Progress in Aerospace Sciences 74 (2015) 152–166

Contents lists available at ScienceDirect

Progress in Aerospace Sciences

journal homepage: www.elsevier.com/locate/paerosci

Sense and avoid technologies with applications to unmanned aircraft systems: Review and prospects

Xiang Yu, Youmin Zhang *

Department of Mechanical & Industrial Engineering, Concordia University, 1455 de Maisonneuve Boulevard West, Montreal, Quebec H3G 1M8, Canada

ARTICLE INFO

Article history:
Received 29 July 2014
Received in revised form
26 December 2014
Accepted 19 January 2015
Available online 31 January 2015

Keywords:
Unmanned aircraft systems
Sense and avoid
Review and prospects

ABSTRACT

Unmanned Aircraft Systems (UASs) are becoming ever more promising over the last decade. The Sense and Avoid (S&A) system plays a profoundly important role in integrating UASs into the National Airspace System (NAS) with reliable and safe operations. After analyzing the manner of S&A system, this paper systematically presents an overview on the recent progress in S&A technologies in the sequence of fundamental functions/components of S&A in sensing techniques, decision making, path planning, and path following. The approaches to these four aspects are outlined and summarized, based on which the existing challenges and potential solutions are highlighted for facilitating the development of S&A systems.

Contents

* Corresponding author. Fax: +1 514 848 3175.
E-mail addresses: xiangyu1110@gmail.com (X. Yu), ymzhang@encs.concordia.ca (Y. Zhang).

http://dx.doi.org/10.1016/j.paerosci.2015.01.001
0376-0421/

1. Introduction

1.1. Why sense & avoid in UASs

Distinctive from manned aircraft, a powered aircraft without a crew on board, which (1) can be operated autonomously or remotely and (2) can carry a payload, is named as an Unmanned Aircraft System (UAS) [1–3]. The latest developments on design principles and fundamentals of UASs are comprehensively discussed in the latest and the first such kind of handbook [3]. Depending on the characteristics of UAS weight, endurance, flying range, and altitude, UASs can be categorized into several groups as indicated in Tables 1 and 2. Moreover, according to different working principles of wings, UASs can be divided into fixed-wing and rotary-wing types, respectively. The typical UASs possessing distinctive characteristics are depicted in Fig. 1.

UASs have drawn significant attention in both civilian and military aspects, due to that they have vast prospects in Intelligence, Surveillance, and Reconnaissance (ISR) applications with less cost and more flexibility rather than manned aircraft [4–7]. Thus, aviation agencies around the world have encountered such a novel sort of aircraft that needs to share the sky with manned aviation [8].

To ensure safety flight of manned aircraft, Detect & Avoid (D&A) systems are capable of detecting airplanes in airspace, determining potential collision hazards, and performing necessary maneuvers to avoid potential collision of intruder aircraft. Even though transponders or radars are equipped in manned aircraft, midair collision avoidance is more dependent on the eyesight of a human pilot as stated by the Federal Aviation Administration (FAA). It is well recognized that both human and devices can play vital roles during the course of D&A in manned aircraft.

Table 1
Classifications of UASs by weight.

Category	Gross weight (kg)
Super heavy	≥ 2000
Heavy	200–2000
Medium	50–200
Light	5–50
Micro	≤ 5

Without a human pilot involved, UASs have to solely rely on Sense & Avoid (S&A) systems when being merged into the National Airspace System (NAS). With regard to UASs, S&A systems are essential to achieve autonomy [9,10], guarantee the safety and obtain the airworthiness certificate eventually [11–13]. Moreover, in accordance with the reference [14], it is desirable that the S&A systems in UASs offer a level of safety equaling or exceeding that of manned aircraft, which makes the development of S&A systems challenging.

1.2. The manner of S&A system

As illustrated in Fig. 2, a complete S&A paradigm consists of sensing hardware, decision mechanism, path planner, and flight controller, respectively. The manner of S&A system is shown in Fig. 3. The information of the UASs and intruders is gathered by equipped sensing devices. Consequently, the mechanism makes the decision whether the trajectory needs to be re-planned or not based on the provided data. If so, the path planner is trying to find an optimal or feasible path under the constraints of the UAS dynamics and fuel economics to avoid collisions. According to the re-planned trajectory and UAS dynamics, the flight controller outputs the control signals to drive the engine and the control surfaces correspondingly so that avoidance maneuvers can be accomplished physically. In addition, as can be observed from Fig. 3, individual functionality of S&A system needs a specific block of time. T_{pf} T_{det} T_{dm}, T_{pp}, and T_{pf} denote the execution time needed by hazard detection, decision making, path planning, and path following, respectively. Therefore, S&A can be also recognized as a time-critical mission. If the total amount of time consumed by the S&A system exceeds the allowable threshold, collision cannot be prevented in practice.

1.3. The major work

The major work of this paper includes (1) surveying the

Table 2
Classifications of UASs according to endurance, range, and altitude.

Category	Endurance (h)	Flying range (km)	Altitude (km)
Long/High	≥ 24	≥ 400	≥ 10
Medium	5–24	100–400	1–10
Low	≤ 5	≤ 100	≤ 1

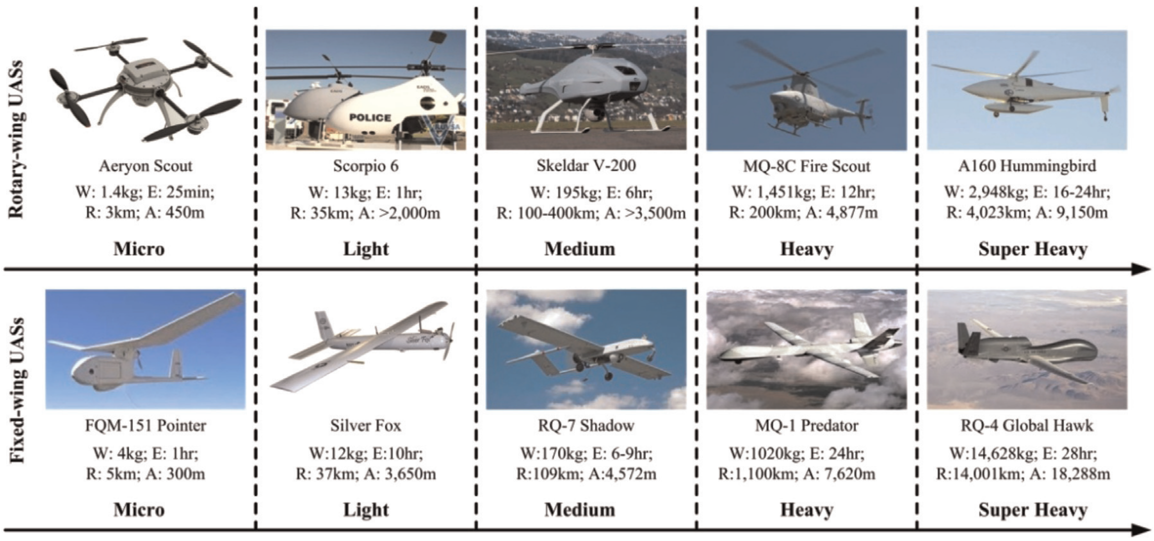

Fig. 1. Typical UAS categories. Note: The letters W, E, R, and A stand for weight, endurance, range, and altitude, respectively.

existing technologies by virtue of various functionalities of S&A systems and (2) presenting the technological challenges and future directions of the development of autonomous S&A systems. The authors sincerely hope that the research and development of practical S&A systems could be benefited from this paper. For the sake of the limited space and easy access to the quoted references, in the current manuscript, the emphasis has been mainly placed on the refereed journal publications. Special effort has been made to select contributions primarily concerned with the key techniques of S&A. Unfortunately many conference publications could not be covered in spite of our best effort, the authors sincerely apologize this in advance.

1.4. Organization

The rest of this paper is arranged as follows. The current sensing technologies to be applied for S&A are presented in Section 2. In Section 3, the decision mechanism techniques are reviewed for facilitating S&A systems development. Path planning methodologies with consideration of UAS dynamics and external disturbances are categorized and described in Section 4. Approaches of path following are surveyed in Section 5. Based on the preceding sections, some challenges and future directions of S&A systems for UASs are proposed in Section 6, followed by the concluding remarks.

