza, D.: Autonomous quadrotor flight despite rotor failure with onboard vision sensors: Frames vs. events. *IEEE Robotics and Automation Letters* **6**(2), 580–587 (2021)
- [193] Syed, F., Gupta, S.K., Hamood Alsamhi, S., Rashid, M., Liu, X.: A survey on recent optimal techniques for securing unmanned aerial vehicles applications. *Transactions on Emerging Telecommunications Technologies* **32**(7), 4133 (2021)
- [194] Liu, G.: Jamming attacks and countermeasures in wireless area networks. Hong Kong Polytechnic University (People’s Republic of China) (2012)

- [195] Mykytyn, P., Brzozowski, M., Dyka, Z., Langendoerfer, P.: Jamming detection for ir-uwv ranging technology in autonomous uav swarms. In: 2021 10th Mediterranean Conference on Embedded Computing (MECO), pp. 1–6 (2021). IEEE
- [196] Gupta, A., Afrin, T., Scully, E., Yodo, N.: Advances of uavs toward future transportation: The state-of-the-art, challenges, and opportunities. *Future Transportation* **1**(2), 326–350 (2021)
- [197] Chen, A., Harwell, J., Gini, M.: Maximizing energy battery efficiency in swarm robotics. arXiv preprint arXiv:1906.01957 (2019)
- [198] Mostaghim, S., Steup, C., Witt, F.: Energy aware particle swarm optimization as search mechanism for aerial micro-robots. In: 2016 IEEE Symposium Series on Computational Intelligence (SSCI), pp. 1–7 (2016). IEEE
- [199] Stirling, T., Floreano, D.: Energy-time efficiency in aerial swarm deployment. In: Distributed Autonomous Robotic Systems: The 10th International Symposium, pp. 5–18 (2013). Springer
- [200] Hassija, V., Saxena, V., Chamola, V.: Scheduling drone charging for multi-drone network based on consensus time-stamp and game theory. *Computer Communications* **149**, 51–61 (2020)
- [201] Zhang, P., Xu, S., Zhang, W., Dong, W.: A cooperative aerial inspection system with continuable charging strategy. In: 2019 IEEE International Conference on Robotics and Biomimetics (ROBIO), pp. 770–777 (2019). IEEE
- [202] Parker, L.E., Rus, D., Sukhatme, G.S.: Multiple mobile robot systems. *Springer handbook of robotics*, 1335–1384 (2016)
- [203] Aznar, F., Pujol López, M.d.M., Rizo, R.: Uav deployment using two levels of stigmergy for unstructured environments. *Applied Sciences* **10**(21), 7696 (2020)
- [204] Das, B., Couceiro, M.S., Vargas, P.A.: Mrocs: A new multi-robot communication system based on passive action recognition. *Robotics and autonomous systems* **82**, 46–60 (2016)
- [205] Sharma, A., Vanjani, P., Paliwal, N., Basnayaka, C.M.W., Jayakody, D.N.K., Wang, H.-C., Muthuchidambanathan, P.: Communication and networking technologies for uavs: A survey. *Journal of Network and Computer Applications* **168**, 102739 (2020)
