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REVIEW

A review of artificial intelligence applied to path planning in UAV swarms

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Abstract
Path Planning problems with Unmanned Aerial Vehicles (UAVs) are among the most studied knowledge areas in the related literature. However, few of them have been applied to groups of UAVs. The use of swarms allows to speed up the flight time and, thus, reducing the operational costs. When combined with Artificial Intelligence (AI) algorithms, a single system or operator can control all aircraft while optimal paths for each one can be computed. In order to introduce the current situation of these AI-based systems, a review of the most novel and relevant articles was carried out. This review was performed in two steps: first, a summary of the found articles; second, a quantitative analysis of the publications found based on different factors, such as the temporal evolution or the number of articles found based on different criteria. Therefore, this review provides not only a summary of the most recent work but it gives an overview of the trend in the use of AI algorithms in UAV swarms for Path Planning problems. The AI techniques of the articles found can be separated into four main groups based on their technique: reinforcement Learning techniques, Evolutive Computing techniques, Swarm Intelligence techniques, and, Graph Neural Networks. The final results show an increase in publications in recent years and that there is a change in the predominance of the most widely used techniques.

Keywords Unmanned aerial vehicle · UAV · Swarm intelligence · Path planning

1 Introduction

Swarms of Unmanned Aerial Vehicles or UAVs are a revolution in both industrial and recreational fields. They make it possible to perform industrial tasks faster and more economical while maintaining safety. Mostly because to their compact size, low cost, and overall ease of management and operation [39]. In this way, UAVs are very useful tools when it comes to carrying out tasks in places that are difficult to access. The battery life can be considered in as a major disadvantage due to their limited operational time. Thus, tasks that require flying over large areas are a problem.

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In addition to the individual advantages and challenges, operating in heterogeneous groups or swarms provides other advantages. Among them, the most important is the time reduction of some operations by performing the same task simultaneously and the capacity to perform tasks that require flying over large areas [15].

Several sectors could benefit from these advantages. One example is the agricultural sector, where these swarms are used in tasks such as field or crop monitoring [2]. Other papers propose applications in military or rescue cases [60]. Within the field of emergencies and rescues, they can also be used in monitoring natural disasters such as floods [7].

Nevertheless, not all applications are purely industrial, other examples are recreational. For example, there are numerous works that coordinate multiple UAVs for image capture and composition, like the work of Moeller et al. [69]. Another recreational activity in which UAV swarms are being used is their use as an alternative to fireworks [22]. This last activity is being highly considered in other countries because of the lack of legislation on autonomous flights over civil populations. Therefore, many countries do not have legislation for this case.

All operations, whether industrial or non-industrial, depend on the flight path. It is important to know the most optimal path possible. In this way, the flight runs quickly and efficiently. This path calculation is known as the Path Planning problem [30]. These problems seek, in addition to path calculation, the autonomous control of the UAVs. Therefore, less operator intervention is required, and they maintain, during the whole operation, the efficiency of the flight regardless of obstacles or other problems that may arise. In other words, reducing personal and aerial distance results in significant cost savings. The most recent works are focused on autonomous swarm coordination. How this coordination is performed could reduce the operations to find the optimal paths.

For better autonomous control of the swarms while maintaining path optimization, the authors are mainly making use of Artificial Intelligence (AI) techniques in their works [83]. Thus, they obtain systems capable of efficiently abstracting knowledge and, from this knowledge, calculating paths and controlling UAV trajectories simultaneously and automatically. The importance of these techniques and their application to Path Planning problems in UAV swarms is discussed in more detail in the following sections.

The main aim of this article is to review the articles on autonomous UAV swarms based on AI. The reason for the choice of AI is that these algorithms make it possible to reduce the number of navigation sensors required by each aircraft. AI can infer information from patterns in the data very efficiently, thus reducing the amount of information to be captured [11]. The fewer sensors, the lower the battery consumption. This allows the surplus energy to be used for longer flight times or to add devices that allow the task to be carried out, such as different multi-spectral cameras. Despite of the existence of works that address this Path Planning problem with a single UAV, this article focuses on the swarms because they add a multitude of challenges in which UAVs can perform tasks that individually they could not or would do with difficulty. In contrast to Artificial Intelligence works applied to a single UAV, the use of Artificial Intelligence applied to UAV swarms has emerged recently. In spite of this, the number of works with swarms is multiplying every year due to their increasingly successful applications. It is therefore a good time to analyze the current state of this field and identify the main trends that will develop in the coming years on the basis of the work already developed.

For this article, 39 articles on AI techniques applied to UAV swarms in Path Planning or Mission Planning problems have been reviewed. This review was carried out in two steps: first, a summary of the found articles was made, and they were grouped by techniques; second, a quantitative analysis was made of the evolution over time of the publications found based on the techniques used, the flight environment and the field of use. In the first step, we found the different groups of techniques used and which models or methods are the most common for each group. Finally, the last step is the quantitative study of the publications found. The end result of this stage helps determine the current state of trends in this knowledge area, as well as the application of the techniques examined and the publishers of the articles discovered.

For the selection of the papers, a search was carried out in the main online search engines. For this purpose, an initial set of search terms was defined. In addition, the references in the papers found were reviewed in order to find even more articles. Once the papers were selected, the most relevant and novel ones were selected. A more detailed description can be found in Sect. 3.1.

For a better understanding of the review, a summary of the papers found has been made. This summary is complemented by a quantitative analysis of the papers found according to the method used, the type of flight environment, and the field of use. An analysis of the results of each paper could not be performed due to the lack of standardization.

The main contributions of this paper are as follows:

- A detailed explanation of the many approaches discovered using AI techniques to tackle the Path Planning problem for UAV swarms.
- The articles were then classified broadly based on the AI approaches used: Reinforcement Learning, Evolutionary Computing, Swarm Intelligence and Graph Neural Networks.
- Identification and discussion of the upward trends based on the number of publications over the years.

Apart from this introductory section, the outline of this paper is structured as follows: in Sect. 2, the aspects inherent to the development of Artificial Intelligence algorithms for the control of UAV swarms are explained; in Sect. 3, there is a summary and classification of the found articles; in Sect. 4, the results obtained from the found articles are discussed; in Sect. 5, the conclusions obtained after reviewing the found articles are listed; finally, in Sect. 6, the possible works and research from which the problem to be addressed can be derived are listed.

2 Fundaments

To have a better understanding of all the technical aspects faced by each AI project in autonomous UAV swarms, and to make the reading more comfortable, the following technical aspects are explained: first, what is a UAV; second, what are UAV Swarms; third, the Path Planning problem; fourth, artificial flight environments; and, finally, Path Planning with Swarm Intelligence using Artificial Intelligence.

2.1 Unmanned aerial vehicle

An Unmanned Aerial Vehicle (UAV), commonly known as a drone, is a semi-autonomous aircraft that can be controlled and operated remotely, without an aircrew onboard, by using electronic intelligence and control subsystem [4]. In recent years, UAVs' popularity has increased, and they are widely used in different professional, and recreational applications. UAVs represent one of the most challenging and high-potential tech available nowadays. Initially limited to military uses, they are now expanding into different commercial and industrial sectors [1]. This is due, in particular, to the improvements in technology and power capacities of these vehicles [5, 38].