2. Survey on aircraft/object detection

In S&A systems of UASs, how to appropriately select sensing devices is of paramount importance due to the factors of UAS payload capability, sensing accuracy, development cost, and maintenance complexity. Depending on how sensing information is being transmitted, the existing sensor technologies can be basically grouped into two categories: cooperative and non-cooperative methods. In general, a UAS taking cooperative sensors also requires others in the airspace carry cooperative sensors so as to complete the aircraft/object detection. As long as non-cooperative sensors do not expect other aircraft possess the identical sensors, both ground and airborne objects can be detected. After reviewing the on-board sensors, the algorithms with low degree of false alarm on how to detect and track potential targets/hazards are surveyed correspondingly.

2.1. Sensor technologies (hardware)

2.1.1. Cooperative methods

The Traffic Alert and Collision Avoidance System (TCAS), which has been widely deployed in manned aircraft, is known as a mature cooperative approach [15]. A transponder is adopted in TCAS to transmit information during the detection process. An airplane equipped with a TCAS is capable of communicating with others which take the TCASs as well to avoid collisions. The enhanced version of TCAS can detect up to a 129 km object and the latest one can detect a 160 km object. TCAS is fit for both the Visual Meteorological Condition (VMC) and Instrument Meteorological Condition (IMC). This sort of technology is considered for potential usage in UASs [16]. However, TCAS may not directly be applied for small/miniature UASs since the payload is rigorously limited as compared to manned aircraft. The communication between manned and unmanned aircraft is another challenging issue. Additionally, TCAS has limited ability to handle the case of multiple aircraft.

Automatic Dependent Surveillance – Broadcast (ADS-B), which broadcasts the identification, position, velocity, and intent of the

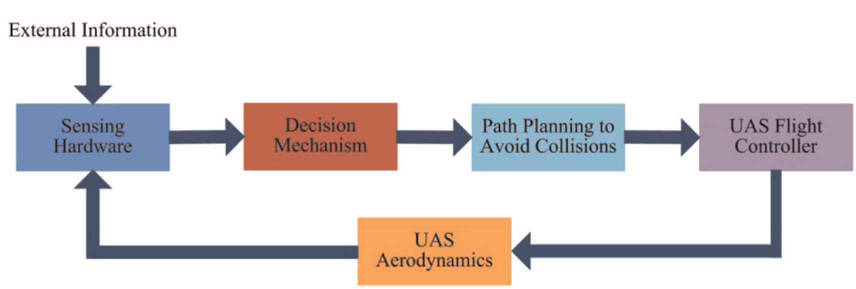

Fig. 2. The structure of S&A functionality in UASs.

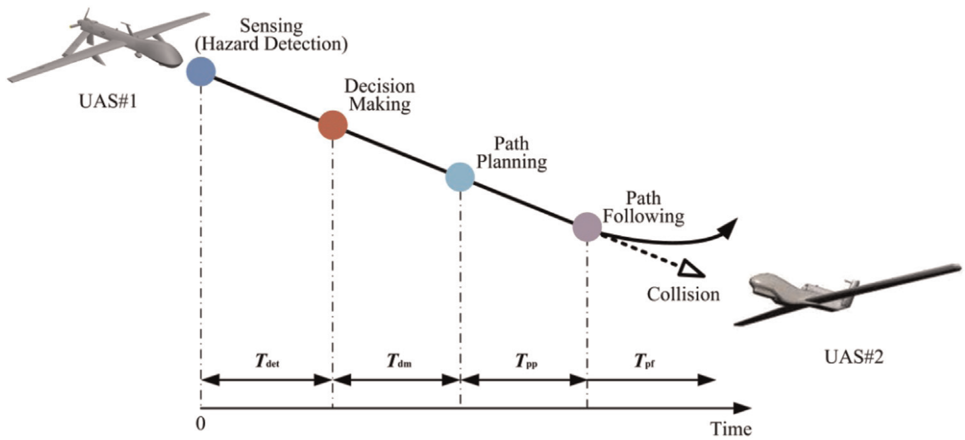

Fig. 3. The process of S&A in UASs.

aircraft to a universal access transceiver, has gained considerable interest in aviation industry as the next generation of surveillance technology [17]. Global Positioning System (GPS) is integrated in ADS-B to obtain the information of the position, altitude, and speed of an airplane. Ground stations and other aircraft within a roughly 240 km radius can receive the data-link broadcast by the aircraft. ADS-B is favorable for UAS S&A since (1) it can provide accurate and reliable information of navigation variables; (2) well-proven communication technology is used; and (3) it possesses flexible structure for easy implementation and incorporation of future techniques. However, ADS-B is ineffective in the case of ground-based obstacles, such as terrain features, towers, or power lines [18].

2.1.2. *Non-cooperative methods*

The taxonomy includes radar, Laser/Light Detection and Ranging (LIDAR), Electro-Optical (EO) system, acoustic system, and Infrared (IR) sensor [18]. The non-cooperative technologies do not require other aircraft to equip the same devices, when sharing the same airspace to avoid collisions. Moreover, the technologies can be applied to detect ground obstacles together with those that are airborne as compared to TCAS and ADS-B.

Synthetic Aperture Radar (SAR) as an active detection device creates an image of the object using multiple radar pulses [19]. SAR equipped in a UAS is applied for detecting motion and determining location, velocity, and size of ground targets. Recent advances in radar for UASs include that: (1) a reconfigurable, polarimetric L-band SAR, developed by NASA's Jet Propulsion Laboratory, is especially designed to apply for UASs [20]. The radar is fully polarimetric with a range bandwidth of 80 MHz and effective distance of 16 km; (2) a Doppler radar system with a light weight (230 g) and X-band (10.5 GHz) is developed for detection and identification for a miniature UAS [21]; and (3) without limiting to a specific type of UAS, the General Atomics Predator B radar prototype which normally carries 2 or 3 separate radar arrays is designed to cover a total of 220° in azimuth and 30° in elevation [22]. SAR systems can be used in all-weather conditions as radar pulses can penetrate storms. However, radar does not provide the same degree of real-time imagery as compared to an EO system.

By illuminating a target with a laser and analyzing the reflected light, LIDAR measures distance. As one of remote sensing technologies, LIDAR has been investigated extensively in UASs to depict targets through the associated collections of spatially distributed points with accurate coordinate triples. A LIDAR system is used to reduce the false positive rate and provide the range of the intruding aircraft in Robotics Institute, Carnegie Mellon University [23]. A novel mini-UAS-borne LIDAR system with flexibility is designed in [24], where tree height estimation and digital terrain model refinement are tested for the evaluation. The Ibeo Lux laser scanner is selected to form the LIDAR in this reference. The detection ranges of LIADR systems usually vary from 200 m to 3 km. The benefit of LIDAR lies in that it is capable of detecting non-perpendicular surfaces at high resolution and identifying objects from 5 mm in diameter to buildings. Likewise it is highly configurable and appropriate for different atmospheric conditions. The disadvantage is that the Field of View (FOV) is limited.

EO systems are to detect objects on a collision course by virtue of natural visible light, which are considered as passive technologies. The Air Force Research Laboratory and Defense Research Associates collaborate to develop an EO-based system for the S&A capability in Global Hawk [25]. It is assembled by three cameras which are able to provide a FOV with dimensions $\pm 100°$ by $\pm 15°$. The design of an EO system with application to S&A on Global Hawk and other UASs is addressed in [26]. In [27], an EO system is developed especially for small UASs. The relationship between the FOV and detection range based on the probability of an intruder is revealed as well. A prototype optical instrument is tested for S&A functionality in [28], where head-on collisions at typical general aviation altitude and velocity are emphasized. It is also indicated by evaluation results that the airborne detection range can reach 6.7 km. The main advantages include low cost, mass, and power requirements related to the sensor [29], and proven effectiveness. The drawbacks are that (1) the sensors may not be effective in the case of weather uncertainty (e.g., smoke, fog, dust); (2) arrays of sensors are required to achieve a wide field in regard with adequate angular resolution; and (3) incomplete information is provided for S&A (i.e., bearing information and target size).

