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Survey on computational-intelligence-based UAV path planning

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ABSTRACT

The key objective of unmanned aerial vehicle (UAV) path planning is to produce a flight path that connects a start state and a goal state while meeting the required constraints. Computational intelligence (CI) is a set of nature-inspired computational methodologies and approaches for addressing complex real-world problems for which mathematical or traditional modelling does not perform well. It has been applied in the field of UAVs since it can yield effective, accurate and rapid solutions. This article provides an overview of studies on UAV path planning based on CI methods published in major journals and conference proceedings. We survey relevant studies with respect to different CI algorithms utilized in UAV path planning, the types of time domain in UAV path planning, namely, offline and online, and the types of environment models, namely, 2D and 3D. It is observed that CI methods outperform traditional methods on online and 3D problems. The analysis is useful for identifying key results from UAV path planning research and is leveraged in this article to highlight trends and open issues.

1. Introduction

In recent years, it has been demonstrated that UAVs represents one of the most challenging and high-potential technologies in aeronautics. Meanwhile, the path planning task is becoming one of the key technologies of UAVs and has been widely investigated by scholars around the world. The main objective of UAV path planning is to design a flight path directed to the target with minimal comprehensive costs, i.e., minimal probability of being destroyed while meeting the UAV performance requirements.

Previous methods for solving this problem, for example, dynamic programming [1] and geometric algorithms such as A-star search [2], have usually formulated the problem as a numerical cost minimization problem. In the process of dynamic programming [3], a local cost is assigned to each link of the grid that spans the area of operation. It assumes that the cost of flying over an area is independent of the path by which the UAV travels to reach the target. Due to this assumption, the considered cost is different from the real cost [4,5]. The A-star algorithm [6], which is a variant of the shortest path algorithm, has difficulty solving problems with multiple constraints. Moreover, algorithms of this kind are strongly based on the cost map, which should be produced and stored, and cost map production is a very time-consuming task. Both dynamic programming and A-star search techniques suffer from relatively slow execution. Computational intelligence (CI) methods [7], as candidates for overcoming these problems, were put forward. These methods are closely related to the human reasoning approach, i.e., they use inexact and incomplete knowledge and can produce control actions in an adaptive way. In the last decade, increasing numbers of studies in the literature have focused on CI methods for solving UAV path planning problems.

Although there are several surveys on UAV path planning methods [8–11], no comprehensive survey has been conducted from the aspect of the application of CI methods to UAV path planning. This article provides a comprehensive analysis of CI methods in application to UAV path planning by reviewing 231 papers published in major journals and conference proceedings. These papers are mainly distributed from 2008 to 2017 because CI methods emerged in large numbers and became mature for application to UAV path planning after 2007. We analyse relevant studies from three dimensions: CI algorithms utilized in UAV path planning; the types of time domain in UAV path planning, including offline and online; and the types of environmental model, including 2D and 3D. From the survey, we have found that CI methods outperform traditional methods in dealing with online and 3D problems. The analysis is helpful for identifying the advantages of applying CI methods to UAV path planning and highlights future trends and open issues.

The remainder of this paper is organized as follows. Section 2 summarizes basic definitions and concepts regarding CI and UAV path planning. In Section 3, we describe the approach that we used to collect research papers. Section 4 presents the classification in terms of CI for analysing multiple types of methods in path planning. Section 5 presents the conclusions of this article.

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2. Concepts

Before analysing the studies of UAV path planning based on CI methods, we will provide several definitions and concepts in this section that will be used in this survey.

2.1. Computational intelligence

Computational intelligence [12] is a set of nature-inspired computational methodologies and approaches. It can address complex real-world problems for which mathematical or traditional modelling is not useful. In the last decade, the principal CI approaches have been fuzzy logic, neuron computing, genetic computing, and probabilistic computing.

The applications of CI approaches in real systems usually incorporate hybrids of paradigms such as artificial neural networks, fuzzy systems, and evolutionary computation systems, which are augmented with knowledge elements. As a result, in contrast to traditional computing, CI can be tolerant of imprecision, uncertainty and partial truth.

In this paper, we regard CI as an implementation that facilitates appropriate actions (intelligent behaviour) in systems in complex and constantly changing environments. It comprises practical adaptation concepts, paradigms and algorithms. More broadly, genetic algorithms, artificial neural networks and fuzzy logic are all within the scope of CI in our paper.

2.2. UAV path planning

UAV path planning involves designing a flight path directed towards a target with minimal comprehensive costs, i.e., minimal probability of being destroyed while meeting the UAV performance constraints. In general, path planning for UAVs has the following attributes [13]:

(1) *Stealth:* This aspect concerns the safety of UAVs. UAVs are usually required to carry out missions in threatening environments. Thus, it is very important to minimize the probability of detection by hostile radar and other UAVs.
(2) *Physical feasibility:* This refers to the physical limitations in the use of UAVs, which include the maximum path distance and the minimum path leg length.
(3) *Performance of the mission:* This refers to whether a path can satisfy the requirements of a specified mission. To complete the mission, various requirements must be met when we design a path. These requirements usually include the maximal turning angle, the maximum climbing/diving angle, and the minimal flying height.
(4) *Real-time implementation:* This refers to the efficiency of path planning. The flight environments of UAVs are usually constantly changing. Therefore, our path-planning algorithm must be computationally efficient. Replanning ability is critical for adapting to unforeseen threats.