- [206] Nawaz, H., Ali, H.M., Laghari, A.A.: Uav communication networks issues: a review. *Archives of Computational Methods in Engineering* **28**(3), 1349–1369 (2021)
- [207] Goddemeier, N., Rohde, S., Wietfeld, C.: Experimental performance evaluation of role-based connectivity management for cooperating uavs. In: 2014 IEEE 79th Vehicular Technology Conference (VTC Spring), pp. 1–5 (2014). IEEE
- [208] Lagkas, T., Argyriou, V., Bibi, S., Sarigiannidis, P.: Uav iot framework views and challenges: Towards protecting drones as “things”. *Sensors* **18**(11), 4015 (2018)
- [209] Gharibi, M., Boutaba, R., Waslander, S.L.: Internet of drones. *IEEE Access* **4**, 1148–1162 (2016)
- [210] Kumar, A., Mehta, P.L.: In: Gupta, D., Hugo C. de Albuquerque, V., Khanna, A., Mehta, P.L. (eds.) *Internet of Drones: An Engaging Platform for IIoT-Oriented Airborne Sensors*, pp. 249–270. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-52624-5_16. https://doi.org/10.1007/978-3-030-52624-5_16
- [211] Boccadoro, P., Striccoli, D., Grieco, L.A.: An extensive survey on the internet of drones. *Ad Hoc Networks* **122**, 102600 (2021)
- [212] Dinh, T.D., Vishnevsky, V., Le, D.T., Kirichek, R., Koucheryavy, A., *et al.*: Determination of subscribers coordinates using flying network for emergencies. In: 2021 23rd International Conference on Advanced Communication Technology (ICACT), pp. 1–10 (2021). IEEE
- [213] Bithas, P.S., Michailidis, E.T., Nomikos, N., Vouyioukas, D., Kanatas, A.G.: A survey on machine-learning techniques for uav-based communications. *Sensors* **19**(23), 5170 (2019)
- [214] Tung, T.-Y., Kobus, S., Roig, J.P., Gündüz, D.: Effective communications: A joint learning and communication framework for multi-agent reinforcement learning over noisy channels. *IEEE Journal on Selected Areas in Communications* **39**(8), 2590–2603 (2021)
- [215] Sadiq, B., Salawudeen, A., Sha’aban, Y., Adedokun, E., Mu’azu, M.: Interface protocol design: a communication guide for indoor fanet. *TELKOMNIKA* **17**(6), 3175–3182 (2019)
- [216] Khan, S., Zeeshan, M., Ayaz, Y.: Implementation and analysis of multicode multicarrier code division multiple access (mc–mc cdma) in ieee 802.11 ah for uav swarm communication. *Physical Communication* **42**, 101159 (2020)
- [217] Kravchuk, S.O., Kravchuk, I.M.: Using rfid technology at operating a drone swarms in communication system mode (2020)
- [218] Shang, B., Marojevic, V., Yi, Y., Abdalla, A.S., Liu, L.: Spectrum sharing for uav communications: Spatial spectrum sensing and open issues. *IEEE Vehicular Technology Magazine* **15**(2), 104–112 (2020)