The signal emitted from a propeller-driven aircraft (acoustic sources) comprises a strong narrowband tone imposed onto a broadband random component. Acoustic sensors are equipped on UASs to detect intruding aircraft using this characteristic. The Passive Acoustic Non-Cooperative Collision Alert System (PANCAS) is developed by Scientific Applications and Research Associates (SARA) Inc. [30]. The PANCAS offers an excellent option of sensing aircraft by means of detecting the sound of their engines, propellers, or rotors. In addition, twenty four [31] and four [32] microphones are integrated in acoustic arrays to locate and track aircraft. The effectiveness is validated by flight tests. Acoustic sensors with high cost-effectiveness are capable of detecting all frequencies and angles allowing for a wide-open range. However, they do not have the enormous long-range capabilities as compared to radar or EO systems. The performance is greatly deteriorated by contrary atmospheric conditions, such as severe wind and temperature conditions. Moreover, time delays exist in the

Table 3
The characteristics of sensor technologies.

	Information provided	VMC	IMC	SWAP	Cost	Others
TCAS	Range Altitude	√	√	×	×	Well proven Widely used
ADS-B	Position Altitude Velocity	√	√	×	×	Well proven
SAR	Range Bearing	√	√	×	×	Typically poor accuracy
LIDAR	Range	√	√	×	×	Easy configuration Narrow FOV
EO system	Azimuth Elevation	√	×	√	√	Data link required Lack of direct range
Acoustic system	Azimuth Elevation	√	×	√	√	Data link required Lack of direct range Delay
IR system	Azimuth Elevation	√	×	√	√	Data link required Lack of direct range

Note: SWAP: size, weight, and power; √: favorable/applicable; and ×: not favorable/applicable.

process of signal transmission [33].

Infrared light radiated from objects is measured, by which potential objects can be detected. The Passive Collision Warning System (PCWS) based on low-resolution (320 × 240 pixels) infrared cameras mounted to the airframe is presented in [34], where the adaptive technique is adopted to filter out measurement noise. The selected cameras have a FOV of 37.5° and 50° in the vertical and horizontal directions, respectively. AggieAir-TIR [35] and a prototype based on infrared sensors [21] are developed for collision avoidance of UASs. Infrared sensors do not require light, which are favorable for night-time usage. The disadvantages are that (1) the range information cannot be provided and (2) it is only functional under VMC.

2.1.3. Summary

The existing sensing technologies have various advantages and drawbacks, which are briefly indicated in Table 3. The cooperative sensors (TCAS and ADS-B) can be used under all-weather conditions, however the cost is high. SAR as one of active non-cooperative technologies can function in both VMC and IMC, but the accuracy needs to be improved. Another typical active technology (LIDAR), which is easily configured, can work at VMC and IMC, but the FOV is very narrow. The advantages of passive non-cooperative technologies (EO, acoustic, and infrared) are the low cost and the ability to detect non-transponder-equipped traffic, including gliders and birds. Prime disadvantages include the inability to measure direct range and poor performance in IMC. In addition, depending on the implementation, this method may consume a high amount of data link bandwidth. Based on the review of cooperative and non-cooperative sensors, the effective detection ranges of typical sensors are illustrated in Fig. 4.

2.2. Detection algorithms (software)

With the advance in sensing devices of UAS S&A, the approaches to data processing at reception have been investigated as well. The algorithms focused on motion estimation and reduction of measurement errors are briefly stated in this section depending

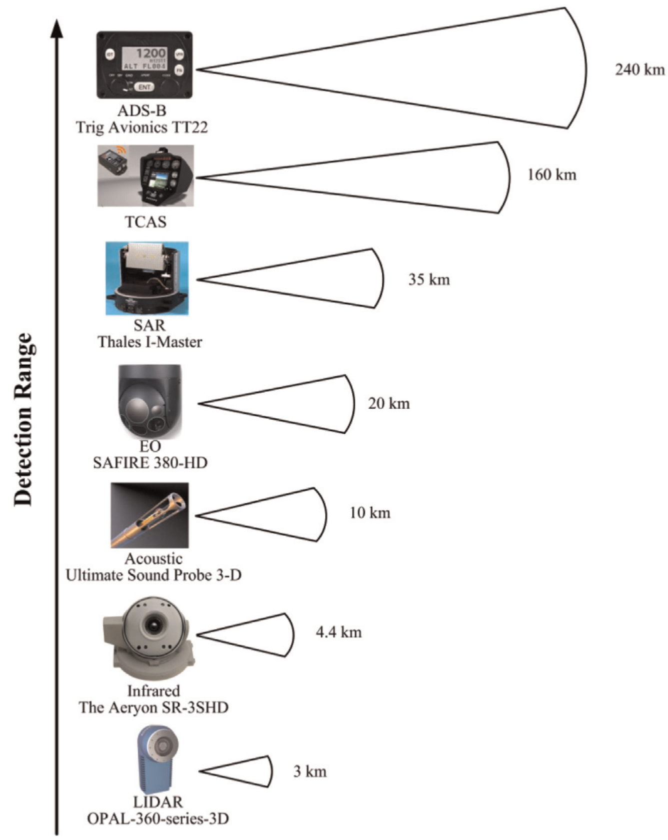

Fig. 4. Illustration of typical sensing devices.

Table 4
The summary of algorithms in sensing devices.

Sensing devices	The problems to be addressed	The cited references
Radar	Decrease the estimated error	[36–40]
	Reduce the measurement uncertainty	[41]
	Multiple targets	[37,41]
LIDAR	Map data with more than 1 pulse/m^2	[24]
	Improve the estimation accuracy	[42]
EO system	Decrease the estimated error	[27]
	Robustness on weather and illumination conditions	[43]
Acoustic system	Deal with acoustic delays	[33,44–46]
	Estimate speed and altitude	[46]
IR system	Decrease the estimated error	[34,47]

on the data sources (S&A sensors). It should be noted that the algorithms applied for non-cooperative sensors are selected only as considering that the relevant methods in TCAS and ADS-B are more mature. The key problems to be investigated together with the applied sensors and the cited references are listed in Table 4.

Based on radar systems, the optimal estimation of both the position and velocity of a ground moving target is investigated on basis of pulse Doppler radars used in UASs. The Cramer-Rao bound is employed to derive the minimum achievable error variance of the estimated variables [36]. Markov chain Monte Carlo data combined with a sliding window are used for multi-target tracking and identity in the case of multiple radar networks [37]. A waveform-diversity-based UAS SAR imaging method is presented to remarkably reduce range and azimuth ambiguity [38]. Regarding the motion errors caused by atmospheric turbulence and aircraft properties, a novel Three-Dimension (3D) motion compensation method [39] and Maximum-Likelihood (ML) weighted phase gradient autofocus based approach [40] are studied, respectively. The identification algorithm based on the joint probabilistic data association and residual-mean interacting multiple-model is developed for the application of the passive radar tracking of aircraft [41]. The presented method is devoted to reducing the measurement uncertainty.

With respect to LIDAR systems, the data processing including coordinate triple, pulse intensity, and multiple echoes per pulse is integrated in the mini-UAS LIDAR system [24]. The effect of point density on the accuracy of tree detection and delineation using tree count, location and crown width is evaluated [42]. The results can also be extended to LIDAR-based S&A systems.

An EO system is designed for small UASs, where Kalman filter, Sequential Quadratic Programming (SQP), and Linear Parameter Varying (LPV) approaches are devoted to the image tracking, reduction of measurement error, and reduction of 3D measurement error of the target [27]. To improve the robustness on weather and illumination conditions, morphological filtering, local image analysis, and multiple frame processing in stabilized coordinates are used for obstacle detection and tentative tracking, which are implemented in the EO system of "Federico II" UAS [43].

Studies on dealing with acoustic delays and estimating the motion of the object are carried out. A model is built to predict the varying time delays for a jet aircraft or other broadband acoustic source with a constant velocity. Based on the model, autocorrelation functions and cepstrum are adopted to estimate the speed and altitude of the aircraft [33]. A ML technique is exploited to estimate the motion parameters of the target using an orthogonal array of four microphones [44]. A closed-form solution to estimate the target motion based on "Closest Points of Approach (CPA) time" is presented in [45], where four separated sensor arrays are used. A nonlinear Least-Squares (LS) approach is developed to estimate the motion of an object whose acoustic emissions are detected by an array of sensors [46].