To satisfy the above attributes, there are several traditional methods for completing UAV path planning missions, such as the rapidly exploring random tree method, the probabilistic road-map method, and the artificial potential field method. Compared with the traditional methods, CI-based methods have strong ability to obtain high-quality solutions in path planning and are easier to implement. For example, typically, an evolutionary algorithm is a population-based solver for trial-and-error problems with a meta-heuristic or stochastic optimization approach. Many variants or extensions of algorithms of this type were proposed to adapt to specific families of problems or data structures and produce highly optimized solutions in a wide range of problem settings. Moreover, when problem settings change, only specification of the length of the problem solution vectors is required. Their encoding, evaluation functions, and the rest of the program do not need to be changed.

3. Analysis of the literature

In this work, we collected papers according to a two-step procedure:

(1) Search keywords in digital libraries. We considered publications from IEEE, AIAA, ACM, Elsevier, Springer, IMechE, Cambridge, Taylor&Francis, SIAM and Wiley, which almost cover all important journals and conference proceedings in UAV fields. The papers were obtained by searching the words “UAV path planning” and “UAV route planning” in the above mentioned digital libraries. These words can only reduce the set of papers to a wide range (e.g., because those UAV path planning methods may contain both conventional and intelligent methods). Then, we identified manually and downloaded papers that utilized CI methods according to the title, abstract and keywords (e.g., genetic algorithm and particle swarm optimization).
(2) Extend papers according to references. We extended the set of papers by inspecting the reference list of each paper and adding to the final literature set the referenced papers that were published from 2008 to 2017 and are relevant to UAV path planning based on CI. Then, these operations were repeated until no more papers could be added.

Through these two steps, we finally obtained a set of 231 papers. Fig. 1 shows the number of papers per year, from which an increasing trend can be observed. The first 7 years from 2008 showed a growth trend, and the rate of growth was increasing slightly, while there was a slight fluctuation from 2014 to 2016. After that time, the last two years showed a more dramatic increase. In this period, multiple new CI methods were proposed and used in UAV path planning.

In Fig. 2, the distribution of publications on the topic in several major digital libraries is presented. IEEE, AIAA, ACM and Elsevier contain the most papers, accounting for approximately 40%, 20%, 14% and 13%, respectively. The IEEE digital library contains the largest number of papers due to its strong correlation with the topic and its huge database. The AIAA and ACM libraries, which mainly contain Aeronautics&Astronautics and Computing Machinery papers, respectively, also published many papers on CI-based UAV path planning. In addition, as one of the largest publishing companies, Elsevier published many journal papers in this field. Researchers from many fields and areas have worked on this hot topic. These papers will be further analysed in the following section.

4. Detailed analysis of CI algorithms in path planning

To provide a framework for analysing the research, we introduce three orthogonal dimensions, which can provide a comprehensive overview of the literature and insights into future research directions. Each dimension consists of a set of classes used to classify the surveyed studies. The dimensions are as follows:

(1) Classification from the aspect of algorithms. This dimension reflects the classification according to the algorithms utilized in the studies. It indicates the usage of different CI algorithms for path planning.
(2) Classification from the aspect of the time domain. This dimension divides UAV path planning methods into offline and online methods in terms of time-domain type. It indicates whether the UAV plans its path in real time or not.
(3) Classification from the aspect of the space domain. This dimension divides UAV path planning methods into 2D and 3D methods in terms of space-domain type. It indicates whether the flight height is considered or not during the planning.

From the above aspects, we will evaluate a diverse group of CI algorithms on UAV path planning, different characteristics on different types of time domain and different environment modelling methods on

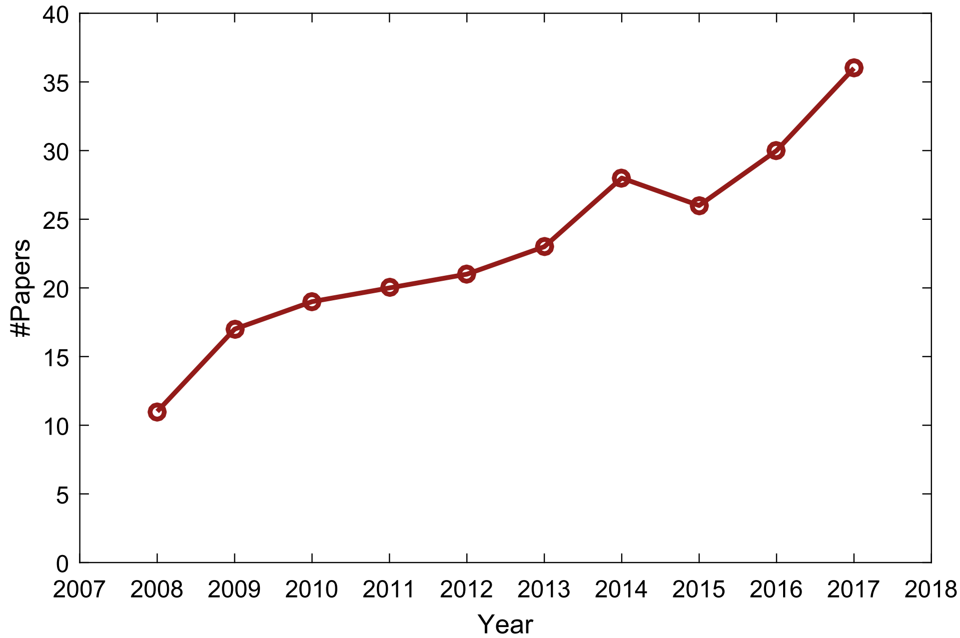

Fig. 1. Number of papers per year.

different types of space domain. As a result, we can obtain a comprehensive overview of CI-based UAV path planning.