- [219] Yang, B., Taleb, T., Chen, G.: On sum rate maximization study for cellular-connected uav swarm communications. In: ICC 2021-IEEE International Conference on Communications, pp. 1–6 (2021). IEEE
- [220] Touati, H., Chriki, A., Snoussi, H., Kamoun, F.: Cognitive radio and dynamic tdma for efficient uavs swarm communications. *Computer Networks* **196**, 108264 (2021)
- [221] Mohanti, S., Bocanegra, C., Sanchez, S.G., Alemdar, K., Chowdhury, K.R.: Sabre: Swarm-based aerial beamforming radios: Experimentation and emulation. *IEEE Transactions on Wireless Communications* **21**(9), 7460–7475 (2022). <https://doi.org/10.1109/TWC.2022.3158866>
- [222] Xiao, Z., Zhu, L., Xia, X.-G.: Uav communications with millimeter-wave beamforming: Potentials, scenarios, and challenges. *China Communications* **17**(9), 147–166 (2020)
- [223] Messous, M.A., Hellwagner, H., Senouci, S.-M., Emini, D., Schnieders, D.: Edge computing for visual navigation and mapping in a uav network. In: ICC 2020-2020 IEEE International Conference on Communications (ICC), pp. 1–6 (2020). IEEE
- [224] Mukherjee, A., Misra, S., Chandra, V.S.P., Obaidat, M.S.: Resourceoptimized multiarmed bandit-based offload path selection in edge uav swarms. *IEEE Internet of Things Journal* **6**(3), 4889–4896 (2018)
- [225] Amodu, O.A., Busari, S.A., Othman, M.: Physical layer aspects of terahertz-enabled uav communications: Challenges and opportunities. *Vehicular Communications* **38**, 100540 (2022). <https://doi.org/10.1016/j.vehcom.2022.100540>
- [226] Alsamhi, S.H., Ma, O., Ansari, M., *et al.*: Survey on artificial intelligence based techniques for emerging robotic communication. *Telecommunication Systems* **72**(3), 483–503 (2019)
- [227] Alsamhi, S.H., Ma, O., Ansari, M., *et al.*: Convergence of machine learning and robotics communication in collaborative assembly: mobility, connectivity and future perspectives. *Journal of Intelligent & Robotic Systems* **98**(3), 541–566 (2020)
- [228] Akhloufi, M.A., Arola, S., Bonnet, A.: Drones chasing drones: Reinforcement learning and deep search area proposal. *Drones* **3**(3), 58 (2019)
- [229] Shen, K., Zhuang, Y., Zhu, Y.: Incremental learning-based land mark recognition for mirco-uav autonomous landing. In: 2020 39th Chinese Control Conference (CCC), pp. 6786–6791 (2020). IEEE
- [230] Wu, W., Payeur, P., Al-Buraiki, O., Ross, M.: Vision-based target objects recognition and segmentation for unmanned systems task allocation. In: International Conference on Image Analysis and Recognition, pp. 252–263 (2019). Springer
- [231] Zhang, T., Hu, X., Xiao, J., Zhang, G.: A machine learning method for vision-based unmanned aerial vehicle systems to understand unknown environments. *Sensors* **20**(11), 3245 (2020)
- [232] Raja, G., Anbalagan, S., Narayanan, V.S., Jayaram, S., Ganapathisubramanian, A.: Inter-uav collision avoidance using deep-q-learning in flocking environment. In: 2019 IEEE 10th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), pp. 1089–1095 (2019). IEEE
- [233] Zhang, J., Yu, Z., Mao, S., Periaswamy, S.C., Patton, J., Xia, X.: Iadr: Imitation augmented deep reinforcement learning enabled ugv-uav coalition for tasking in complex environments. *IEEE Access* **8**, 102335–102347 (2020)
- [234] Batra, S., Huang, Z., Petrenko, A., Kumar, T., Molchanov, A., Sukhatme, G.S.: Decentralized control of quadrotor swarms with end-to-end deep reinforcement learning. In: Conference on Robot Learning, pp. 576–586 (2022). PMLR
- [235] Loquercio, A., Kaufmann, E., Ranftl, R., Müller, M., Koltun, V., Scaramuzza, D.: Learning high-speed flight in the wild. *Science Robotics* **6**(59), 5810 (2021)
- [236] Lu, L., Redondo, C., Campoy, P.: Optimal frontier-based autonomous exploration in unconstructed environment using rgb-d sensor. *Sensors* **20**(22), 6507 (2020)
- [237] Hartman, J., Barzilov, A., Novikov, I.: Remote sensing of neutron and gamma radiation using aerial unmanned autonomous system. In: 2015 IEEE Nuclear Science Symposium and Medical Imaging Conference (NSS/MIC), pp. 1–4 (2015). IEEE
- [238] Almeshal, A.M., Alenezi, M.R.: A vision-based neural network controller for the autonomous landing of a quadrotor on moving targets. *Robotics* **7**(4), 71 (2018)
- [239] Nägeli, T., Oberholzer, S., Plüss, S., Alonso-Mora, J., Hilliges, O.: Flycon: real-time environment-independent multi-view human pose estimation with aerial vehicles. *ACM Transactions on Graphics (TOG)* **37**(6), 1–14 (2018)
- [240] Gainer Jr, J.J., Dawkins, J.J., DeVries, L.D., Kutzer, M.D.: Persistent multi-agent search and tracking with flight endurance constraints. *Robotics* **8**(1), 2 (2018)