Their structure, configuration and equipment vary depending on the task to be performed [38]. Having different configurations and equipment implies an improvement in terms of electricity consumption, operation time, and safety risks in the operation. This results in a reduction in costs due to the improvement in the efficiency of the operation. Apart from their original military use [13], other new utilities of the UAVs such as photography, air rescue, or agriculture stand out. However, with the growing popularity and use of drones for consumer applications, the number of incidents involving drones is increasing dramatically [64]. This increase in air accidents is due to the increase in this type of air traffic and the lack of knowledge of the use by some users. Mainly because many UAVs can be acquired without licenses or aptitude tests.

2.2 UAV swarms

Most risky or laborious tasks often require several UAVs. This is due, in particular, to a large amount of time required for operation and the limited autonomy of these small vehicles. When at work, available vehicles assume the function of those that fail. Thus, the task is developed in parallel and the necessary time is shortened compared to when each drone is used one by one.

This strategy is based on the group behavior of natural biological models such as birds or ants [80]. Individuals of these species are able to coordinate and interact with each other when carrying out a task for a common goal, such as flying to warm places or transporting food to their colonies, as well as with their environment. This leads to different groups of swarms being considered to be flocks or herds, depending on the organism.

In Computer Science, Swarm Intelligence (SI) or Swarm Behavior is known as the complex collective, self-organized, coordinated, flexible, and robust behavior of a group of individuals that follows common simple rules [12]. Back in the 1970s, some works about the application of swarm intelligence to small and non-air vehicles can be found, while not until 1990s the UAVs appeared together with the first studies on these devices [67]. It may be due to improvements in the performance of these vehicles and their communications, which speeds up experimentation. The main objective of this experimentation is the ability to achieve algorithms that facilitate navigation and self-organization of a group of UAVs in order to achieve an objective without human interaction.

Robotic swarms are proving their ability to perform certain tasks with respect to cases with a single robot [99]. Especially with UAVs, where each vehicle is part of the assigned task in conjunction with other vehicles perfectly coordinated automatically [14]. In this way, the group is more fault-tolerant, and a shorter execution time is required [84]. This means a significant reduction in costs and operation time.

There were methods previously used to solve path planning problems, especially in individual systems. Algorithms, such as dynamic programming [8] or geometric algorithms like A* search [56], have usually formulated the problem as a heuristic-based numerical cost minimization problem, regardless of computational cost or path correction. During the dynamic programming process, a local cost is assigned to each subdivision of the grid that forms the operation map [6]. It is assumed that the cost of flying over a subzone is independent of the path taken by the UAV to reach the target. Therefore, the cost considered is different from the actual cost [58, 59]. On the other hand, A* algorithm [102], which is a variant of the shortest path algorithm, has difficulties in solving problems with multiple constraints. This type of algorithm is largely based on the cost map, which must be calculated and stored at all times, and the production of the cost map is a time-consuming and error-prone task. All these methods suffer from relatively high execution time. AI methods were proposed as candidates to overcome these problems. These methods use inaccurate and incomplete knowledge and can produce control actions in an adaptive way. This is similar to the inference of knowledge performed by biological systems like humans. In the last decade, an increasing number of studies in the literature have focused on AI methods to solve path planning problems, with one or multiple vehicles.

2.3 Path planning problem

Path planning is the process of using accumulated sensor data and initial information to allow an autonomous robot to find the best path to reach a goal position. It is a very common problem within the problems with any type of mobile robot, not only UAVs. They are also known as Mission Planning problems. This term is very common within the military. Thus, the term Path Planning is mostly reserved for the civilian field.

It is composed of two main steps: first, compiling all the available information into an effective and appropriate configuration space; and second, using a search algorithm to find the best path in that space [30].

With respect to the first step, there are different types of representation of the flight environment information:

- Cell-maps: this is the most used technique. The map is divided into a set of representative areas known as cells. In those cells, several authors describe the characteristics of the world for each of the cells (elevation, permissibly to fly, etc.).
- Roadmaps: this type of map attempts to describe the world in terms of how to get from a place of origin to a place of destination, taking into account the cost of moving between them. They are much more difficult and time-consuming to create than the previous maps. As an advantage, they are faster to process once created.
- Potential Fields: each UAV is represented as an object under the influence of a field of potentials created by goals and obstacles in the world. These potentials influence the UAV as if it were a physical quantity. This method has most often been used for local obstacle avoidance in mobile robots, but can also contribute to efficient path planning.

At present, it involves a high cost to fly over a real area of the world. In addition, there is a lack of legislation for experimental flights in many countries. Therefore, most authors use artificial flight environments.

The second step is the most critical, as it is responsible for the path calculation and control of the UAVs. Due to the complexity of the problem and the need to automate the process, the most commonly used methods are those based on Artificial Intelligence techniques.

These techniques must be able to overcome as much as possible all the challenges present in this type of problem. These include:

- Path length: the shorter the path, the more optimal it is. If a path is shorter than another and connects the same points, it means that it has fewer loops and fewer curves, making it more energy-efficient.
- Obstacle avoidance: the system must be capable of permiting UAVs to avoid any obstacle that appears during flights. Whether dynamic or fixed.
- Restricted areas: the system must be able to control that UAVs do not fly over restricted areas. Thus, the user is not exposed to legal risk situations
- Fault tolerance: especially in swarms, the system must be able to reorganize the paths of the UAVs in case one fails. Thus, the other UAVs can complete the task.
- Completeness: it is necessary that the system can satisfy a completeness criterion according to the assigned task. If the objective is to map as much terrain as possible, it is of interest that the system searches for the solution that covers the most area of that terrain taking into account the constraints of the UAVs. On the other hand, in tasks such as logistics, it is of interest that the UAVs cover the distance from the warehouse to the recipient in its entirety.
- UAV configuration: the system must be able to adapt the path to the limits of each UAV. That is, depending on factors such as the number of engines, their layout, or their autonomy, the path must be adapted so that the UAV can fly it.
- Other external factors: another challenge is to be able to take into account external factors that influence the trajectory of UAVs. Factors such as wind, birds, rain, or solar storms are obstacles in the paths.

2.4 Artificial flight environments

The development of Swarm Intelligence (SI) with UAV for the Path Planning problem studies involves experimentation with vehicles and robots in real conditions. This is not always possible, due to economic requirements, the need for controlled spaces, or the legislation in force in each country.

Fortunately, more and better artificial flight environments and simulation libraries are being developed. They mimic the limitations and underlying physical forces of UAVs in different environments. In addition, these environments mimic different conditions that a real UAV may face in a real environment.

Among the most used and modern simulators there is Microsoft's AirSim [89]. This simulator is aimed at developing algorithms for autonomous vehicles. To do this, AirSim allows the capture of data from many scenarios in order to train different agents. It can handle multiple drones in real 3D environments. Users can create environments with countless variables that can be modified, such as the intensity of the wind or its direction. AirSim also has the possibility of handling land vehicles for the development of algorithms for autonomous land vehicles.