4.1. Classification from the aspect of algorithms

In Fig. 3, the pie chart presents the percentages of various CI algorithms utilized for UAV path planning from 2008 to 2017 through our research. The genetic algorithm was the most common algorithm, accounting for 21%. Ant colony optimization and artificial neural networks, as two of the most popular intelligence algorithms, occupy the second and third positions with 16% and 15%, respectively, followed by learning-based methods (due to advances in deep learning technology, increasingly many machine learning algorithms are utilized in UAV path planning), particle swarm optimization and fuzzy logic algorithms. Several other CI algorithms were utilized for UAV path planning, such as simulated annealing, the artificial immune method and other swarm optimization methods (e.g., the bat algorithm, bee colony, the firefly algorithm and the wolf colony algorithm).

In the following, we present our studies according to the categories of CI algorithms and discuss the developments of algorithms in each category. We choose several popular approaches with detailed interpretations from the algorithmic point of view. In addition, we summarize these methods and the research trend of each UAV path planning algorithm.

4.1.1. Genetic Algorithm (GA)

In the application of GA in path planning [14], a population of candidate solutions or called individuals to an optimization problem is evolved toward better path planning solutions. Each path planning candidate solution has a set of properties (its chromosomes or genotype) which can be mutated and altered. The evolution usually starts from a population of randomly generated solutions. In each generation,

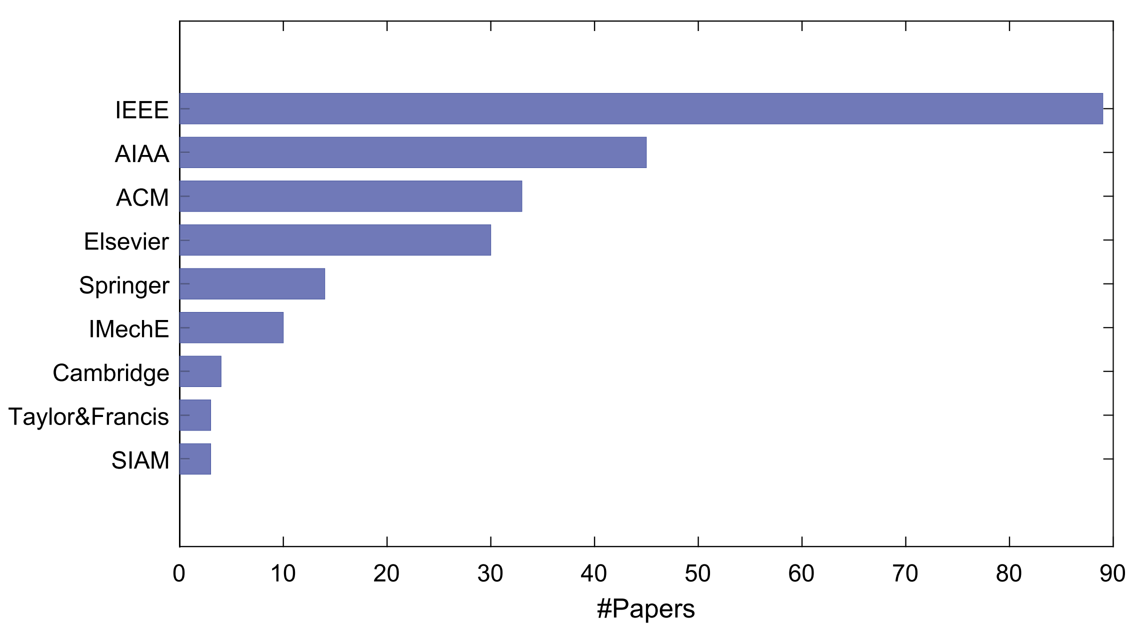

Fig. 2. Number of papers in major digital libraries.

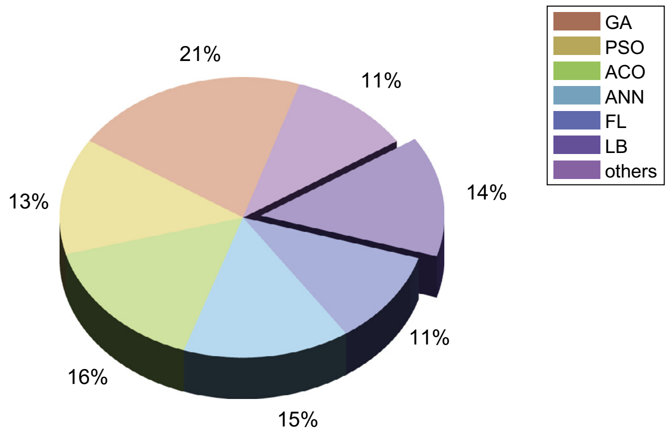

Fig. 3. Classification of CI methods by algorithm.

the fitness of every solution in the population is evaluated; the fitness is usually the value of the objective function in the path planning optimization problem being solved. The more fit solutions are selected from the current population, and each solution is modified to form a new generation. The new generation of candidate solutions is then used in the next iteration of the algorithm. To improve the performance, especially the speed and accuracy of UAV path planning [15], many researchers have utilized GA in UAV path planning in the last decade [16–20].