For the improvement of estimation accuracy of IR systems, morphological filter and low-stop filter are utilized to remove large-scale clutter and stationary background clutter, respectively [47]. In order to improve the efficiency of IR systems, an interacting multi-model estimator is employed for estimation of the measurement noise variance of the sensor and consistency of the tracks [34].

3. Survey on decision mechanism in UASs

After receiving data from sensing devices, whether re-planning path to avoid potential hazards or not is determined by decision mechanism. The preliminary idea is to find a way to duplicate the nature of pilot decision making and then extend to UASs. In [48], the Recognition Primed Decision Making (RPDM) model to represent intuition-based decision making and Rasmussen's model are introduced. Since not many references on decision making especially for S&A have been published to the best of the authors' knowledge, it is reasonable to adopt the algorithms which are applied for other functionalities in UASs to the development of S&A decision making. In the following, Markov Decision Process (MDP) and Logic-based Multiple Domain Matrix (MDM) are reviewed, respectively.

3.1. MDP

Based on a stochastic model, MDP is a well-established framework to find decision rules for optimizing an objective function by discretizing the system into a finite number of states and actions [49]. At each step, an action of transitions between states is taken, while a time-additive objective function is accumulated as well.

On the basis of MDP, autonomous UAS decision-making against uncertainty [50], a general health management approach for UAS persistent surveillance [51], and UAS planning in the presence of model uncertainty [52] are investigated, respectively. In [50], using potential fields and probabilistic maps, the mechanism formulated by MDP includes Bayesian techniques and joint likelihoods to fuse teammate-communicated information regarding target observations. In [51], a health management system of designing mission systems is designed, which is capable of selecting actions to counteract the adverse impacts of system anomalies. The health management issue is described by MDP firstly. The formulation is then characterized to provide persistent surveillance coverage based on a group of UASs, where uncertain fuel usage dynamics and interdependence effects between UASs are taken into account. The authors propose a robust adaptive MDP with integration of adaptation mechanism to recursively update the uncertainty set, so that a robust policy can be generated in the presence of uncertainty [52].

For furthering the application of S&A, the preliminaries of MDP [49] are briefly explained herein. A MDP comprises a finite state space $i \in S$ of cardinality N and an action space $u \in U$ of cardinality M with a corresponding rule mapping states to actions $\mu: S \to U$. The MDP can be represented by a transition model $A_{ij}^{u} = Pr\left(j_{k+1} | i_k, u_k\right)$, which denotes the probability of switching from a state i at time k to state j at time $k+1$ by the action u_k. The reward model $g(i_k, u_k)$ stands for the value of being in a state i_k and taking action u_k. The time-accumulative objective under μ which starts from a state i_0 is

$$J_\mu(i_0) = \sum_{k=0}^{N} \phi^k g_k(i_k, u_k), \tag{1}$$

where $0 < \phi \le 1$ is known as a discount factor. Consequently, the objective is to find the optimal control policy μ^*, which maximizes the expected reward starting at an initial state i_0

$$\mu^* = \arg\max_\mu E\left[J_\mu(i_0)\right]. \tag{2}$$

It is worth emphasizing that on the basis of the general formulation of MDP, the specific problems with respect to UASs can be recast into the reward model and objective function, as can be seen in [50–52].

3.2. Logic-based MDM

A logical MDM model is exploited to explicitly represent both structure and logical behaviors of UASs [53]. A MDM model with integration of the specification of logical dependency structures turns to a logical MDM. A choice among different transitions is specified by a logical "OR" relationship in the transition model. The probabilities and transition conditions are indicated by the transition arcs. Influence diagrams are generalized by Bayesian networks to make decisions under uncertainty. In particular, for each node within a MDM, a logical dependency structure is integrated to denote the logical relationship among the nodes. The specification augments the conventional MDM model by specifying the logical means, in which the dependencies combine.

In [53], the logical-MDM modeling framework is applied for the UAS swarm surveillance. The objective of the UAS swarm is the surveillance of targets, influenced by uncertain requirements in the revisit rate of the targets. The investigation is aimed at identifying alternative mechanisms and real options to deal with the revisit rate uncertainty. Real options are weighted to decide which alternative is the most appropriate to manage the uncertainty. The discrete outcomes of the uncertain revisit rate for the surveillance targets are formulated by Low Revisit Rate (LRR) and High Revisit

Table 5
Logical-MDM of multiple UASs.

		Product			**Goals**			**Process**		
		4SR	4LR	2SR +2LR	Maintain surveillance of targets	LRR	HRR	Deploy sparse swarm	Deploy dense swarm	Logical formula
Product	4SR									–
	4LR									–
	2SR+LR									–
Goals	Maintain surveillance of targets					1	1	1	1	(3)
	LRR									–
	HRR									–
Process	Deploy sparse swarm		1	1		1				(4)
	Deploy dense swarm	1	1	1			1			(5)

Rate (HRR), respectively. As shown in Table 5, the MDM is constituted by the UAS configurations, operational processes, and mission goals. Alternative swarms include three modes: (1) four UASs with a short-range communication system (4SR); (2) four UASs with a long-range communication system (4LR); and (3) heterogeneous swarm consisting of two short-range and two long-range UASs (2SR+2LR). Deploying sparse and dense swarms are considered as the operational processes. The mission requirement of the studied scenario is the target revisit rate which is uncertain.

The last column of Table 5 refers to the logical formulas in Disjunctive Normal Form (DNF), which is transformed from a logical dependency structure. The entries in each row represent the dependencies from which the logical formula is constructed. The logic formulas are detailed by (3), (4), and (5), respectively. Formula (3) denotes the possible ways of achieving the surveillance by either deploying a dense swarm or a sparse swarm when an LRR mission is commissioned. Since the node "Deploy Sparse Swarm" depends on having an LRR mission and UASs with LR communication or alternatively having an LRR mission and a heterogeneous set of UASs, and (4) represents exactly this characteristic. On the other hand, deploying a dense swarm relies on having any of the swarm configurations, but the LR and heterogeneous swarms are employed in a dense swarm only in the condition of an HRR mission. Formula (5) is provided to reflect this logical relation.

$$(\text{LRR} \wedge \text{Deploy Sparse Swarm} \wedge \neg\, \text{Deploy Dense Swarm}) \vee (\text{Deploy Dense Swarm} \wedge \neg\, \text{Deploy Dense Swarm}). \quad (3)$$

$$(\text{LRR} \wedge 4\text{LR} \wedge \neg\, 2\text{LR} + 2\text{SR}) \vee (\text{LRR} \wedge 2\text{LR} + 2\text{SR} \wedge \neg\, 4\text{LR}). \quad (4)$$

$$(4\text{SR} \wedge \neg\, 4\text{LR} \wedge \neg\, 2\text{LR} + 2\text{SR}) \vee (\text{HRR} \wedge 4\text{LR} \wedge \neg\, 4\text{SR} \wedge \neg\, 2\text{LR} + 2\text{SR}) \vee (\text{HRR} \wedge 2\text{LR} + 2\text{SR} \wedge \neg\, 4\text{SR} \wedge \neg\, 4\text{LR}). \quad (5)$$

In (3)–(5), the operators ¬, ^, and ˅ denote negative, conjunction, and disjunction, respectively. These operators are the basic connectives of propositional logic that are used to construct logical formulas, by which the behavior among multiple variables that influence each node is modeled. In summary, the logical-MDM offers a viable option to clearly describing the relationships among subsystems, functions, and objectives, based on which the commands and maneuvers of UASs can be scheduled (Fig. 5).

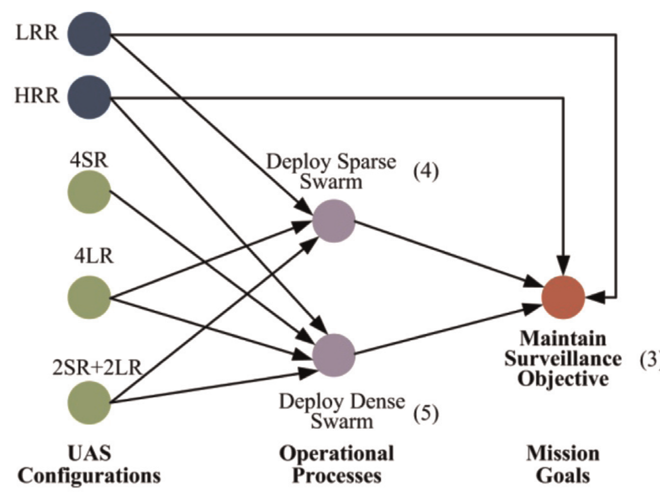

Fig. 5. Network representation of the logical-MDM.