- [241] Facinelli, D., Larcher, M., Brunelli, D., Fontanelli, D.: Cooperative uavs gas monitoring using distributed consensus. In: 2019 IEEE 43rd Annual Computer Software and Applications Conference (COMPSAC), vol. 1, pp. 463–468 (2019). IEEE
- [242] Cristiani, D., Bottonelli, F., Trotta, A., Di Felice, M.: Inventory management through mini-drones: Architecture and proof-of-concept implementation. In: 2020 IEEE 21st International Symposium On "A World of Wireless, Mobile and Multimedia Networks"(WoWMoM), pp. 317–322 (2020). IEEE
- [243] Kapoutsis, A.C., Michailidis, I.T., Boutalis, Y., Kosmatopoulos, E.B.: Building synergetic consensus for dynamic gas-plume tracking applications using uav platforms. *Computers & Electrical Engineering* **91**, 107029 (2021)
- [244] Duisterhof, B.P., Li, S., Burgués, J., Reddi, V.J., de Croon, G.C.: Sniffy bug: A fully autonomous swarm of gas-seeking nano quadcopters in cluttered environments. In: 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 9099–9106 (2021). IEEE
- [245] Zhu, X., Vanegas, F., Gonzalez, F., Sanderson, C.: A multi-uav system for exploration and target finding in cluttered and gps-denied environments. In: 2021 International Conference on Unmanned Aircraft Systems (ICUAS), pp. 721–729 (2021). IEEE
- [246] Zheng, X., Chunyao, M.: An intelligent target detection method of uav swarms based on improved km algorithm. *Chinese Journal of Aeronautics* **34**(2), 539–553 (2021)
- [247] Márquez-Vega, L.A., Aguilera-Ruiz, M., Torres-Treviño, L.M.: Multi-objective optimization of a quadrotor flock performing target zone search. *Swarm and Evolutionary Computation* **60**, 100733 (2021)
- [248] Yu, L., Yang, E., Yang, B., Loeliger, A., Fei, Z.: Stereo vision-based autonomous navigation for oil and gas pressure vessel inspection using a low-cost uav. In: 2021 IEEE International Conference on Real-time Computing and Robotics (RCAR), pp. 1052–1057 (2021). IEEE
- [249] Kim, J., Eggleton, C.D., Wilkerson, S.A., Gadsden, S.A.: Cooperative sensor-based selective graph exploration strategy for a team of quadrotors. *Journal of Intelligent & Robotic Systems* **103**(2), 1–14 (2021)
- [250] Liu, S., Erskine, J., Chriette, A., Fantoni, I.: Decentralized control and teleoperation of a multi-uav parallel robot based on intrinsic measurements. In: 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 6329–6335 (2021). IEEE
- [251] Guérin, F., Guinand, F., Brethé, J.-F., Pelvillain, H., *et al.*: Towards an autonomous warehouse inventory scheme. In: 2016 IEEE Symposium Series on Computational Intelligence (SSCI), pp. 1–8 (2016). IEEE
- [252] Bae, S.M., Han, K.H., Cha, C.N., Lee, H.Y.: Development of inventory checking system based on uav and rfid in open storage yard. In: 2016 International Conference on Information Science and Security (ICISS), pp. 1–2 (2016). IEEE
- [253] Falco, A.D., Narducci, F., Petrosino, A.: An uav autonomous warehouse inventorying by deep learning. In: International Conference on Image Analysis and Processing, pp. 443–453 (2019). Springer
- [254] Awasthi, S., Gramse, N., Reining, D., Roidl, M., *et al.*: Uavs for industries and supply chain management. arXiv preprint arXiv:2212.03346 (2022)
- [255] Mourtzis, D., Angelopoulos, J., Panopoulos, N.: Uavs for industrial applications: Identifying challenges and opportunities from the implementation point of view. *Procedia Manufacturing* **55**, 183–190 (2021)
- [256] Khosiawan, Y., Nielsen, I.: A system of uav application in indoor environment. *Production & Manufacturing Research* **4**(1), 2–22 (2016)
- [257] Novák, A., Sedláčková, A.N., Bugaj, M., Kandra, B., Lusiak, T.: Use of unmanned aerial vehicles in aircraft maintenance. *Transportation Research Procedia* **51**, 160–170 (2020)
- [258] Martínez-Rozas, S., Rey, R., Alejo, D., Acedo, D., Cobano, J.A., Rodríguez-Ramos, A., Campoy, P., Merino, L., Caballero, F.: Skyeye team at mbzirc 2020: A team of aerial and ground robots for gps-denied autonomous fire extinguishing in an urban building scenario. arXiv preprint arXiv:2104.01834 (2021)
- [259] Sanchez-Lopez, J.L., Fernández, R.A.S., Bavle, H., Sampedro, C., Molina, M., Pestana, J., Campoy, P.: Aerostack: An architecture and open-source software framework for aerial robotics. In: 2016 International Conference on Unmanned Aircraft Systems (ICUAS), pp. 332–341 (2016). IEEE
- [260] Sampedro, C., Bavle, H., Sanchez-Lopez, J.L., Fernández, R.A.S., Rodríguez-Ramos, A., Molina, M., Campoy, P.: A flexible and dynamic mission planning architecture for uav swarm coordination. In: 2016 International Conference on Unmanned Aircraft Systems (ICUAS), pp. 355–363 (2016). <https://doi.org/10.1109/ICUAS.2016.7502669>
- [261] Gusenbauer, M.: Google scholar to overshadow them all? comparing the sizes of 12 academic search engines and bibliographic databases. *Scientometrics* **118**(1), 177–214 (2019)