One of the most used UAV control libraries is DroneKit [23]. It is an Open Source library made in Python [110], which allows its combination with AI or UAV camera management libraries. It is known for its simple handling and the ability to receive and send large amounts of information to the vehicle. There are other options for commercial UAV like PyParrot [65], made for controlling Parrot UAV. It was developed to teach children STEM concepts, such as programming, in Parrot mini-drones.

2.5 Path planning with swarm intelligence using artificial intelligence

Path planning depends on various factors such as telecommunications [15] or Artificial Intelligence (AI) algorithms [118]. This study is oriented to AI techniques for path planning, so it relies on the second option.

The concept of SI was initially introduced by Gerardo Beni et al. applied to cellular robotic systems [10]. Beni's swarm agents act like AI agents, where they autonomously learn and take action based on an environment [83]. In this way, the agent is able to abstract high-level knowledge without being explicitly programmed. The knowledge is often difficult to represent in its entirety due to its complexity or its wide range of cases. Because of this similarity between SI robots and AI agents, most experts considered SI as a sub-technique of AI.

The main idea is that desired swarm behaviors are not explicitly coded with hierarchical command or control structure but are instead an emergent consequence of the interaction of individual agents with each other and their environment [9]. This kind of algorithm or distributed problem-solving device is inspired by the collective behavior of biological social groups like insect colonies and other animal societies [91]. The agents at the group use simple local rules to govern their actions and via the interactions of the entire group the swarm achieves its objectives [57].

All the agents in a swarm abstract knowledge from information obtained. The great advantage of SI is that agents can be heterogeneous. Therefore, the knowledge abstracted by each agent can be obtained differently. Unlike in a homogeneous swarm, all agents can be trained in different ways to abstract information. For this reason, SI makes use of other techniques of AI to reach its objective.

There are different approaches, all of them based on different AI techniques. In the State of the Art, path planning studies with one or multiple vehicles that use Reinforcement Learning (RL) and Evolutionary Computing (EC) are the most common. For example, Hüttenrauch et al. use Deep RL for controlling groups of agents [45]. On the other hand, Zhao et al. combine EC with other techniques to develop a new SI method [120].

Rules followed by the agents that make up the swarms, and the strategy taken before them, are those that characterize each of the existing types of SI algorithms. There are two main approaches among all the existing ones: the first one makes use of RL-based algorithms; and, the second one of EC-based. We introduce the necessary concepts for ease of understanding of the most common kinds of algorithms.

2.5.1 Reinforcement learning

The first named approach, Reinforcement Learning (RL), is a set of algorithms where the agent must learn behaviors by trial-and-error interactions with a dynamic environment [47, 97, 111]. The goal is to optimize the behavior of the agent with respect to a reward signal that is provided by the environment. The actions of the agent can also affect the environment, complicating the search for the optimal behavior [103].

All RL algorithms follow a common structure. The only difference is the learning strategies. There are several types of these strategies. They all follow different policies that allow them to deal with different problems. The most common types of RL strategies used in SI are explained below.

Q-Learning [108] is one of the most used strategies amongst RL-based algorithms at SI. It follows a model-free strategy [31], so it updates its knowledge following a policy purely by trial-and-error. It is based on off-policy learning, it permits the agents to use their experience for learning the values of all the policies in parallel, even when they can follow only one policy at a time [98]. Q-Learning's classical learning optimal function for computing Q-table values ($Q(s, a)$) is based on Bellman's Equation (Eq. 1).

$$Q(s,a) \leftarrow r + \gamma \times \arg\max_{a'}(Q(s',a')) \quad (1)$$

There are several examples where Q-Learning is used in swarm robotics. For instance, Hung et al. developed an algorithm for controlling flocks of small fixed-wing UAV and tested it in a non-stationary stochastic environment [44]. On the other hand, Rui et al. use Q-Learning to tune the corresponding parameters of a fuzzy multi-UAV formation controller [81].

Using exclusively Bellman's Equation may present abstraction issues in some scenarios. In certain cases, the Q-table values are calculated based on predictions from

Deep Learning models [54]. These models learn from the actions taken, their rewards, and the surrounding environment. This results in a model that is able to abstract more concepts from available data and calculate all future Q values more accurately. This type of algorithm is known as Deep Q-Learning and is part of the well-known Deep RL [68].

Deep Learning [54] is a branch of Machine Learning [66] known for being able to make high-level abstractions automatically. In other words, there is no need for experts to extract characteristics from the data in order for the model to learn them.

The most used and common models used in Deep Learning are known as Artificial Neural Networks (ANN). These networks are large structures formed by connected layers of nodes. Each node is known as an artificial neuron [78]. In Fig. 1 there is an example of the most neuron in an ANN. Neurons perform as summing and nonlinear mapping junctions. The main purpose of ANN is to be able to reproduce some flexibility and power of the human brain by the artificial means [77, 126]. Neural networks applied to Deep Q-Learning are known as Deep Q-Networks.

Deep Q-Learning is the most widely used variant of Q-Learning in UAV swarms. It is also the technique used in the most recent works such as Yijing et al. [116] and Baldazo et al. [7].

Similarly to Q learning, State-Action-Reward-State-Action (SARSA) [82] is a close approach. The key difference is that SARSA is an on-policy learning algorithm [98]. Therefore, that SARSA learns Q-table values based on the action performed by the current policy instead of the greedy policy. This implies that SARSA has constraints over the next action. This is the reason why Q-Learning is utilized less frequently.

Like Q-Learning, there is the Deep SARSA approach [122]. This version with Deep Learning models also shows more flexibility and power of abstraction than its classic version.

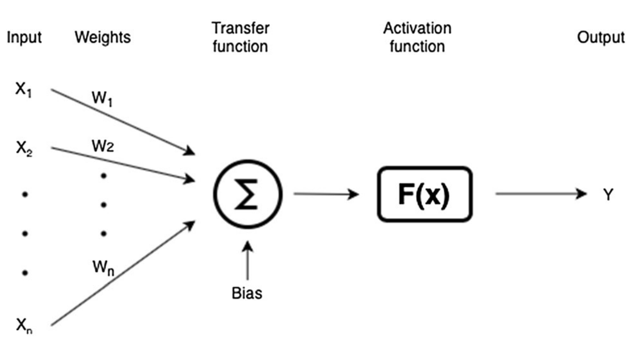

Fig. 1 General schema of an artificial neuron. First, the inputs are multiplied each by its corresponding weight and added with the bias. Then, this result is used as input to the activation function. The output of the neuron is the result of this function

The use of SARSA in UAV and robotics is recent. Most of the publications found show an increasing trend in its use as the years go by. There are SI studies with multiple UAVs like Luo et al. [63] and Speck et al. [93].

2.5.2 Evolutionary computation

The second approach, Evolutionary Computation (EC), is about algorithms based on Charles Darwin's theory of natural evolution. These algorithms try to achieve the best heuristic based on populations and their inheritance from one generation to the next one [20, 92].

The whole process of natural selection begins with the selection of the fittest elements or individuals from an initial population. Combinations of some of them produce offspring [29]. These descendants inherit some characteristics from their parents and will be added to the next generation in addiction with some random probability of mutations and of inheriting some characteristics [94]. If parents have the best fitness, their offspring will be better than their parents and will have a better chance of surviving. The process keeps on repeating over generations until convergence is reached or there are no generations remaining. Finally, a generation with the fittest individuals will be found. This generation will be able to solve the given problem in the most optimal possible way [33, 52].