4. Survey on path planning in UASs

Aircraft trajectory planning is basically inspired by fuel economics of civilian airplanes [54–59] and minimum risk of military aircraft [60,61]. In the last decade, path planning in UASs is more challenging than preliminary strategies: the UAS constraints, atmospheric turbulence, uncertainty in UASs, partial information of environment, and limited sensor capabilities make a pre-planned trajectory greatly difficult to work [62,63]. A large amount of path planning approaches have been studied with applications to UASs [62–66], the categories of the existing path planning approaches deployed for UASs can be glanced in Fig. 6. Each class of path planning design methods is discussed in the following.

4.1. *Sampling-based path planning approaches*

Within the scheme of sampling-based approaches, the path planning problem turns to find a feasible one within a limited quantity of candidates from a continuous state space. According to the principles of the search algorithms, this sort of approaches can be mainly divided into two categories: deterministic and probabilistic methods, respectively.

4.1.1. *Deterministic search approaches*

The overall state space of the UAS is discretized into a finite set of points, in which the minimum-time path is searched by numeric root finding methods [67–69]. A Finite One-in-Set Traveling Salesmen Problem (FOTSP) is used to approximate a Polygon-Visiting Dubins Traveling Salesmen Problem (PVDTSP) so that a roadmap is constructed. Subsequently, the Noon-Bean transformation is applied for solving the FOTSP [70]. In the above cited references, the impacts of winds and UAS constraints are taken into account at the stage of path planning. However, how to avoid collisions is not addressed. This type of approach may not be

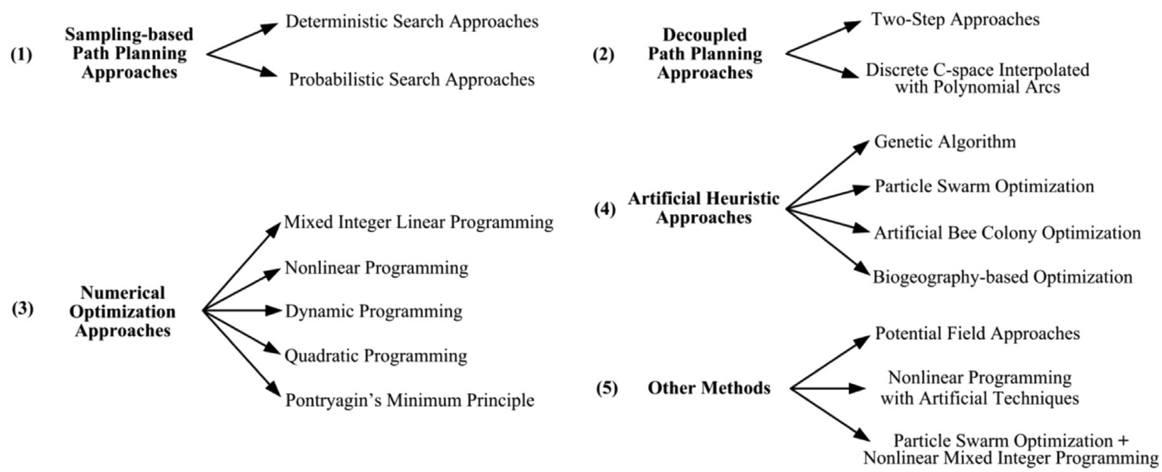

Fig. 6. Categories of UAS path planning approaches.

appropriate for path planning/re-planning in the event of encountering other aircraft since the roadmap is solely dependent on *a priori* knowledge. In [71], the coverage map can be updated promptly with the help of the on-board camera, thus UAS path can be planned accordingly. In the proposed architecture, detailed knowledge of the workspace is no longer needed *a priori*.

4.1.2. Probabilistic search methods

Recent effort on planning the path of UASs by randomized algorithms has been devoted [72]. Generally, the UAS's configuration space is randomly sampled into a one-dimensional graph. A stochastic search over the body-centered frame of reference is carried out, and a tree of feasible trajectories is built on-line by expanding branches towards randomly generated target points [73–75]. In [73], it is reported that an incremental roadmap building algorithm is capable of coping with moving obstacles and system dynamics. A Rapidly-exploring Random Tree (RRT) based search algorithm is subsequently applied for path planning in the presence of fixed and moving obstacles. In [74], a RRT based path planning method is developed for anti-collision of Miniature Air Vehicles (MAVs). A depth map representing the range and bearing to obstacles is obtained, and RRT algorithm is exploited to find a collision-free path. Given appropriate technical conditions, the probability of finding a path from origin to goal can converge to one if a feasible path exists, which indicates that it is probabilistically complete. In [75], to deal with uncertain dynamic obstacles, the chance constraint framework to account for uncertainty is integrated into a RRT based path planner. Moreover, a number of heuristics are exploited in the proposed path planning algorithm to improve the computation performance. Mode Goodness Ratio (MGR) heuristic is proposed to prioritize search areas, by which effective paths for a UAS can be found in the parameter space at various levels of resolution [76]. However, there is no proof of the convergence rate or of the optimality because of its random exploration.

4.2. Decoupled path planning approaches

The philosophy of this approach is that firstly a discrete path through the configuration space is found by the relevant algorithms (i.e. A*, probabilistic roadmap, Voronoi approach), and then the resulting path is used as the basis for the generation of a trajectory that is feasible for the dynamic-constrained UAS. In this sense, the computation efficiency can be guaranteed, but it is difficult to theoretically prove completeness and optimality.

4.2.1. Two-step approaches

The first step tries to obtain an optimal trajectory under the specific constraints. In the second step, the UAS has to be steered out of dangerous regions. The trajectory generation with known obstacles and conflicts is investigated [77]. In [78], two steps are involved in the path planning of a rotary-wing UAS. At the initial step, A* search algorithm is applied for searching the optimal route between the start and destination points with constraints of distance, hazard, and UAS maneuvering. Subsequently, the planned route is further smoothed by a route filter. Based on geometric shapes to represent conflicts and A* search algorithm to obtain path solutions, the authors present an approach of planning path which can resolve the transition issue for fully autonomous UAS applications [79]. The problem that when one can switch back to the first step is addressed as well. The proposed method in [80] comprises of two phases. At the first phase, a near-optimal trajectory is generated which is evaluated with a more sophisticated 5 Degree-of-Freedom (DOF) performance model, whereas at the second phase the parameters affecting the optimization are adjusted correspondingly. In [81], an initial path with consideration of time or fuel constraints is produced. Risk estimates of individual path segments are subsequently employed in the final process of planning. The concept of path planning with obstacle avoidance in [82] is to firstly utilize a geometric branching strategy based on the decision between passing an obstacle clockwise or counter-clockwise, and secondly solve the resulting sub-problems by constructing simple solutions on each selection. However the work in [82] is only studied in the case of fixed obstacles. The Voronoi graph is applied to generate an initial path, which is subsequently refined by proposing a simplified parameter-identification procedure in cluttered environments [83].

4.2.2. Discrete C-space interpolated with polynomial arcs

An ordered set of waypoints generated by a discrete planner are fitted with a spline constructed by polynomial arcs. This spline is set up so that the path can be satisfied without violating acceleration constraints, which typically encompasses circular arc segments and straight segments. This sort of concept is exploited not only to generate a path but also re-generate an appropriate path in the presence of faults [84,85]. The proposed approaches of path planning and re-planning are validated by flight tests of a quad-rotor UAS. However, some waypoints are not reachable due to the approximation feature of the planning method.

4.3. Numerical optimization approaches

A trajectory planning problem is recast as a numerical optimization problem by mathematical programming methods, which aims at obtaining an optimal path with respect to a specific objective in the resolution sense. The numerical optimization approaches to path planning are primarily concentrated on Mixed Integer Linear Programming (MILP), Nonlinear Programming (NP), Dynamic Programming (DP), Quadratic Programming (QP), and Pontryagin's Minimum Principle (PMP), respectively.