- [262] Martín-Martín, A., Orduna-Malea, E., Thelwall, M., López-Cózar, E.D.: Google scholar, web of science, and scopus: A systematic comparison of citations in 252 subject categories. *Journal of informetrics* **12**(4), 1160–1177 (2018)
- [263] Purkayastha, A., Palmaro, E., Falk-Krzesinski, H.J., Baas, J.: Comparison of two article-level, field-independent citation metrics: Field-weighted citation impact (fwi) and relative citation ratio (rcr). *Journal of Informetrics* **13**(2), 635–642 (2019)
- [264] Goodfellow, I., Bengio, Y., Courville, A.: Representation learning. *Deep learning*, 528–559 (2016)
- [265] Jassowski, M.A., Thirunahari, A.S.: Drone swarm for increased cargo capacity. Google Patents. US Patent 10,324,462 (2019)
- [266] Huijun, G., Li, Z., Xidi, X., Weichao, S., Xuebo, Y., Xinghu, Y.: Indoor monocular navigation method based on cross-sensor transfer learning and system thereof. Google Patents. US Patent 11,561,544 (2023)
- [267] Ottenheimer, A.: Remote object capture. Google Patents. US Patent App. 16/638,274 (2020)
- [268] Salem, A.: Self charging lightweight drone apparatus. Google Patents. US Patent 10,424,231 (2019)
- [269] Rahmes, M.D., Chester, D.B.: Radio frequency (RF) communication system providing enhanced RF equipment configuration updates for mobile vehicles based upon reward matrices and related methods. Google Patents. US Patent 11,184,232 (2021)
- [270] Arsenian, R.J., Fried-Gintis, A.M.: Control system for autonomous locomotion devices. Google Patents. US Patent 10,365,651 (2019)
- [271] Dürr, P.: Concept for designing and using an uav controller model for controlling an uav. Google Patents. US Patent App. 16/824,720 (2020)
- [272] Shattil, S.: Airborne relays in cooperative-MIMO systems. Google Patents. US Patent App. US10444766B2 (2019)
- [273] Fisher, J.M., Davis, B.J., Fisher, R.E.: Apparatus, systems and methods for unmanned aerial vehicles. Google Patents. US Patent 10,370,122 (2019)