To improve the application performance of GA in UAV path planning, researchers have made many improvements on each phase of the algorithm, such as the objective function and population initialization, selection and mutation. According to the basic strategy of GA, the characteristics of the optimal path can be represented in the form of objective functions. Some researchers designed multi-objective functions by producing line segments, circular arcs and vertical helices, which reduce the execution time of solutions [21]. In addition, improvements have been made based on the genetic operators and the GA chromosome encoding to propose methods for solving a wide class of complex path planning tasks [22]. Dual-population GA is a type of multi-population GA that uses an additional population as a reservoir of diversity to adjust the distance dynamically and achieve an appropriate balance between exploration and exploitation [23]. An improved dual-population genetic algorithm uses different fitness functions for different populations and utilizes several methods to generate new offspring. Using this approach, it improves the global search and local search capabilities of GA to ensure that the global optima of the flight path are obtained [16]. Another research group advocated the use of a new mutation application strategy and additional types of diversity, such as global random and local random diversity. The developed algorithm is called the multi-frequency vibrational genetic algorithm [24]. A study was conducted on the performance of GA under various selection schemes and population sizes [25], in which each generation is anticipated to be better than its previous generation [18], which increases the possibility of reaching the best solution (or at least an acceptable solution) [26]. Several NP-hard problems, for example, the multiple travelling salesman problem (mTSP) in multi-UAV reconnaissances, have been studied by utilizing GA for multi-UAV systems [17], which has been implemented as a parallel algorithm [27] in a multi-core environment [28].

GA does not easily fall into a local optimum because in each iteration, GA searches in the entire set randomly and produces a new population through crossover and mutation. GA is based on schema theory, and its genotypes are described in terms of various features, which implies that the search process is a parallel process. In summary, as a CI path planning method, GA has the advantages of approximating the global optima and a high processing capability.

4.1.2. Particle Swarm Optimization (PSO)

A basic variant of the PSO algorithm works by having a swam of candidate solutions or particles. These particles are moved around in the search-space according to a few simple formulae [29]. In UAV path planning problems, the movements of the particles are guided by their own best known position in the search-space as well as the entire swarm's best known position. When improved positions are being calculated, these will then come to guide the movements of every particle. The process is repeated and by doing so a satisfactory solution of path will eventually be discovered [30–32].

The PSO algorithm allows particles to memorize information shared globally, which yields lower complexity and better feasibility. Therefore, it has been introduced into UAV path planning [33]. Several researchers created an encoding method that satisfies the constraints of the cost function for implementing PSO algorithms with high efficiency. For example, the azimuth angle and altitude angle of a track point are represented in a concentric spherical coordinate system [34]. In another example, a control problem can also be encoded as particles. The best control points can be calculated by the PSO algorithm, with the skeletonization of the pre-processing procedure and the use of B-spline curves as a smoothing tool [35]. Another hot issue in PSO research is preventing calculation results from becoming trapped in local optima. A UAV path planning method [36] based on hybrid particle swarm theory has been put forward with a contraction factor based on the genetic approach to avoid falling into a local minimum. In the recent years, new variants of the PSO algorithm, namely, the phase-angle-encoded and quantum-behaved PSO method [37] and the fitness-scaling adaptive chaotic PSO method [38], have been proposed as fast and robust methods for UAVs in various known threat environments. Even in an environment with different types of threats, a novel path planner for UAV has been designed to generate a safe and flyable path based on differential evolution and the quantum-behaved PSO method [39].

Instead of carrying out the processes of selection, crossover and mutation as in GA, PSO algorithms focus on tracking a single particle and sharing collective optimal information to accomplish the optimal space search. The PSO algorithm is different from GA because it ignores some of the individual internal links. As a result, it often falls into local optima. Therefore, if we merge SA or GA into the PSO algorithm, we can avoid this problem. From another point of view, the PSO algorithm is used to determine the one-way movement of the entire cluster. Thus, when combined with GA, it can converge faster.

4.1.3. Ant Colony Optimization (ACO)

The main concept of applying ACO algorithm to the optimization problem is that the walking path of ants is used to express the feasible solution of the problem to be optimized. In path planning problem, all the paths of the whole ant group constitute the solution space for the optimization problem. As time goes on, the concentration of pheromone accumulated on shorter paths is increasing, and the number of ants choosing the path is increasing. Eventually, the whole ant will concentrate on the best path under positive feedback, and the corresponding solution is the optimal solution to the path planning optimization problem [40].

The original ACO model easily falls into local optima [40], and the convergence speed is slow in solving complex problems [41]. However, many researchers have performed effective optimizations based on this algorithm. ACO algorithms are usually implemented by dividing a flying area into a grid and optimizing a path between a grid point and the destination point for UAV path planning [42]. To make the search for the optimal path rapid and efficient [43], a modified algorithm is presented with the help of a 3D grid and a new climbing weight parameter [44]. An improved ACO algorithm is obtained by computing the flying cost on every side, which represents a method that addresses an overall formation. In this method, each UAV plays a substantial role in combat effectiveness [45], which can increase the destruction efficiency. In addition, ideas from the MAX-MIN ant colony algorithm [46], which has been applied extensively to many NP-hard problems, such as the travelling salesman problem (TSP) and the quadratic assignment problem (QAP) [41], make the optimum worst results have lower deviation [47] in each iteration. When executed on GPU in a parallel manner [48], the ACO algorithm has great potential for acceleration and solving many complex tasks such as UAV path planning problems [40].

Compared with other CI algorithms, the ACO algorithm has strong robustness and ability to search for a better solution. Moreover, the ACO algorithm is a population-based evolutionary algorithm that is intrinsically parallel and easy to implement in parallel. To improve the algorithm's performance in path planning problems, the ACO algorithm can be easily combined with a variety of heuristic algorithms.