There are two main domains among all domains in EC: first, Genetic Algorithms (GA) [34]; and, second, Genetic Programming (GP) [50]. The main difference is that Genetic Algorithms use real values-based exploration and GP is an extension of GA tree-based exploration [42, 51].

There is a great variety of work with EC in UAV swarms. This is because it was one of the first approaches tested when applying SI to UAV. It is possible to find work such as Duano et al. [24], Lamon et al. [53] and Gaudiano et al.[28].

2.5.3 Other methods

The methods explained above are the most widely used. This does not imply that other methods are not being exploited with satisfactory results. These include some approaches that are explained below.

Another of the most commonly used methods is pure Swarm Intelligence (SI) based methods. As stated above, these AI methods try to mimic the complex collective, self-organized, coordinated, flexible, and robust behavior of a group of homogeneous or heterogeneous individuals [12].

There are many variations of these methods. The most common are distributed optimization based ones. These techniques are widely used in minimization problems because of their potential. Therefore, they are used to minimize path lengths [113]. Among the most commonly used in Path Planning are Ant Colony Optimization [21] and Particle Swarm Optimization [48].

To coordinate these swarms it is necessary to employ communication mechanisms between group members. More biologically puristic approaches employed mechanisms that mimicked communication by means of odor or pheromones.

The most recent publications are based mostly on pheromones. These techniques are known as virtual pheromones based methods [73]. In this way, the agents employ mechanisms that imitate the pheromones used by insects such as ants.

The use of pheromones to coordinate and interact with the environment is known as stigmergy [100]. The concept was first introduced by Grassé when he observed interactions in two species of termites: *Bellicositermes Natalensis* and *Cubitermes* [36].

In this variant of SI, the work of Parunak et al. [72] is very relevant, although new approaches are emerging.

Classic Deep Learning [54] effectively captures hidden patterns of Euclidean data, like images or text recognition, but there is an increasing number of applications where data are represented in the form of graphs [112], like molecules or proteomics. Graph Neural Networks extend existing neural network methods for processing the data represented in graph domain[87].

Unlike the data used in classical Deep Learning models, graphs do not have a defined structure. A node on a graph may have no connections or many connections, which may not be directed. Graphs in a data set can have a varying number of nodes and edges arranged in different ways. Based on their different distributions, graphs can be acyclic, cyclic, set, or unset. In general, it makes the data handling process more computationally expensive.

In this discipline, it is possible to find some of the most recent work. Among them are those of Li et al. [55] and Tolstaya et al. [101].

3 Artificial intelligence applied to path planning in UAV swarms

Being a dynamic and relatively new knowledge field, it is difficult to identify which works are related to and to identify the future challenges that this newborn area should tackle in the upcoming years. In this section, an analysis is proposed based on the 39 works found from 2016 to 2021. The last 5 years have been chosen because they are a close time period that can sufficiently indicate the current trend of the field. In this analysis, articles are grouped by the type of AI technique used for making reading easier.

3.1 Methodology

The well-known online tools Google Scholar [35], Scopus [88], Web of Science [109], IEEE Xplore [46] and arXiv [3] were used to obtain the articles related to the topic. In them, searches were performed for the terms listed in Table 1.

The references of the works found are also reviewed. Thus, more relevant ones can be found that have not appeared in the search tools. Then, the whole set of articles found is selected by the year. In this way, the most recent and relevant ones are found.

3.2 Content review

This sections presents a summary of the main points of the articles found and selected. For ease of reading, they have been grouped by the technique used.

3.2.1 Reinforcement learning

Starting with the discipline of Q-Learning, Hung et al. manage fixed-wing UAV flock in which there are a leader and a set of followers [44]. Thus, it gets groups of autonomous UAV that move in a synchronized way, similar to a flock of birds. Using a leading aircraft improves the computation time since it is important to improve the leading path and the others would be derived from it. Nevertheless, in case of failure of the leading UAV, it would be more expensive to recalculate all the paths. If there was no dependence between paths, only the UAVs closest to the fallen aircraft would be affected. The use of fixed-wing UAVs greatly limits their application due to their more complex control and lower stationary flight capability. Khalil et al. succeed in making a multi-agent system by improving the classical Q-Learning, which they call economic Q-Learning [49]. In their system, they copied the decision techniques used in Economic Theory. In the described technique, it is considered that what is most chosen is what is most useful and frequent in the future.

There are variations of the algorithm, like the work of Hafez et al. where Fuzzy Systems with Q-Learning are combined for control of UAV swarms for military use [37]. Their method shows robustness to failure. In this way, it can be recovered in the event of a UAV falling. In this article, the UAVs have to maintain a formation, which conditions the computation of the paths. Moreover, they were tested in closed indoor environments, so they do not contemplate changes in the wind or dynamic flying obstacles such as birds. Also, combined with Fuzzy Logic, Su et al. make use of fuzzy matrices as a reward function to recalculate paths of groups of drones [96]. In this case, the

Table 1 Table with search terms grouped by category

Category	Terms
Vehicles	Unmanned aerial vehicle, UAV, aircraft, drone, remotely piloted aircraft, RPA
Group of vehicles	Multiple, multi, swarm, group, flock, formation, collaborative
Technique	Artificial intelligence, swarm intelligence, reinforcement learning, evolutionary computation, Q-learning, SARSA, artificial neural network, ANN, genetic programming, genetic algorithm, particle swarm optimization, PSO, ant colony optimization, ACO
Problem	Path planning, mission planing, mission control, autonomous flight, autonomous control, navigation
Field of application	Civilian, agriculture, emergency, forestry, military, surveillance, photography, filming

use of clustering techniques for the initial distribution of the land makes it dependent on the initialization parameters. Therefore, a good study of the parameters should be made so that they can be used in a variety of real environments. Continuing with fuzzy computing, in 2020, Yang et al. [114] also propose to combine it with Q-Learning. A very important point in their project is that it is one of the few that take into consideration the battery level. Also in 2020, Chen et al. [18] propose a multi-agent Q-Learning system based on constrained actions. Thus, they facilitate autonomous in-flight decision-making by taking into account the uncertainty of the location of each landmark. Their system was tested with a different number of UAVs. They showed that as the number of UAVs increases, the task failure rate increases.