A METHOD OF LITERATURE REVIEW

This SLR is based on the guidelines suggested by [37], and the process followed is explained below and is similar to [38]. The three-step pipeline of the method is illustrated in Figure 7. Based on Inclusion Criteria, a list of potentially relevant publications is created. During the selection process, three experts from the robotics domain at every stage either rejected a publication or assigned it to the next stage based on the predefined scope of this review. Publications that reached Stage IV are considered relevant for the literature analysis. Relevant tags are added to every publication, which helps categorize the publications and answer the guiding questions.

A.1 Inclusion criteria

This work includes all the published works from 1 Jan 2011 – 30 Dec 2021 that is available to researchers to get a mental picture of the overall academic activity. Moreover, we also included some relevant literature from the year 2022. Google Scholar (GS) facilitates literature discovery by indexing every scholarly document it finds. A detailed list of the sources of Google Scholar can be found in [39]. GS has a more comprehensive coverage than Scopus, Web of Science and also IEEE Explore, and includes the great majority of the documents that they cover [40]. GS's broad coverage and fast indexing speed have made it one of the most comprehensive academic search engines [261] [39]. In addition, GS provides a comprehensive insight into the impact publications have on their respective academic communities [261]. Therefore, it is used for querying literature in this work.

Harzing's Publish or Perish (PoP) is used as the API to perform a google scholar search for indexing. The interface of PoP allows for writing queries, applying filters, sorting, and exporting results to various formats

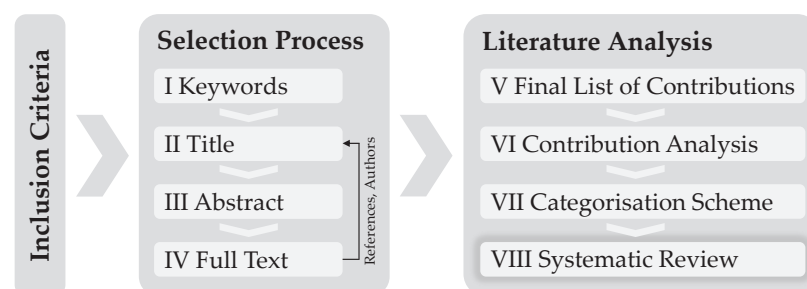


Fig. 7: Method of the literature review [38]

[262]. The search in PoP is carried out using the following set of keywords in the keywords field:

- (“indoor”OR “ warehouse” OR “intralogistics”) AND
- (“drone swarm” OR “UAV swarm” OR “MAV swarm” OR “swarm behavior” OR “unmanned aerial vehicle swarm” OR “aerial swarm” OR “quadcopter swarm” OR “unmanned aerial system swarm”)

This work focuses on UAV swarm in an indoor industrial setting. Therefore, all publications focused at industries would have the word indoor, warehouse or intralogistics present in the text. Moreover popular synonyms of UAVs are considered to include all related publications.

The keywords used in title field:

- (-“agriculture” AND -“military” AND -“outdoor”)

The ‘-’ means NOT. Thus, the literature with agriculture, military, and outdoor in the title field is excluded. Moreover, the contributions in English published between 1 January 2011 and 30 December 2021 are considered. Going back in time would be challenging to capture state of the art in a rapidly progressing field of research such as Micro UAV. Moreover, student degree theses, patents, and paid content are excluded from the reviewing process to ensure the quality of the observed material. The inclusion criteria are objective; therefore, reviewers work individually without discussion to create an initial literature list. Finally, the individual lists are merged, and duplicates are removed. The search procedure

generates 1997 articles from 1 January 2011 and 30 December 2021, which are then carefully examined in the next stage. Additionally, we included some relevant works from the year 2022.

A.2 Selection Process

The selection process is performed for the entire literature list obtained after the inclusion criteria. In this stage, each of the three reviewers independently reviews the publications first based on the title and abstract. Publications that focus on military-based research or designing drones or are specific to outdoor applications such as disaster relief, search and rescue, agriculture, construction monitoring, and UAV-assisted wireless networks are rejected at this stage. Only the newest contribution is considered when an author wrote several papers with the same scope or refined the applied methods. The contributions that reached Stage IV and related surveys (see Section 3) served as a starting point for further literature analysis.