4.3.1. MILP based method

By formulating the path planning problem into a class of discrete decisions between linear constraints, the problem can be represented by linear constraints on a mixture of continuous and integer variables [86]. MILP is used within a receding horizon framework to re-route trajectories of a minimum fuel cost to mitigate persistent contrail formation [87]. More recently, with considerations of the quad-rotor dynamics, current states, and current control inputs, the future trajectory of the vehicle is estimated to avoid collisions [88]. The computation complexity is remarkably increasing as the increase of obstacles and dynamic constraints.

4.3.2. NP based method

The optimization problem of cooperative 3D conflict resolution is investigated in [89], which is solved by NP. The idea is to calculate trajectories not only to minimize the specified objective but also maintain safety distance between each aircraft. In [90], the path planning approach based on NP is proposed to avoid collisions between UASs. The trajectory optimization is formulated as a NP problem with the constraints of system states and control inputs [91]. Then the NP problem is solved by the proposed algorithm of calculating an appropriate non-uniform grid. A path with maximal surveillance time of a target can be generated based on NP, in which the sensor mounted on a UAS is also accounted for [92]. Using local Hermite interpolating polynomials and the Legendre–Gauss–Lobatto points to represent state equations and interpolation respectively, NP is subsequently applied for solving the path optimization problem [93]. The authors in [94] exploit NP to optimize a controllable and reachable trajectory for MAVs in the presence of winds.

Gradient methods that fall into nonlinear programming are developed for path planning in [95,96]. The authors in [95] try to investigate a practical planning strategy for multiple UASs performing cooperative sensing; whilst more emphasis has been placed on trajectory generation for aircraft avoidance maneuvers in [96].

4.3.3. DP based method

The principle is to divide the optimization problem into smaller and smaller sub-problems until a simple case is reached that can be easily solved. DP applied to path planning is the calculation of the shortest path from a starting point to an ending point over a group of connected nodes. In [97], an autonomous trajectory planner is proposed based on DP to obtain a minimum-time trajectory with safety terminal (to avoid non-fly zone) and state constraints.

4.3.4. QP based method

QP is utilized to route a path for cooperative attack with consideration of system dynamics and sensor performance [92]. In addition, under the constraints of system states, QP is also employed to generate trajectories in the cases of turbulence avoidance [98], obstacle avoidance [99], and loss of radio communication link [100], respectively.

4.3.5. PMP based method

An algorithm of optimal trajectory generation which is aimed at avoiding contrails in the presence of winds is developed in [101] for cruising aircraft. In this reference, PMP is used to solve the optimization problem. However, the path planning of feasible maneuver is not accounted for, even though it is of paramount importance in the course of collision avoidance.

4.4. Artificial heuristic approaches

Due to the power and convenience during the optimization process, considerable research interest of artificial heuristic approaches is also attracted in path planning. The relevant methods include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Artificial Bee Colony Optimization (ABCO), and Biogeography-based Optimization (BBO), respectively.

4.4.1. GA based approach

GA is a heuristic search initiated from the process of natural revolution [102], which can be potentially used to address a path planning optimization problem. A function is applied to each individual solution in order to evaluate their "fitness". Then, using a series of operations inspired by genetics, a new population of trajectories is generated. In [103], a modified GA is adopted at the design stage of an offline/online path planner for UASs. The authors also use GA to optimize the path of UASs flying over a given terrain [104]. An enhanced GA named as multi-frequency vibrational GA is proposed to address the path planning problems of autonomous UASs [105]. The computational load of the developed algorithm is dramatically reduced as compared to the classical ones. More recently, by incorporating UAS dynamics, the optimal path is obtained by GA [106].

4.4.2. PSO based approach

PSO is considered as a population-based algorithm by mimicking animals' social behaviors [107,108]. The principle of PSO can be stated as: A population called swarm has a set of candidate solutions, in which each solution is named as a particle. These particles are moved around in the search-space in terms of their own positions and velocities. The movements of the particles are steered by their own best known position (local) in the search-space as well as the entire swarm's best known position (global). The PSO algorithm performs global search at the beginning and local search later on.

Under the constraints of UAS dynamics, environment, and real-time requirements, the path planning design is formulated as a hybrid optimization problem. PSO is applied to yield a real-time optimal path in the presence of terrain and random threats [109]. A modified version of PSO named as phase angle-encoded and quantum-behaved PSO is presented to solve continuous function optimization problems of path planning in [110]. Furthermore, a hybrid differential evolution with quantum-behaved PSO is developed for UAS path planning in the presence of various threats [111]. The improved PSO becomes more appropriate to be applied for UAS path planning with faster convergence speed and stronger robustness.

4.4.3. ABCO based approach

ABCO algorithm is an optimization algorithm motivated by the intelligent collective behavior of honey bees [112]. It is proven that ABCO algorithm is a sound alternative for function optimization problem. It is capable of conducting both global and local searches at every single iteration so that the chance of achieving optimal parameters is highly increased. ABCO-based path planner is proposed in [113], by which a feasible flight route under complex combat environment can be generated for Uninhabited Combat Air Vehicles (UCAVs). Chaos theory is also adopted in this reference so as to improve the robustness of ABCO-based planner.

4.4.4. BBO based approach

BBO is an evolutionary algorithm derived from the science of biogeography to globally optimize an objective [114]. Global optimum is searched by two steps: migration and mutation. Solutions are maintained from one iteration to the next, and the solutions can also be improved by migration. With application to UCAVs, a minimum-fuel trajectory is designed based on an advanced BBO, which ensures the UCAV avoids hazardous threats and arrives at the intended destination [115]. The chaos theory is firstly integrated in the migration operation for facilitating the global optimal solution search. Subsequently, the concept of predator-prey is adopted to improve the diversity of the population and global convergence.

4.5. Other methods

4.5.1. Potential field approaches

Potential field methods are based on the idea of assigning a potential function to the free space, and simulating the vehicle as a particle reacting to forces according to the potential field [116]. The goal point possesses the lowest potential to attract the UAS, while obstacles push the vehicle instead. As a result, it is popularly applied for path planning of collision avoidance.

An analytically tractable potential field model of free space is established in [117], where collision avoidance between the object and obstacle can be guaranteed subsequently. An improved harmonic potential field is developed to tackle environments that can only be probabilistically described, based on which the path planner is designed correspondingly [118]. Provided that positions of the UASs are detected autonomously, collision avoidance between the UAS and hazards are addressed by potential fields in [119].

4.5.2. NP with artificial techniques

Since each type of path planning methods has its own advantages and drawbacks, the combined approaches of path planning have received research interest. With the help of artificial techniques [120,121], the path planning based on NP is improved from a real-time calculation aspect. In [120], GA is presented to quickly provide initial guesses, by which NP can be used to obtain the minimum-time trajectory. In [121], the objective functions and system dynamics are approximated by a NN, which is good at offering accurate computation of gradients. Since formulation of analytical gradients is no longer needed, thus the method is more easily extended to complex applications with different objective functions and constraints.

4.5.3. PSO+nonlinear mixed integer Programming (NMIP)

In the reference [122], PSO is exploited to search near-optimal solutions to trajectories with various objectives (minimum fuel, minimum time of computation, etc.). By virtue of runtime selection caused by PSO, optimal paths can be found by solving instances of NMIP problems with the swarm intelligence. The accuracy of solutions can be improved by integrating PSO into the path planner.

4.6. Summary

According to [62], a trajectory planning algorithm is considered to be *optimal* when the optimal path can be gained in the sense of specific objectives. The characteristics of the discussed techniques of UAS path planning are briefly listed in Table 6.

5. Survey on UAS control for path following

In order to accomplish S&A functionality, a sound path following should be capable of ensuring the UAS follow the routed/re-routed path accurately in two or three dimensions even in the presence of external disturbances [123]. The path following problem can be defined as: the position of UAS $p(x, y)$ is required to reach and track a geometric path $p_d(\gamma)$, which is parameterized by the path variable γ. The objective is to design a control law such that $p(x, y) \to p_d(\gamma(t))$ as $t \to \infty$ for a given timing law $\gamma(t)$ and the velocity error $\left|\dot{\gamma}(t) - v_d(\gamma(t))\right| < \epsilon$, for $\epsilon > 0$.