4.1.4. Artificial Neural Network (ANN)

The construction concept of an ANN is inspired by the operation of biological neural networks. It is based on a set of connected units called artificial neurons. And each connection between artificial neurons can transfer a signal from one to the other. The artificial neuron that receives the signal can process it and then signal artificial neurons connected to it. In an ANN implementation of UAV path planning, the signal at the connection between artificial neurons is a real number, and the output of each artificial neuron is calculated by a nonlinear function of the sum of its inputs. They are usually optimized through mathematical statistical methods based on fitting large amounts of data. After that, we can obtain an appropriate solution which can be expressed by functions.

The ANN algorithm can reduce the computational complexity by removing the requirement for collocating the computational environment and providing fast computation equipment [49]. However, since an ANN is always constructed by using parallel computing [50], the convergence is usually fast, and the constructed path is optimal and safe [51]. In existing research papers, two main types of ANN methods have been utilized in UAV path planning: In the first type, a UAV bases its path on a sample trajectory and uses a direct collocation method to compute and optimize the trajectory [52]. Methods of the other type utilize neural networks to approximate the system dynamics, objective functions, and gradients, which removes the requirement for collocation, thereby reducing the nonlinear programming (NLP) problem size [53]. At present, methods of the second type are more popular. They have then been extended to demonstrate their advantages in solving multiple-UAV problems [54]. In addition, ANNs have usually been hybridized with other algorithms [55,56], such as the potential field method, GA and PSO, to maximize their advantages.

A deep neural network is a multi-layer NN and has been widely used in the field of artificial intelligence recently, such as for image processing and speech recognition. Due to its ability to extract and characterize features accurately, it can be used in the future to facilitate UAV path planning in complex scenarios.

4.1.5. Fuzzy Logic (FL)

FL originates from imitating the human brain, especially judgement in uncertain situations and the ability to deal with incomplete knowledge. It is a form of multi-valued logic in which the true values of variables can be any real number between 0 and 1. And it is utilized to deal with the concept of partial truth, where the true value can range between completely true and completely false. Due to its adaptability to unclear and unbounded objects, FL has been widely used in UAV path planning area especially control and decision problems [57].

In the field of UAV path planning, FL has been utilized to deal with ambiguous optimization objectives and decision problems. With local path-searching behaviours and global goal-seeking behaviours in different ranges, an FL method infers behaviour weights using fuzzy reasoning and coordinates the behaviours to generate new reference waypoints [58]. To meet the real-time requirements of online UAV path planning, a proportion coefficient based on fuzzy logical reasoning can be changed to adapt to changes in the situation [59]. In addition, FL is usually utilized to control and make decisions in combination with other CI algorithms. For example, to satisfy all constraints, a value is generated by the fuzzy system and used to develop the fitness function of GA [60]. In another study, a fuzzy ant colony system [47] uses fuzzy logic to integrate heuristic data into the ant colony framework to balance aircraft physics. Wang et al. applied an FL method to a single UAV path planning problem [61]. In the research, a new multi-objective fuzzy optimization method was proposed to make the performance of flight path planning more stable by taking the costs of fuel and radar threat as goals.

The FL method is rarely used alone in UAV path planning due to the difficulty in adjusting membership functions. However, the relevant ideas can be combined with other types of methods.

4.1.6. Learning-based methods

Learning-based Methods. Recently, many learning algorithms, such as the Q learning algorithm [62,63], cooperative and geometric learning algorithm [64] and reinforcement learning algorithm [65], have been proposed for the solution of UAV path planning.

Generally, learning-based methods in UAV path planning can be divided into two classes. The one is based on imitation learning [66] and the other is based on reinforcement learning [67]. Imitation learning is a kind of supervised learning method, which needs a supervisor to teach the UAV how to fly in a particular state or scene [68]. This kind of methods were first applied to mobile robots [69] and autonomous vehicles [70,71], then are transformed to UAVs. Reinforcement learning in UAV path planning areas is more popularly used [72–74]. Different from imitation learning, reinforcement learning does not need a supervisor. They generate and update the selection strategies of UAV actions according to the environmental rewards which are based on the UAV's last state and last action. There are several types of methods in reinforcement learning: value-based methods (such as Q learning algorithm) [75], policy-based methods (such as policy gradient) [76] and actor-critic methods [77].

With the development of computation and algorithms, multi-layer neural networks were combined with learning methods, which were called deep learning [78]. In UAV path planning areas, the applications of deep learning methods are just in the beginning. Some researches utilized deep neural networks to fit Q value in deep Q learning [63]. other methods based on policy gradient can output continuous motion space according to neural networks, such as DDPG algorithm [79], advantage actor critic algorithm [80] and A3C algorithm [81]. In addition, in some researches, convolutional neural networks are used to process the state information or observation of UAV according to its powerful feature extraction capability [82,83]. With the consideration that UAV path points are sequential, the recurrent neural networks, LSTM networks are utilized to predict UAV path whose results are better than fully networks [84].

Based on these learning-based methods, the constraints imposed by complex environments and cost functions can be reduced. As a result, the planning process can be simplified to some extent.

4.1.7. Other CI methods

In addition to the CI algorithms discussed above, there are many other algorithms that can solve UAV path planning problems or help improve performance, such as simulated annealing (SA), artificial immune (AI), and differential evolution (DE).