Table 14 explains the four stages through which the contributions could advance during the selection process while adhering to the Selection criteria given in Table 13. During the selection process, reviewers encountered some publications that performed experiments on a single MAV deployed indoors or outdoors. However, the method used by the authors can potentially be transferred to a swarm of MAVs flying indoors. Therefore, such publications are also analyzed in this review.

Table 13: Selection criteria

Selection Criteria	Description
(1) UAV swarm	Method is focused at a Micro UAV swarm or easily transferable.
(2) Experiments	Experiments must be conducted on UAVs or easily transferable to UAVs.
(3) UGVs	Methods and Experiments should not be specific for only unmanned ground vehicles (UGVs).
(4) Applicationoriented	Perspectives for deploying the proposed method in indoor industrial environment is conceivable.
(5) No focus on hardware	Selecting and assembling various hardware components to design a UAV or explaining and comparing UAV components is not the focus of this review.
(6) Environment	The publication should be relevant for a swarm of UAVs in an indoor logistic environment.
(7) Clear Method	Publications should have a clear method with relevant performance metrics to test the results.

Table 14: Stages I–IV of selection process.

Stage	Description
(I) Keywords	The Keywords of the publication match with the Inclusion Criteria. The reviewers have not yet examined the publications at this point.
(II) Title	The reviewers read the title of every publication, and the publication whose title did not conflict with the Selection Criteria or it is ambiguous reached this stage. In addition, duplicates are removed, and the publications from 2011-2018 having 0 citations are excluded from the list as they have not had a significant impact in their respective domain.
(III) Abstract	The publications whose abstract did not conflict with the Selection Criteria or it is challenging to comprehend the abstract reached this stage.
(IV) Full Text	Reading the full text confirms compliance with all Selection Criteria. Relevant tags and comments are recorded for each publication in Excel.

A.3 Literature Analysis

Once the selection process is complete, a systematic literature analysis is conducted for all publications assigned to the fourth stage. In Stage V, the final list of relevant publications is extended by including the Field Weighted Citation Impact (FWCI): “FWCI is an indicator of mean citation impact and compares the actual number of citations received by a document with the expected number of citations for documents of the same document type (article, review, book, or conference proceeding), publication year, and subject area” [263]. FWCI is often used by researchers to understand the impact of their work in a specific research field. Therefore, recording the FWCI will give valuable insights into the contribution’s relevance for their respective domain. The metric is taken from the Scopus Database www.scopus.com/sources on 15 Jan 2021. Once the general information is acquired, each contribution’s striking features regarding this review’s guiding questions are analyzed. Thus, Stage VI required the reviewers to read all relevant literature and briefly summarize based on the following:

- application area;
- technological scope to achieve autonomous UAV behavior;
- specifications and characteristics of the UAV and UAV swarm;
- testing environment;
- the methodology and empirical results; and
- further research demand.

This procedure enabled the reviewers to get a quick overview of a publication. Based on the contribution analysis, a categorization scheme is derived by the reviewers in the stage. VII. This scheme consists of two layers—root categories and subcategories. The reviewers create the initial categories. Then, the points of disagreement are discussed among the reviewers. Based on the discussion, the initial categories are subject to change when allocating the contributions in

the the following stage. The systematic review of the literature is accompanied by continuous refinement of the categorization scheme – ultimately leading to the one illustrated in Table 15. Artificial intelligence (AI) encompasses various techniques such as machine learning (ML), deep learning (DL), reinforcement learning (RL), imitation learning, and representation learning [264]. After defining the categorization scheme, all publications are allocated accordingly in Stage VIII. Most publications focus on a single technological area and are thus assigned to a specific category, from localization, guidance system, safety and security, UAV charging, AI, control, communications, and applications. Few publications are a part of multiple subcategories. For instance, a publication can use machine learning with UWB technology to achieve localization and RL to achieve optimal control. Thus, it is analyzed in three categories: AI techniques, localization, and control. Figure 1 visualizes the various categories covered in this review.