The best known variation of Q-Learning is DQN, because of its power of generalization and its proposed professional applications. One of the most important approaches is the one proposed by Roudneshin et al. in which they perform ANN to control swarms composed of UAVs and heterogeneous robots [79]. This work of military nature does not present a work purely in UAVs but adds terrestrial robots. However, this is a problem of swarm path planning with greater difficulty than using only UAVs. This increase in the difficulty of the problem is due to the different limitations presented by air and land vehicles. Thus, a land vehicle can encounter non-geographic obstacles and has more limited movements. As a practical utility, they expose the capabilities for use in search and rescue missions. Also in emergency or rescue conditions, Baldazo et al. propose a DQN model to coordinate multiple UAV for flood monitoring and minimize damage costs [7]. This paper has a very good choice of the type of UAV when it comes to flood monitoring. Fixed-wing UAVs are the most efficient solution for long-distance travel because of their higher speed. As they have less stationary flight capability than other configurations, fixed-wing UAVs require smooth flight paths, without sudden changes. If applied in real scenarios, the paths calculated should have mechanisms to smooth out the curves due to possible abrupt changes in case of obstacles. Later, in 2020, Zhao et al. [119] proposed a variation of Deep Q-Learning known as Wire Fitting Neural Network Q (WFNNQ) learning. Combining this technique with hill-climbing algorithms successfully creates smoothed flight paths in simulated environments. Despite the computational cost, his system avoids having to perform a final phase of path smoothing. Venturini et al. also created a system capable of controlling multiple UAVs using DQN techniques. In 2020 proposed a system capable of operating on square cell maps [104]. In 2021 the maps were simulations of real maps [105]. While it is a project that demonstrates capabilities to operate on different maps, it is necessary to establish targets to direct the paths. Therefore, it is very dependant on the initialization.

Goh et al. designed a DQN model with Convolutional Recurrent Neural Network [32]. In this way, they could control multiple UAVs to pursue the target. The most remarkable thing about their project is the freedom of movement of the UAVs. For added visibility, their system has been tested in the AirSim simulator.

On the other hand, with the SARSA algorithm less recent approximations were found. However, they show satisfactory results in different cases. Luo et al. tested their Deep-SARSA algorithm in dynamic environments, where the obstacles can change [63]. The paper offers an efficient method in dynamic environments. This demonstrates its ability in changing environments, which reinforces its usefulness in the real world. However, the model requires a pretraining phase, which may limit its deployment in novel environments due to the time required for pretraining. Speck et al. combine object-focused learning with the SARSA algorithm in order to improve the algorithm itself [93]. This paper presents a very efficient decentralized approach in terms of generalization. The capacity for generalization may be limited when dealing with fixed-wing UAVs for the same reasons as the papers cited above. Thus, the configuration of the UAV limits the range of application of the system to cases where it is optimal to use fixed-wing UAVs. The paper written by Zhao et al. shows a new method for the coordination of UAV swarms in mesh networks [121]. These networks are very important in disaster areas to maintain communications. In this way, their approach contemplates the limitations of communications in these cases. Despite contemplating such limitations, mesh networks cannot always be deployed if the environment is rugged or very difficult to access. Therefore, consideration should be given to limiting the number of paths needed to make it as viable as possible.

3.2.2 Evolutionary computation

In the field of EC, another huge volume of papers is available. For example, Sathyan et al. combine GA with Fuzzy logic to improve accuracy during path planning [86]. The paper approaches the problem from a very interesting point of view, as they interpret the paths as polygons. Thus, they quickly solve the problem of each UAV returning to the starting point at the end of the operation as if it were part of the path itself. The main drawback of this article is that they do not take into account fuel consumption or possible collisions. Thus, paths can have great lengths or abrupt changes of direction that the range cannot support. In addition, paths can be so close that UAVs can collide.

Ramirez et al. use, in some of their works, variations of the Multi-objective Genetic Algorithm (MOGA) for mission planning with multiple UAVs [75, 76]. In their work, they carry out an exhaustive evaluation of their system and show the evolution of the results as the complexity increases. In both works, there is a lack of detail in the description of the data sets they use, so it is vague whether these changes in complexity are correctly interpreted. Cekmez et al. find control points in the terrain by using K-means clustering [16]. Then, a parallel genetic algorithm solves the multi-UAV path planning problem of each subset of control points. The advantage of this genetic algorithm is its implementation on CUDA, which allows for faster experimentation. The use of K-means clustering can be limiting for area partitioning. Many clustering algorithms, such as K-means or K-medians, are known to be strongly dependent on the initialization parameters. Therefore, this partitioning should be tested in a huge amount of different environments until satisfactory parameters are achieved.

There are also approaches such as the one made by San et al. [85], in which genetic algorithms of chromosomes with multidimensional genes are used. In this paper, the shortest possible path is computed, as it is for parcel UAVs. For this purpose, two fitness functions are considered, one for the weight of the load and another for the path, which achieves great results. UAVs tend to consume more battery power if they need to be constantly stabilized, so they should consider the oscillation of the load during the flight to minimize the battery. Otherwise, a heavy object with many oscillations increases battery consumption because the aircraft needs to be constantly correcting its trajectory. Liu et al. employ Genetic Algorithms to adjust ANN for flight path generation [61]. Relying only on the ANN for path computation makes it dependent on more parameters than weights. Therefore, other parameters such as learning rates or adjusting the architecture of the ANN should be adjusted. Duan et al. also improve a genetic algorithm, in this case with a local search algorithm. To do so, they combine a memetic algorithm with the VND search algorithm [25]. In their work, an initial individual is generated based on the heuristics of the nearest neighbors and the other initial individuals are configured as random. Using the closest neighbors can greatly limit the generation of individuals. Especially if there are many equally close neighbors. In that case, a criterion should only be established to determine whether the individual is a member of a group.

Cimino et al. employ Differential Evolution for UAV swarms to detect targets collaboratively [19]. The major difference between Differential Evolution compared to other Evolutionary Computing algorithms, such as GA, is that it depends more on the mutation operator [95] than on the crossover operator. Thus, a descendant can be the exclusive mutation of a parent. Having less dependence on one type of operator than the other makes it more difficult to find new individuals in the population. Therefore, it can be more expensive to find the optimal path. In the work of Zhou et al. multiple UAVs are made to fly over a portion of terrain in the presence of dynamic targets. For this, they make use of the Immune Genetic Algorithm (IGA) [125]. The drawback of their method is the need for path smoothing.

Olson et al. also designed GA for multi-UAV systems [70]. In their case, they seek to create 3D maps using multiple UAVs. To do this they simplify the flight map to a 2D map. Once created, their system searches for paths that maximize coverage and reduce flight time. The use of flight time in GA is also used by other authors, such as Huang et al. [43]. In their paper, they take into account the time taken by each UAV to find a target. A great point to note in their work is that it is one of the few that take into account the attributes of the UAVs. Other authors take into account the flight time of the entire swarm depending on the task to be performed. As in the case of Ye et al. where they seek to minimize the overall flight time of the swarm [115]. Thus, it may be more efficient in global terms to minimize the time of one UAV even if the time of another is not minimized. Time is calculated using Dubin's car model. This model usually refers to the shortest curve connecting two points in the two-dimensional Euclidean plane. It may not be the most optimal way to obtain UAV paths and times because it only considers curves.

In 2021, Pan et al. combined GAs with Deep Learning to compute optimal paths for multiple UAVs to capture data from multiple nodes [71]. Through this combination, they improve the results concerning using purely GAs in case of having numerous nodes.