The SA algorithm is utilized to provide acceptable solutions [85,86] due to its capability of escaping from local minima [87,88]. For example, to improve the convergence speed, a hybrid Taboo [89] search-simulated annealing algorithm [90] was proposed. AI, which is similar to GA in terms of computing process, can also effectively improve the convergence speed and prevent premature convergence [91]. DE is usually applied to modify an optimal feasible path of a UAV [92] during the planning process [39]. Central force optimization (CFO) is a new

Fig. 4. Trend from the aspect of algorithms.

computational intelligence algorithm [93]. Recently, a modified CFO method (MCFO) was proposed for solving the problem, which combines the main strategy of PSO with the mutation operator from GA [94]. Several swarm-intelligence-based algorithms based on ACO and PSO have been put forward for their own advantages and utilized by researchers in path planning, including the bat algorithm [95], artificial bee colony [96], the firefly algorithm [97] and the wolf colony algorithm [98,99].

4.1.8. Research trend from the aspect of algorithms

Fig. 4 shows the trend of algorithm development from 2008 to 2017. From this figure, we observe the following:

- The ratios of GA, PSO and ACO algorithms all peaked in 2013 and 2014 and then had a dropping trend.
- FL was rarely utilized in UAV path planning after 2012.
- The ratios of ANN and learning-based methods grew dramatically after 2013.

From these observations, we conclude that traditional CI methods may have reached a bottleneck stage. Comparatively, with the development of deep learning technology, increasing numbers of researchers began to apply machine learning and deep learning technology to UAV path planning, as shown in Fig. 4 by the blue and purple columns. In the future, it may become a hot research topic.

4.2. Classification from the aspect of the time domain

In this section, we will classify the 231 collected articles by time-domain type: online and offline. An online method is a method that can plan the UAV paths in real time. In other words, the UAV can identify changes in the environment and react to them. In contrast, an offline method performs path planning based on offline information instead of real-time information. Only 29.9% of methods are online, and most methods focus on offline algorithms and their improvements, accounting for approximately 70.1% of methods.

We focus on the details of offline and online methods and study the history of these two types of methods. After that, we discuss the future trend of the research on UAV path planning algorithms from the aspect of the time domain.

4.2.1. Offline path planning

Offline UAV path planning is a classical problem in which a UAV searches for appropriate paths using information in the whole environment with some specific constraints. There are several classes of constraints in UAV path planning problems, such as obstacle and threat constraints, velocity and acceleration constraints, and minimum path and fuel consumption constraints, which affect the planning results.

Many researchers focus on minimizing the length of a path with obstacle or threat constraints in the environment. The optimization problem is multi-modal in nature because for every set of obstacles or threats, there can be multiple sets of paths with varying costs. Thus, CI methods such as GA or PSO would be highly suitable for optimizing the generated paths. Researchers have shown that CI methods have obtained high-quality solutions because they are computationally efficient on a wide variety of multi-modal unconstrained problems. In addition, CI methods have various attractive features. For example, they do not easily fall into local optima, which makes them very suitable for path planning problems in which the obstacles or threats are complicated.

4.2.2. Online path planning

Online path planning for UAVs is a basic issue in implementing real intelligent flight. It can be efficient, accurate and adaptable to real environments. Online path planning is a dynamic multi-objective optimization problem. A key technology of intelligent flight [100] for UAVs is the ability to react to changes in the environment.

The most popular online path planning algorithms are based on GA and FL. A two-stage GA planner has been put forward for solving global and local planning problems [101]. The local planner uses sensory information as its input. Once it has detected previously unknown or unencountered obstacles, it performs online preplanning to navigate around the newly discovered obstacle. Similarly, Liu et al. presented a feedback-based compositional rule of inference [102] (FBCRI)-based path planning method that satisfies the requirements of real-time navigation, smooth optimization and probabilistic obstacle avoidance with local path-searching behaviours in regional ranges and global goal-seeking behaviours in holistic ranges. Different from the above methods, Dong et al. proposed a novel fuzzy virtual force method [103] with a fixed step size that meets the real-time requirements of online UAV path planning. Kermani et al. [60] addressed an online path planning algorithm based on GA for an unmanned aerial vehicle (UAV). In the research, the planned path satisfies several objectives such as minimum distance, collision-free travel and maximum power of the communication system, while there are some no-fly zones in the area. In the same year, Wang et al. presented an approach [104] that combines static path planning with dynamic path planning for multiple cooperative UAVs based on a PSO algorithm. In addition to the above swarm CI methods, a novel path planning method based on a neural network [50] can simplify path planning in a complex environment, especially for a real-time situation.

4.2.3. Research trend from the aspect of the time domain

According to Fig. 5, as the total number of papers increases, researchers increasingly focus on online path planning methods compared to the flat trend of offline methods especially in the last three years. By analysing these papers, we identify two conflicting issues for online path planning: the computation speed requirement and the integrity of information on the environment. The former limits the time for UAVs to compute the path during flight The latter represents the degree to which UAVs are aware of the environment [105]. Most algorithms require complete information on the environment to explore an optimal path and escape a local optimum. Comparatively, some algorithms can perform path planning based on only local or incomplete environment information.

Nowadays, increasing numbers of UAVs are applied in war, transportation, detection and agriculture. Thus, UAV path planning is urgently needed for planning and preplanning online in reaction to changing scenes. In future research, real-time planning will become a research hot spot.

4.3. Classification from the aspect of the space domain

In this section, we will classify the 231 collected articles by space-domain type: 2D and 3D. A 2D path planning method can only plan UAV paths in a two-dimensional environment. A 3D method can perform path planning in both a three-dimensional environment and a two-dimensional one. 55.8% of articles explore 2D path planning methods, while 44.2% of articles explore 3D methods.