B TECHNOLOGY READINESS LEVEL (TRL)

The TRL scale typically ranges from TRL 1 to TRL 9, with each level representing a specific stage in the technology’s development:

- **TRL1:** Basic principles observed and reported.
- **TRL2:** At this stage, the technology concept is defined and its feasibility is assessed.
- **TRL3:** A proof of concept is created to demonstrate the functionality of the technology in a controlled environment.
- **TRL4:** Technology is validated in a laboratory environment.
- **TRL5:** Technology is validated in relevant environment such as an industrially relevant environment.

- **TRL6:** Technology is demonstrated in a relevant environment.
- **TRL7:** A fully functional prototype is demonstrated in an operational environment.
- **TRL8:** This stage focuses on verifying the technology’s readiness for production and deployment.
- **TRL9:** The technology is fully developed, tested, and proven to work successfully in its intended operational environment. It has been deployed and is being used in real-world applications [36].

Table 15: Categorization scheme.

Root Category	Description
Localization	
Optical	Includes Infrared and light detection and ranging sensor based localization
Vision Based	Use a single or multiple cameras
RF	Radio Frequency: Includes Ultra Wide Band and RFID based localization
INS	Inertial Navigation System: employ an inertial measuring unit
Sound Based	Ultrasonic and acoustic based localization
Control	
Single UAV Control	Linear, non-linear and Intelligent controllers
Collaborative Control	
Formation Control	Leader-follower, virtual structure, behavior-based, consensus-based
Guidance System	
Path Planning	
Collision Avoidance	Categorizes collision avoidance algorithms into Geometric Methods, Force Field Methods and Optimization Based Methods
Safety and Security	Categorizes based on sensor faults, actuator faults and process faults
UAV charging	Energy requirement management and charging stations
Communication	Implicit communication, explicit communication and passive action recognition
Artificial Intelligence	
AI techniques	Machine learning, reinforcement learning, deep learning, imitation learning, representation learning
Application in Indoor Logistics	Transportation, exploration, target search, gas seeking, inspection, inventory management, search and rescue
Testing Environment	
Indoor	Testing hall or a laboratory
Simulator	Using a UAV simulator or software simulations
Industry	Tested in a real industry or factory or a warehouse
UAV Characteristics	
Weight	The weight of individual UAV
Number	How many UAVs constitute the swarm

C PATENT

Table 16 lists all patents that were obtained in the review process that hold significance within the context of this study.

Table 16 lists all the patents that are relevant in the scope of this work.

Pub.	Company	Year	Title	Focus Point
[265]	Intel	2019	Drone swarm for increased cargo capacity	Transportation of objects using two or more drones.
[266]	Harbin Institute of Technology	2021	Indoor Monocular Navigation Method Based on Cross-Sensor Transfer Learning and System Thereof	Uses a deterministic policy gradient deep reinforcement learning method.
[267]	Ottenheimers Inc	2020	Remote object capture	Drone swarm detects remote objects using vision or detecting signals emitted from objects.
[268]	Mores Inc.	2019	Self-charging lightweight drone apparatus	Drones collectively position a surface apparatus to a desired location.
[269]	Eagle Technology LLC	2020	Radio frequency (RF) communication system providing enhanced RF equipment configuration updates for mobile vehicles based upon reward matrices and related methods	RF communication between mobile nodes in an RF network.
[270]	Nutanix Inc	2019	Control system for autonomous locomotion devices	The authors use a virtual environment.
[271]	Sony Corp	2020	Concept for designing and using a UAV controller model for controlling a UAV	The authors use a wind generator to replicate a real environment for UAV flight.
[272]	Tybalt LLC	2019	Airborne relays in cooperative-MIMO systems.	
[273]	Foundation Productions LLC	2019	Apparatus, systems, and methods for unmanned aerial vehicles	Authors propose universal docking ports that can be incorporated on stationary and mobile objects.