3.2.3 Swarm intelligence based methods

Among the proposals of SI for this type of problem is a great variety of algorithms. Cekmez et al. make use of Ant Colony Optimization (ACO) for planning optimal UAV paths while avoiding complex obstacles such as radars [17]. In their paper, they implement a version of the algorithm for GPUs allowing them to perform more iterations of that algorithm at the same time. This allows getting closer to the optimal solution. They consider constant flight speed, so the curves to be made for each UAV may not be the most efficient. Perez-Carabaza et al. also use this technique to plan flight paths so that multiple UAVs can find targets in unknown environments in the minimum possible time [74]. The use of its heuristics is very accurate, because of the speed of computation. In addition, correctly defined heuristics can reduce the computational cost. As the authors state, paths should be smoothed or it would be limited to a certain number of UAV types. Another approach to this technique is its use in cooperative search-attack mission planning for multiple UAVs [123]. These types of problems are very similar to path planning. In these cases, it is usually a matter of finding a target and getting closer to attack. In particular, they tend to face more changes in paths because the targets frequently change. In this work, they also consider constant flight speeds. If they are high speeds, plotted curves may not be feasible. Following ACO, Zhen et al. proposed a distributed version of ACO in 2020. A respectable aspect of their paper is that their system is one of the few that considers flight range constraints among all the constraints considered [124].

Vijayakumari et al. make use of another well-known SI technique known as Particle Swarm Optimization (PSO) for optimal control of multiple UAVs in a decentralized way [106]. In their work, they manage to simplify the computation of the problem by means of discretization. For collision avoidance, they rely on distances. Although this is a dynamic variable, in certain types of non-stationary flight UAVs, such as fixed-wing UAVs, it does not guarantee collision avoidance. In these cases, a metric that predicts the state of the UAV and the obstacle in future instants is of interest and thus makes a decision. Otherwise, the UAV would continue to move forward while the decision is being computed. Li et al. also use this technique for UAV swarm control and demonstrated the effectiveness of the results in several terrains at Shaanxi province in China [62]. It is one of the few found studies applied to agricultural UAVs that have been tested in real field simulations. It is a great indicator of the project's viability and potential. The paths shown in the images have abrupt changes in direction, so the path should be smoothed. Otherwise, some UAVs would not be able to take the bends. More recently, there is work such as that of Hoang et al. in which they employ a variation of PSO known as Angle-Encoded PSO for the planning of flight paths in UAV swarms [41]. The main advantage of the proposed model is that it considers flying height. Most works consider 2D flights where UAVs do not need to vary their height. The 2D flight does not guarantee that the path traced in the presence of obstacles is optimal. In many cases, a sudden change of direction can be avoided by varying the height. The paper uses waypoints to assist the path. This makes the model very dependent on the initialization of the waypoints. Also, with an improved version of PSO, Shao et al. proposed the coordination of multiple UAVs by comprehensively improved PSO [90]. In this type of PSO, parameter tuning is done adaptively. Thus, the parameters are better tuned than in classical versions of PSO. In March 2021, He et al. proposed their improvement of PSO for cooperative UAV systems on 3D maps [40]. Despite good results, the paths need to be smoothed and UAV formations should be fixed.

In 2020, Wang et al. proposed a Path Planning system for multiple UAVs using the Pidgeon-Inspired Optimization algorithm [107]. The main point that makes it distinguishable from the SI papers described above is that, unlike the others in general use, it employs a specific SI algorithm for path planning with aerial robots [26]. Another algorithm different from those mentioned above is the Bean Robot Optimization Algorithm used in UAV swarms for target searching by Zhang et al. [117]. The algorithm takes into account the free-moving space of individual UAVs and adds a free-space search mechanism to improve target search efficiency.

3.2.4 Graph neural networks

Finally, in the newest technique, Graph Neural Networks, a single article was found. In it, Li et al. [55] make use of these neural networks for path computation in robotic systems. Thus, they achieve more capacity for generalization in the face of new cases than other more widely used techniques. Since we are dealing with two ANNs, previous training is necessary in different and very varied cases.

Table 2 Summary of works where artificial intelligence methods are applied to path planning in UAV swarms

Publication	Technique	Year	Flight environment
Hung et al. [44]	RL	2016	Artificial environment
Khalil et al. [49]	RL	2021	Artificial environment
Hafez et al. [37]	RL	201	Real environment
Su et al. [96]	RL	2016	Artificial environment
Yang et al. [114]	RL	2020	Artificial environment
Chen et al. [18]	RL	2020	Artificial environment
Roudneshin et al. [79]	RL	2019	Artificial environment
Baldazo et al. [7]	RL	2019	Artificial environment
Luo et al. [63]	RL	2018	Artificial environment
Speck et al. [93]	RL	2018	Artificial environment
Zhao et al. [119]	RL	2020	Artificial environment
Venturini et al. [104]	RL	2020	Artificial environment
Venturini et al. [105]	RL	2021	Artificial simulation over a real environment
Goh et al. [32]	RL	2021	Artificial environment
Zhao et al. [121]	RL	2019	Artificial environment
Sathyan et al. [86]	EC	2016	Artificial environment
Ramirez et al. [75]	EC	2017	Artificial environment
Ramirez et al. [76]	EC	2017	Artificial environment.
Cekmez et al. [16]	EC	2016	Artificial environment
San et al. [85]	EC	2016	Artificial environment
Liu et al. [61]	EC	2019	Artificial environment
Duan et al. [25]	EC	2018	Artificial simulation over a real environment
Cimino et al. [19]	EC	2016	Artificial environment
Zhuo et al. [125]	EC	2020	Artificial environment
Olson et al. [70]	EC	2020	Artificial environment
Huang et al. [43]	EC	2020	Artificial environment
Ye et al. [115]	EC	2020	Artificial environment
Pan et al. [71]	EC	2021	Artificial environment
Cekmez et al. [17]	SI	2018	Artificial environment
Perez-Carabaza et al. [74]	SI	2018	Artificial environment
Zhen et al. [123]	SI	2018	Artificial environment
Zhen et al. [124]	SI	2020	Artificial environment
Vijayakumari et al. [106]	SI	2019	Artificial environment
Li et al. [62]	SI	2016	Artificial simulation over a real environment
Hoang et al. [41]	SI	2019	Real environment
Saho et al. [90]	SI	2020	Artificial environment
Wang et al. [107]	SI	2020	Artificial environment
Zhang et al.[117]	SI	2020	Artificial environment
Li et al. [55]	GNN	2019	Artificial environment

Otherwise, ANNs may be overfitted in several flight areas and swarm structures.

A summary of the publications cited above is shown in Table 2.

3.3 Bibliometric analysis

For the bibliographic analysis, the number of publications, the number of publishers, and their evolution over the last 6 years will be taken into account. These three factors, along with their relationships, provide quite a bit of information on how UAV swarm AI applications are doing for path planning and mission control problems.