We focus on the details of 2D and 3D methods and study the history of these two types of methods. After that, we discuss the future trend of the research on UAV path planning algorithms from the aspect of the space domain.

4.3.1. Path planning in 2D environments

In traditional path planning methods, environment information has usually been described by a 2D scene. In this case, it is supposed that the UAV flies by maintaining its flight height or manual adjustment. From the optimization point of view, a 2D path planning problem is an NP-hard problem; thus, no common solutions exist. Fortunately, CI algorithms reduce the requirements of computing the gradients of cost functions and constraint functions, which enables the NP-hard problem to be solved and optimized.

Generally, 2D path planning algorithms can be divided into three types according to the constraints on the UAV: Algorithms of the first type model the UAV as a particle. In this case, planners can focus on the calculation of optimal paths. However, this calculation is still not easy to implement since it is an NP-hard problem that can be equivalently transformed to a spatial-search problem with the optimal path constraint. Although NP-hard problems have no common solutions, multiple CI methods [63,106] can optimize the path planning problem by

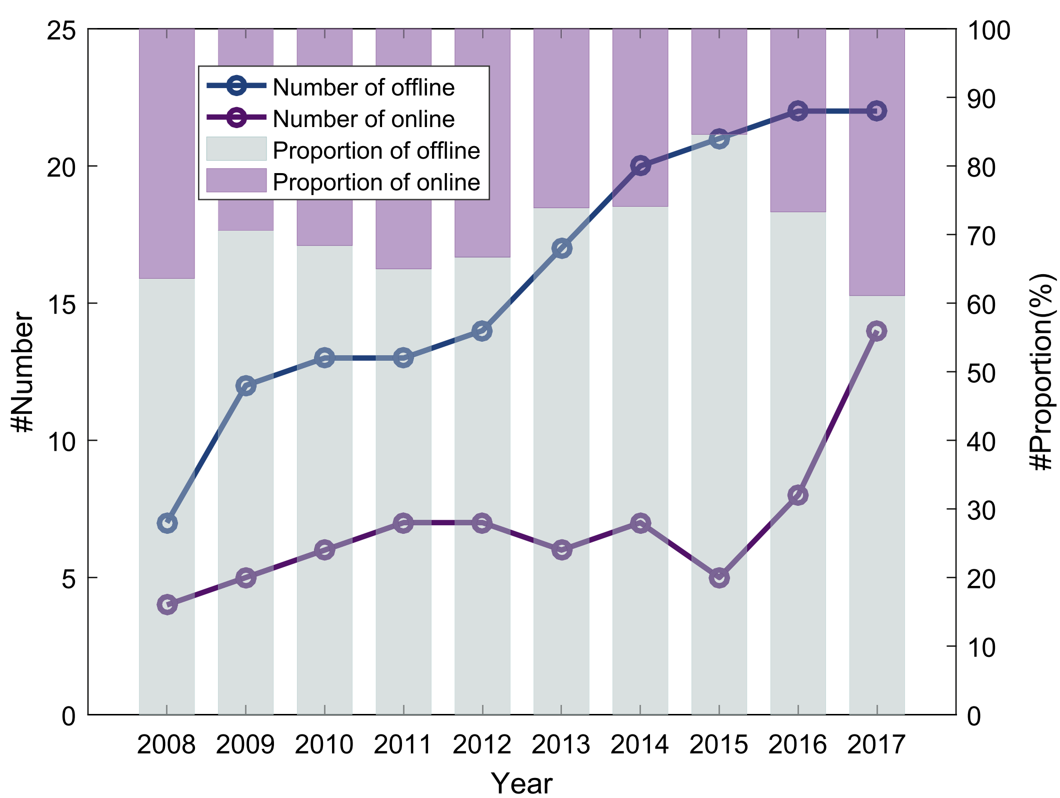

Fig. 5. Trend from the aspect of the time domain.