Thus, flight controllers to drive UASs maneuvers play a predominant role in this case. From the literature, there exist two sorts of design approaches, (1) separated design of guidance and control and (2) integrated design of guidance and control, respectively.

5.1. Separated design

In terms of the individual design philosophy, the UAS guidance and control problems are separated into an outer guidance loop and an inner control loop. A variety of control techniques are used to design the inner control loop especially for purpose of path following. Robust nonlinear control theory is widely adopted [124–129], since it can not only be directly related to nonlinear aerodynamics but also fit for any type of path. Other studies on path following are conducted by using linear quadratic control [130], pure pursuit method [131], back-stepping [132–134], Takagi-Sugeno (TS) fuzzy control [135], Proportional-Integral-Derivative (PID) control [136], piecewise affine control [137], sliding mode control [138,139], adaptive control [140–142], nested control [143,144], receding horizon control [145], optimal control [146], and decentralized switched control [147], respectively. It is worthwhile emphasizing that the path following algorithms developed by the references [124,128,129,131,136,138,139,141,143–145] have capabilities of disturbance attenuation. Additionally, the conditions of delayed output [126], non-measurement of velocity [132], unmodeled linear or nonlinear dynamics [134], model uncertainty [139,141], UAS physical constraints [144], and intermittent sensing [147] are taken into account during the controller design phase.

5.2. Integrated design of guidance and control

Even though the path following controller in individual design approaches is normally designed with sufficiently large bandwidth to track the path. However, due to the fact that guidance and

Table 6
Characteristics of path planning techniques.

	Optimality	Complexity	Comments
Sampling-based trajectory planning	No	No	Easily apply to high-dimensional C-space
Decoupled trajectory planning	No	Yes	The decomposition is arbitrary
Mathematical programming	Yes	Yes	Heavy load of computation; quite dependent on initial guesses
Artificial heuristic approaches	Yes	Yes	Reliable in dynamic environments; sensitive to uncertainty
Potential fields	No	No	Easy to implement; local-minima are a major concern

control systems are effectively coupled, finite tracking errors are induced by the individual design scheme [148]. The most concrete difference between these two approaches lies in that whether the real-time state information of UASs is transferred into the guidance loop [149]. Since the integrated design can achieve superior performance than the separated one, attention to integrated design methodologies for UASs has been gradually gained.

Gain-scheduling based integrated design method for UAS trajectory tracking is developed in [148]. It is revealed that by means of the proposed design, (1) steady-state tracking error can be eliminated in the case of any trimming trajectory and (2) the stability of the combined guidance-control system can also be maintained. In [150], a guidance-control scheme is presented based on sliding mode theory. Under the supervision of the integrated scheme, a UAS that is flying at a constant velocity can patrol the border and avoid obstacles on account of following the planned route. Analogously, sliding mode control approach is exploited in the design of integrated guidance and control system [151], where the stability is analyzed with explicit consideration of measurement and model uncertainties. When wind turbulences occur, the performance of path following is acceptable as well.

5.3. Summary

The individual design of path following is relatively simpler when comparing to the integrated design. However, it is exemplified that the integrated design method can achieve superior performance and faster reactive speed in comparison to the individual design approach. Using the real-time information of system state, the integrated design meets more practical requirements in UASs. Thus, this sort of methodologies needs to be deeply studied for the deployment of UASs.

6. Technological challenges and future directions

Despite S&A systems are extensively invented as can be seen from the books [1–3,18], survey papers [7,8,62,64–66,78,95,123,152] and the references therein, none are certified yet. Without airworthiness certificate, the UASs are prevented from a wider spread even though the UAS applications become increasingly urgent. For facilitating the development of certified UAS, the major challenges and future directions are analyzed hereafter.

6.1. Technological challenges of developing S&A for UAS

(1) As stated in Section 2, cooperative and non-cooperative sensing technologies have been developed. Cooperative sensors have been mandatorily equipped in manned aircraft for D&A functionality, whilst much effort has been put on non-cooperative sensors which are potentially utilized for UASs [18]. Different sorts of sensing technologies have their own advantages and drawbacks. Now the challenge turns to that should UAS sensing devices be uniformed, and if so, how much degree should be reached up to? A consequent question is that is it possible to create a single algorithm for all UAS types, or alternatively, can a general structure with a high-level standard be designed to handle diversities?
(2) Regarding the decision making in UAS S&A, the current research is mainly focused on how to make decisions in terms of the well-established rules [78]. How to make the proper decision right away in the case of a harsh environment, or in other words, how to cope with the situations which are beyond the bounds of prescribed condition set?
(3) Based on the review of UAS path planning in Section 4, UAS dynamics and actuator constraints are considered in most of the cited references. However, from a practical aspect, the properties of equipped sensing devices have to be also integrated at the path planner design stage since reactive planning is fundamentally dependent on the sensing devices [61,70,71,92,95,98,100,153,154]. Another challenge in UAS path planning is that the strategy needs to be investigated in the presence of partial knowledge of the environment or external disturbances [63,79,155]. Moreover, a time delay in beginning an avoidance maneuver needs to be accounted for when the path is being updated to avoid the detected intruder.
(4) With respect to TCAS that is maturely utilized for collision avoidance, the agreed safety range defined by FAA is with 500 feet of horizontal separation and ± 100 feet of vertical separation, respectively [152]. In accordance with the intended usage and the physical limits of UASs, different criteria may be modified. To achieve the ultimate goal (to be accepted in the NAS), 3D path following may be recognized as an essence, while only altitude change is required based on TCAS in manned aircraft. As considering that the factors of model uncertainty, pop-up threats, external disturbances, and potential mechanical faults during the flight, how to guarantee that the planned/re-planned route can be tracked within a limited spectrum of time instead of asymptotical convergence has to be addressed also.
(5) Within the S&A architecture, the information collected by sensors is conveyed into the decision making process for the prompt demands. Then the path planner and flight controller are adjusted accordingly. On the other hand, the response rate of the information is determined by various sensing technologies. The lagging safety-critical information may not only degrade the performance of the overall S&A system, but also deteriorate the safety of aircraft in the NAS. It is a practical demand to design the S&A system robust to the lagging information.

6.2. Future directions of S&A development

(1) Due to the limitations of the current centralized air-traffic management, a next-generation air transportation system should allow airplanes (manned and unmanned) to change their flight paths during the flight without approval from a centralized route control [156]. It becomes possible that a decentralized scheme is applied when manned and unmanned aircraft share the NAS. One of the most significant merits of decentralized scheme is to avoid a secondary conflict when many airplanes exist in the same region of airspace [157].
(2) Learning mechanism can be probably integrated in the course of decision making since the pre-defined rules can be reasonably extended as the flight experience of UAS increases. By this means, interruption of external uncertainty may be possibly attenuated. Another alternative is that by fully utilizing the cognitive skills and expertise of experienced pilots/operators, the decision model can be considerably enriched.
(3) As long as the S&A can be recognized as a time-critical mission (shown in Fig. 3), time delays will lead to catastrophic events without being effectively accommodated. At the phase of hazard detection, trajectory estimation, and path planning, prediction techniques have been widely exploited in air traffic controllers for manned aircraft [157,158]. In regard to UASs, the authors would also recommend predictive methodologies to compensate the negative effects of delays. By adopting predictive techniques, the appropriate maneuver will be performed before the collision occurrence, in other words, UASs may “earn” enough time to react in the presence of intruder

aircraft [159–163].

(4) For fulfilling the requirements of safety, the concept of fault-tolerance should be also integrated into the controller design [2]. Analytical redundancy enables the UAS to recognize the type, amplitude, and potential impact of a fault induced by malfunction of actuators, sensors, and other system components, while flight control is reconfigured to ensure the safety of the faulty UAS by utilizing the hardware redundancy together with analytical redundancy [164]. Therefore, in the event of faults, path following can be still completed within a graceful degree of degraded performance instead of mission failures. Without any doubts, one has to thoroughly consider the factors of design cost, UAS weight and capable payload to configure hardware redundancy (normally configured for key components). Furthermore, finite-time convergence control is also a viable candidate of enabling the path to be followed within a specific amount of time.