The first chosen graph (Fig. 2), the evolution of the number of publications in the last 6 years, shows the interest in the subject and the evolution of the field based on the State of the Art. The Fig. 2 shows a decline in the publications found over the years until 2018. This

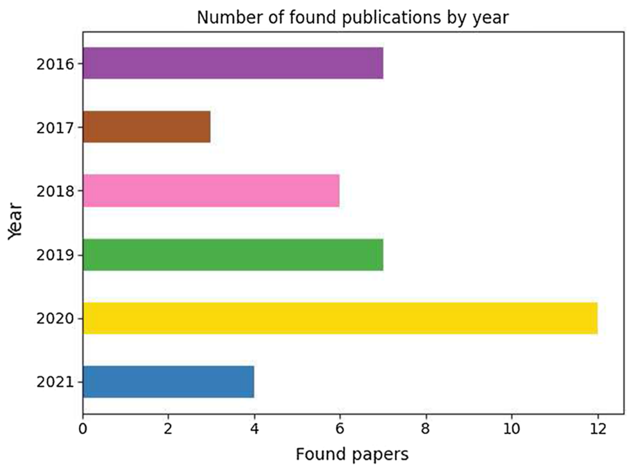

Fig. 2 Relevant and novel publications found per year. The bar of the year 2021 is the number of papers of the first quarter

coincides with the regularization of legislation in many countries, facilitating development in the field. For example, in Europe, EASA regulated the situation in 2018 by establishing the basis for all member countries [27]. Having a solid and current legislation applied to UAVs favors development and innovation in these aircraft. Being able to conduct experiments in a safe and controlled manner by having guidelines increases confidence in research and reduces fear of legal consequences due to uncertainty. In 2020, a large number of articles have been found, thus reinforcing the growing trend in the number of UAV projects. In 2021 quite a few publications were found considering that they are only those belonging to the first quarter.

As mentioned above, RL and EC are among the most widely used techniques. Figure 3 shows how RL outperforms EC, but they are still the most widely used techniques. The reduction in the cost of computational resources means that more and more authors are opting for these more expensive but more efficient methods compared to SI techniques. Taking into account the scope of use of the systems proposed in the papers, civil publications use different cited techniques in a variety of ways (Fig. 4). In spite of this, RL and EC continue to be the most widely used techniques. In general terms, they are always the most used regardless of the purpose.

In 2019, the most used technique was RL (Fig. 5). Its evolution contrasts sharply with 2016 when it was in the minority. Unlike EC, its popularity in this type of problem has been increasing. This change in trend may be due to the normally lower computational cost of the RL and its greater ease of development. On the other hand, an equal number of EC, RL, and SI papers were found in 2020. The elevated number of publications shows indications of the high impact of UAV swarms. Thus, each year seems to be increasing.

Figure 6 shows that most of the studies found are for civil purposes. Years ago, most articles were for military purposes or rescue operations. The change in purpose reinforces the fact that these aircraft found a niche in civil functions and operations. Studies applied to non-civil purposes remain constant and scarce over the years. On the other hand, the number of studies on civil purposes found is much higher. The decrease in 2018 may be caused by regulatory changes in many countries. These changes often bring uncertainty and loopholes that are corrected later. These corrections may explain the increase, again, of publications in 2018.

Figure 7 shows that most studies use artificial environments. This may be due to the difficulty in reserving airspace for experimentation. In many countries, these requests are expensive and take a long time to confirm. Publications for non-civil purposes are those that make the most use of real flight environments. Normally, military authorities in countries usually have airspace reserved for

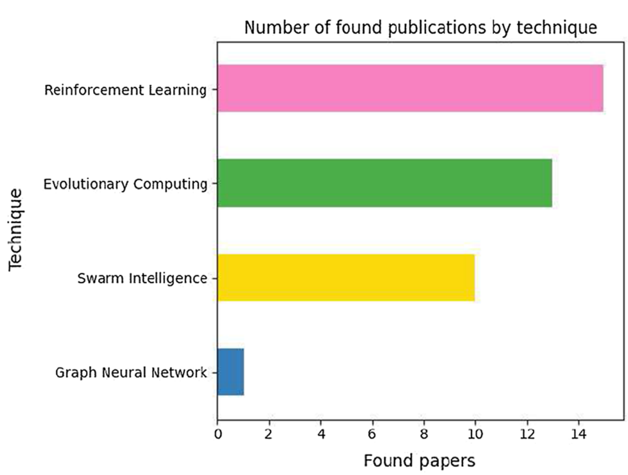

Fig. 3 Relevant and novel publications found per technique

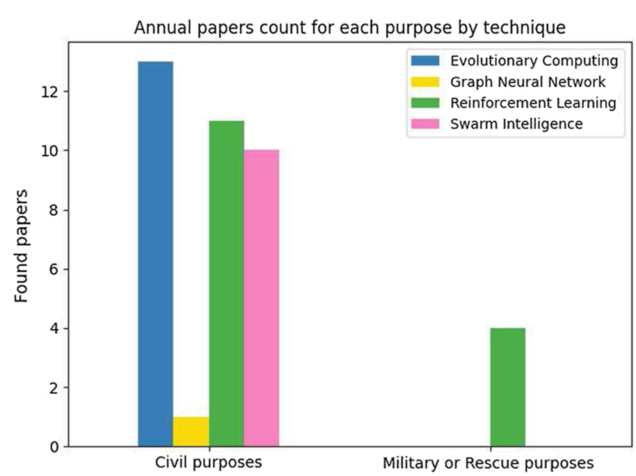

Fig. 4 Publications per technique for each different purpose

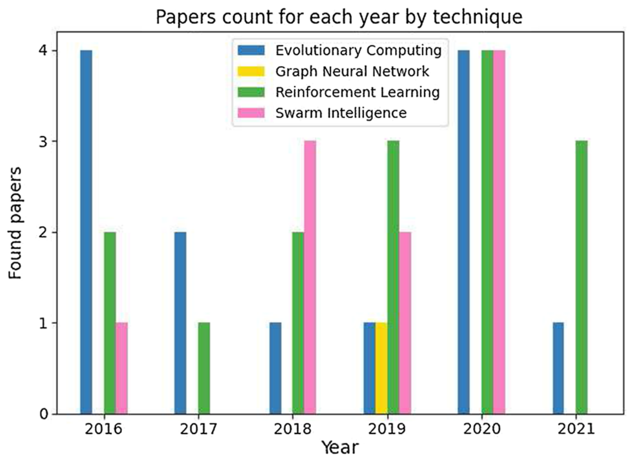

Fig. 5 Evolution of publications per technique for each year

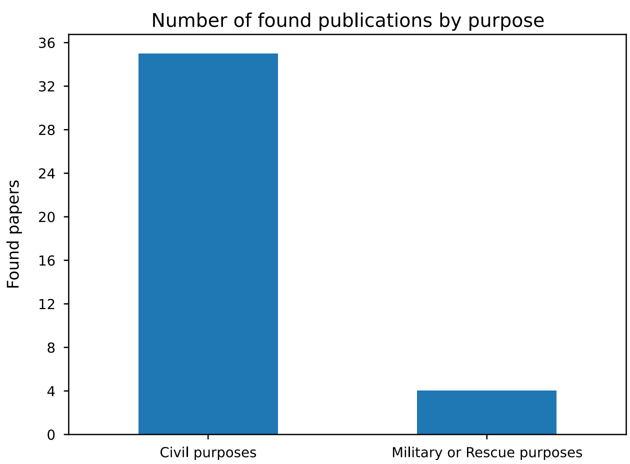

Fig. 6 Publications per purpose

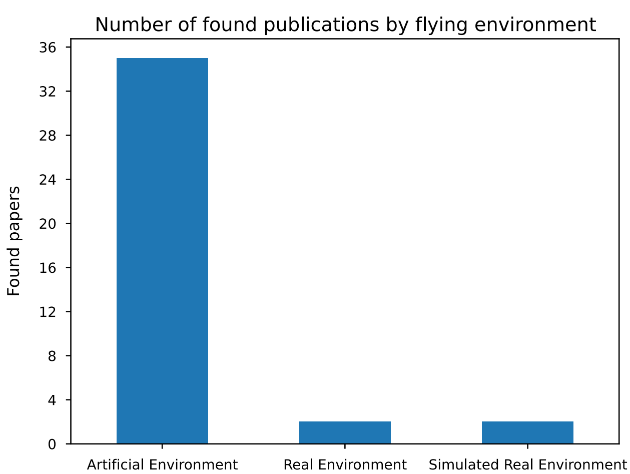

Fig. 7 Publications per flight environment

their flights. In addition, they are more likely to reserve airspace when necessary. Quite a few publications use simulations of real locations. In these cases, they map real environments and then simulate them virtually. In this way, there is no need to reserve the flight area, but the mapping is often expensive.