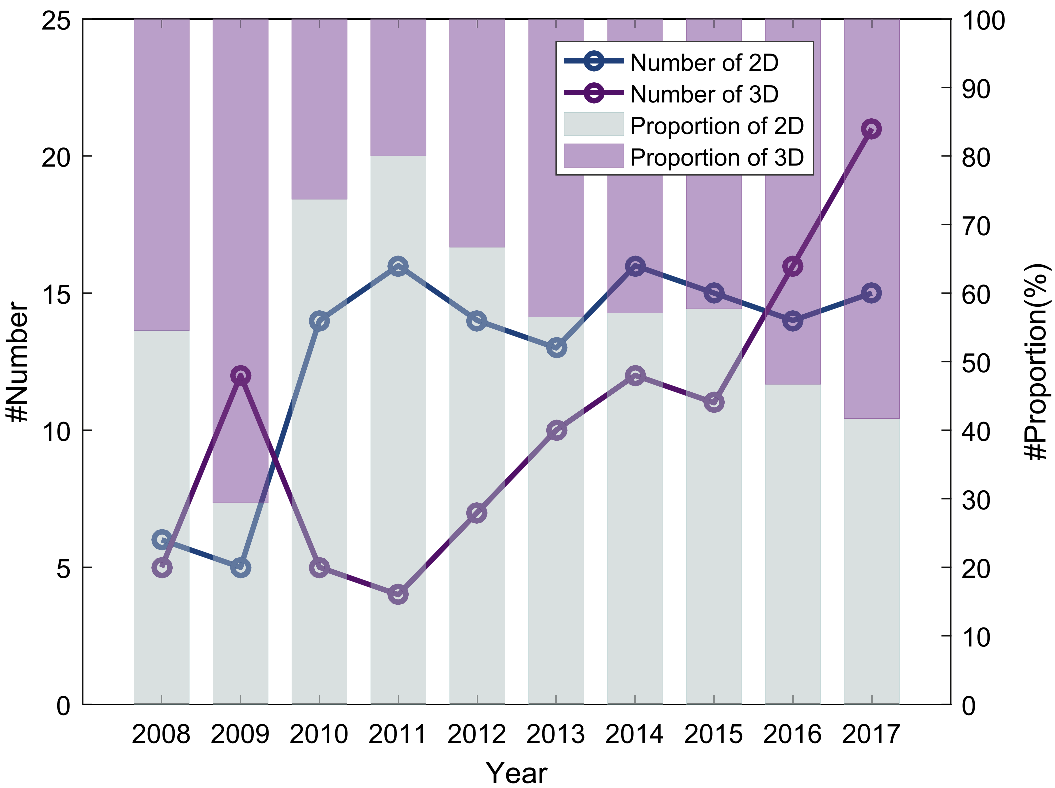

Fig. 6. Trend from the aspect of the space domain.

simplifying the computation of the gradients of the cost functions and constraint functions. Methods of the second type model a UAV according to its shape. In this case, the problem needs to be transformed [107] by considering two-dimensional shape parameters such as wing span and centre of gravity. After that, it can be solved by a method of the first type. Methods of the third type model a UAV according to its kinematic and dynamic constraints, for example, its min and max turning radii. Compared with the first two types, the last is more complex but more practical for applications. By taking the kinematic and dynamic constraints in consideration, CI methods [108] can produce advantages in terms of the calculation speed and convergence rate.

4.3.2. Path planning in 3D environments

An increasing range of fields, such as transportation, detection, navigation, and operations, require the application of UAVs. Due to the complexity of the environments, which tend to be unstructured and full of uncertain factors, 3D path planning algorithms are urgently needed. Although UAV path planning in 3D environments shows great potential, unlike 2D path planning, the difficulties increase exponentially with kinematic constraints. One classical problem is modelling the environment while taking the kinematic constraints into consideration to plan a collision-free path. Taking into account kinematic constraints (including geometric, physical, and temporal constraints) in 3D path planning, traditional CI algorithms face several problems, such as wider exploration and slower convergence.

In the following, we focus on the 3D methods and discuss how to solve the above problems. They have different characteristics and advantages when combined with appropriate CI methods. To overcome the issues of premature convergence and slow convergence in 3D path planning of UAV low-altitude penetration, several GA-based path planning methods [109,110] were proposed. The improved PSO methods [111,112] can avoid blind wide exploration and perform detailed optimization to identify an ideal path in the 3D space. Modified ACO methods [113] for 3D planning have been proposed, which can also improve the speed of selection and decrease the probability of obtaining locally optimal solutions. Unlike swarm intelligence algorithms, FL algorithms have usually been used in UAV vision navigation to facilitate image detection and decisions [114]. To address UAV attack path planning problems, hybrid neural-network-based methods have been proposed. These methods can easily be accelerated by parallelization techniques. Nowadays, with the development of computing chips, the strict computing conditions of machine learning and deep learning methods [115–117], which require high-performance and long-time computing, have been satisfied. Machine learning and deep learning methods can be utilized in 3D UAV path planning to solve the NP-hard problem more precisely in a large search space.

4.3.3. Research trend from the aspect of the space domain

According to Fig. 6, the number as well as the proportion of papers on 3D methods grew dramatically, while that on 2D methods dropped slightly. The number of papers that explore 3D methods is larger than the number of papers that explore 2D methods after 2016. This is mainly due to the development of computation hardware. Hardware with high performance is provided for UAV systems. Thus, increasing numbers of 3D methods can be implemented on the systems, even if they have a high level of complexity. Moreover, UAVs have been widely applied to transportation, detection and photography in recent years. To optimize the above applications, researchers have focused on 3D methods. These methods are highly suitable in practice because they can directly deal with complex real environments, in which there are many structural constraints and uncertainties.

Nowadays, 3D path planning algorithms for UAV navigation are urgently needed, especially in complex environments such as forests, caves, and urban areas. Therefore, UAV path planning research in 3D environments will become mainstream in the future.

5. Conclusions

This article provides a comprehensive analysis of CI based UAV path planning literature, by reviewing 231 papers published in major journals and conference proceedings in the last decade. We survey relevant studies with respect to different CI algorithms utilized in UAV path planning, the types of time domain in UAV path planning, namely, offline and online, and the types of environment models, namely, 2D and 3D. The analysis is useful for identifying key results from UAV path planning research and is leveraged in this article to highlight trends and open issues. The contributions of this article are:

(1) A comprehensive analysis of UAV path planning from the perspective of CI algorithms which include GA, PSO, ACO, ANN, FL and learning-based algorithms, is provided. It can help related researchers have a full review of most advanced path planning methods in UAV.
(2) A comprehensive analysis of CI methods about time-domain classification (e.g., online and offline) is taken, which can be a guidance to choose different methods with different time-domain characteristics according to actual conditions.
(3) Another significant analysis of CI methods is based on the space-domain classification (e.g., 2D and 3D). It contributes to different ways of modeling the environment during UAV path planning.

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