4 Discussion

The development of systems for Path Planning with UAVs is a common problem, but it is in the early stages. Despite this, there are more and more applications and studies of their use at the professional and domestic levels. One of its most novel applications of systems for Path Planning is in UAV swarms. Thus, costs and operation time can be reduced by having several aircraft operating at the same time in a coordinated manner. To assist in the coordination of the swarms, more and more authors are making use of AI techniques, which is the focus of this review.

One of the factors triggering this boom is the decrease in their market price and the regulation of the laws concerning their use. Consequently, more and more people can access them and have their airspace reserved. This facilitates their use for developing activities and tests with them. In Fig. 2 this increase in the last few years is shown, as 2018 is one of the years with the most changes in the law. Despite this, more papers are being published every year. In 2020, this growth will be even more accelerated. In the first quarter of the year 2021, there is a significant number of papers, which may indicate that in 2021 there will numerous papers. It could even surpass the year 2020.

With respect to the techniques reviewed, RL and EC are the main ones in the number of publications (Fig. 3). Many of these articles may present the use of these techniques because of tradition and because they are more developed. Other techniques such as SI usually present ad-hoc methods or a great diversity of different methods. However, the most commonly used are distributed optimization based ones because of their ability to minimize the length of the paths. GNN is the technique with the fewest publications, being the only one in pre-published status. As it is a very new technique, few studies are sufficiently advanced to be published no matter the discipline in which they are applied.

Over the last 6 years, it seems there has been a change in the trend. The techniques of EC present fewer publications, while those of RL are on the rise (Fig. 5). This may be due to different factors such as the generally lower computational cost for RL techniques or the fact that many RL articles have yet to be published in the field.

Most of the publications found are for civil purposes. This may be because they are becoming more accessible to the public. As a result, these aircraft can be used in a wider range of sectors and tasks.

Artificial environments are the most used among civil-purpose publications. It may be caused by the difficulty in reserving airspace for testing. On the other hand, publications for non-civil purposes have more facilities for this, so they are usually tested in real environments.

In general terms, few publications have been found on the subject of the study. This is due to the novelty of the problem. In other words, the advantages of the use of UAV swarms are still beginning to be perceived.

The results achieved in the reviewed papers cannot be compared. In the few cases where it is possible to compare them, it is almost impossible to obtain a meaningful interpretation of the comparison. This issue involves multiple factors such as the variables to be taken into account or the type of Path Planning problem to be solved.

The most important factor is the lack of common evaluation methods to communicate the results and demonstrate the goodness of the methods. This seems to be a fairly common factor in new research areas. In this situation, the authors of new contributions are not sufficiently informed or do not have access to sufficient previous work. This leads to a lack of information which, in turn, causes authors to opt for different approaches to communicating results. Some of them are the time consumed, the length of the paths or the number of solutions found by the system. Nevertheless, with the summary and classification of the papers found, together with the proposed figures, an attempt is made to provide as objective a review as possible of the most recent and novel projects.

As a final summary, the lack of standardization of the results together with the growing number of studies reinforces the idea that this is an increasingly important field of research. The most commonly used methods are RL and EC. This convergence may be limiting in the development of new systems, as there is less innovation in other different and possibly more promising methods. There are more and more applications in the civilian field, mainly characterized by the use of artificial flight environments. The use in non-real environments can be limiting since in real environments, there are usually more obstacles and external factors than many authors consider.

5 Conclusion

AI techniques applied to Path Planning problems with UAV swarms are booming and continuously developing. The increasing use of AI techniques in UAV swarms for Path Planning problems over the years may be an objective indicator of it. More and more papers are being published. Even in 2021, there may be many publications due to the already high number published in the first quarter. Moreover, in the quantitative analysis, it can be seen that RL and EC are the most used methods regardless of the domain. To test these methods, mostly artificial flight environments are used. Therefore, many of these methods may have difficulties operating in real environments due to the large number of external elements that may affect the UAV.

As these are novel systems that use AI for the control of UAV swarms, there are still shortcomings. Especially the lack of standardization of the results. As each paper focuses on a different aspect of Path Planning, each one focuses on a different variable. This can be limiting in the development of new systems due to the lack of criteria to evaluate which approach is better. On the other hand, it is indicative of this being a novel topic. In addition, it may also be indicative that Path Planning problems should be divided into subproblems, each focusing on its variable of interest. Thus, there would be branches that would try to find the solutions with the shortest flight time, another where the solutions involve the routes with the fewest number of turns, etc.

In conclusion, the low but growing number of publications shows that this is a recent problem. The late emergence of UAV swarms coincides with the late incorporation of UAVs in non-military fields. Being more accessible and cheaper allows the public to experiment with them, finding more possible fields of application.

6 Future work

Based on the graphs shown it can be understood that the use of AI techniques for UAV swarms in path planning problems is growing. This growth will be greater as countries adapt their laws to swarms of autonomous vehicles. Other sectors such as self-driving cars will also contribute to this increase with studies that can also be taken to the world of UAVs.

As there is an increase in UAV swarm works and studies more sectors will be able to benefit from them. In addition, other new fields within the sectors are appearing. For example, the 3D animation sector as a substitute for fireworks has emerged in the recreational sector.

With only one article on the GNN technique and in a pre-publish status, a new research path is opened in the domain. The existence of a single paper demonstrating the possibility of the use of GNN in UAV swarms encourages many researchers to take it as a starting point for their research.

The change of tendency experienced in the papers found of RL and EC indicates that the majority of possible works will be of RL. This is not a definitive statement, since it may be more about fashion than about improving results. Therefore, many future works may end up combining both techniques, just as it is used in swarms of other robotic systems. On the other hand, in 2020 there have been a large number of SI articles, so in 2021 there may also be a large number of them.

Finally, improvements in swarming other types of vehicles and improvements in UAV navigation to require fewer sensors may work together. In this way, information collected on the paths of other vehicles, such as autonomous aircraft, can benefit the computation of UAV paths. And vice versa, information collected from UAV paths can complement the computation of paths for other vehicles such as avoiding congestion in self-driving cars.

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Availability of data and material Not applicable

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Code availability Not applicable

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