(5) Information issues that may negatively affect S&A solutions have been pointed out in [2,165], the systematic study for the entire S&A system in the case of information delay/loss still needs to be carried out. The updated rate of the relative kinematics and the content of the information exchanged between aircraft in the NAS can be referred to the term "lagging of safety-critical information". The information of position (P), velocity (V), and attitude (A) with respect to the UAS and intruders, can be combined for decision making, which is defined as $INFO=\{[P], [V], [A], [P,V], [V,A], [P,A], [P,V,A]\}$. With the advances of TCAS and ADS-B, it becomes possible to offer the "intent" information (I) [17], which can be added into the information combination as well. In this research direction, the intent information integrated with the prediction concept plays an important role in addressing the lack of safety-critical information. Moreover, in the case of partial knowledge, more conservative strategy [162] has to be designed to meet the minimum requirement of safety rather than strive for optimal performance.

To provide the UAS community the insight into designing a feasible S&A system, another two directions are worthwhile mentioning. (1) Although notable achievements from a technological perspective have been earned, critical investigation on the compatibility and potential impact on safe operations in the NAS helps understand a real S&A system. (2) It is reported by Aerospace Industries Association (AIA) that a draft rule for the operation of small UAS (less than 55 lbs) has been developed [166,167], additional standards and regulations capable of covering entire UAS types are underway to be developed, based on which more emphasis on developing S&A has to be placed so that the autonomy of UAS can be achieved in a long run.

7. Conclusions

Due to the potentials of prosperous applications in both civilian and military domains, UASs have recently attracted tremendous attention ranging from universities to commercial entities. For UASs, S&A systems are the key to guarantee the seamless and safe integration in the NAS and obtain the airworthiness certificate. A review of technical development in S&A has been presented from the standpoints of sensing technology, decision making, path planning, and path following. The existing approaches corresponding to these four aspects have been described and summarized as well. Several challenging problems and future directions have been introduced to ease the path of designing a feasible S&A system. Since many disciplines across various fields are involved in this research area, one needs to be aware of the authorized standards, rules, and regulations to make sure the progress is on the right track. Finally, views on academic and industrial communities having to cooperate with each other to ensure that UASs eventually share the NAS with manned aircraft are briefly outlined.

Acknowledgments

The authors would like to express their sincere gratitude to the Editor-in-Chief and anonymous reviewers whose insightful comments helped to significantly improve the paper. The authors would also like to acknowledge the financial support from The Natural Sciences and Engineering Research Council of Canada (NSERC) through Discovery Grant and Engage Grant for the work reported in this paper. Special thanks to Phil Cole and Puthy Soupin from Marinvent Corporation for their valuable suggestions through the NSERC Engage Grant.

References

[1] J. Gundlach, Designing Unmanned Aircraft Systems: A Comprehensive Approach, American Institute of Aeronautics and Astronautics, Reston, Virginia, USA, 2012.
[2] P. Angelov, Sense and Avoid in UAS: Research and Applications, John Wiley & Sons, Hoboken, NJ, USA, 2012.
[3] K.P. Valavanis, G.J. Vachtsevanos, Handbook of Unmanned Aerial Vehicles, Springer, Dordrecht, Netherlands, 2015.
[4] R.W. Beard, T.W. McLain, D.B. Nelson, D. Kingston, D. Johanson, Decentralized cooperative aerial surveillance using fixed-wing miniature UAVs, Proc. IEEE 94 (7) (2006) 1306–1324.
[5] B. Grocholsky, J. Keller, V. Kumar, G. Pappas, Cooperative air and ground surveillance, IEEE Robot. Autom. Mag. 13 (3) (2006) 16–25.
[6] N. Nigam, S. Bieniawski, I. Kroo, J. Vian, Control of multiple UAVs for persistent surveillance: algorithm and flight test results, IEEE Trans. Control Syst. Technol. 20 (5) (2012) 1236–1251.
[7] F. Kendoul, Survey of advances in guidance, navigation,and control of unmanned rotorcraft systems, J. Field Robot. 29 (2) (2012) 315–378.
[8] K. Dalamagkidis, K.P. Valavanis, L.A. Piegl, On unmanned aircraft systems issues, challenges and operational restrictions preventing integration into the National Airspace System, Prog. Aerosp. Sci. 44 (7–8) (2008) 503–519.
[9] J.P. How, C. Fraser, K.C. Kulling, L.F. Bertuccelli, O. Toupet, L. Brunet, et al., Increasing autonomy of UAVs, IEEE Robot. Autom. Mag. 16 (2) (2009) 43–51.
[10] T. Tomic, K. Schmid, P. Lutz, A. Domel, M. Kassecker, E. Mair, et al., Toward a fully autonomous UAV: research platform for indoor and outdoor urban search and rescue, IEEE Robot. Autom. Mag. 19 (3) (2012) 46–56.
[11] FAA, Airworthiness Certification of Unmanned Aircraft Systems, FAA Order 8130.34, Washington, D.C., USA, 2008.
[12] DoD, Unmanned Aircraft Systems Roadmap 2005–2030, Department of Defense (DoD), Washington, D.C., USA, 2005.
[13] ASTM, Standard Practices for Unmanned Aircraft System Airworthiness, Standard F 2501-062006.
[14] RTCA, Guidance Material and Considerations for Unmanned Aircraft Systems, Radio Technical Commission for Aeronautics (RTCA) DO 304, 2007.
[15] T.B. Billingsley, M.J. Kochenderfer, Collision avoidance for general aviation, IEEE Aerosp. Electron. Syst. Mag. 27 (7) (2012) 4–12.
[16] A.D. Zeitlin, M.P. McLaughlin, Safety of cooperation collision avoidance for unmanned aircraft, IEEE Aerosp. Electron. Syst. Mag. 22 (4) (2007) 9–13.
[17] E. Valovage, Enhanced ADS-B research, IEEE Aerosp. Electron. Syst. Mag. 22 (5) (2007) 35–38.
[18] R.K. Barnhart, S.B. Hottman, D.M. Marshall, E. Shappee, Introduction to Unmanned Aircraft Systems, Taylor & Francis Group, Boca Raton, FL, USA, 2012.
[19] S. Lentilhac, UAV flight plan optimized for sensor requirements, IEEE Aerosp. Electron. Syst. Mag. 25 (1) (2010) 11–14.
[20] P.A. Rosen, S. Hensley, K. Wheeler, G. Sadowy, T. Miller, S. Shaffer, et al., UAVSAR: new NASA airborne SAR system for research, IEEE Aerosp. Electron. Syst. Mag. 22 (11) (2007) 21–28.
[21] A. Moses, M.J. Rutherford, K.P. Valavanis, Radar-based detection and identification for miniature air vehicles, in: Proceedings of the 2011 IEEE International Conference on Control Applications, Denver, CO, USA, 2011, pp. 933–940.
[22] M.P. Owen, S.M. Duffy, M.W.M. Edwards, Unmanned aircraft sense and avoid radar: surrogate flight testing performance evaluation, in: Proceedings of the IEEE Radar Conference, Cincinnati, OH, USA, 2014, p. 0548–0551.
[23] C. Geyer, D. Dey , S. Singh, Prototype sense-and-avoid system for UAVs, CMU-RI-TR-09-09, Robotics Institute, Carnegie Mellon University, Pittsburgh, Pennsylvania, USA, 2009.
[24] Y. Lin, J. Hyyppa, A. Jaakkola, Mini-UAV-borne LIDAR for fine-scale mapping, IEEE Geosci. Remote Sens. Lett. 8 (3) (2011) 426–430.

[25] McCalmont J., Utt J., Deschenes M., Taylor M. Sense and avoid, phase I (man-in-the-loop) advanced technology demonstration. In: Proceedings of Infotech@Aerospace, Arlington, VA, USA, 2005. p. AIAA 2005-7176.
[26] J.D. Griffith, M.J. Kochenderfer, J.K. Kuchar, Electro-optical system analysis for sense and avoid, in: Proceedings of the AIAA Guidance, Navigation and Control Conference and Exhibit, Honolulu, Hawaii, USA, 2008, pp. AIAA 2008-7253.
[27] J. Kim, D.W. Lee, K. Cho, S. Jo, J. Kim, C. Min, et al., Development of an electro-optical system for small UAV, Aerosp. Sci. Technol. 14 (7) (2010) 505–511.
[28] C. Minwalla, P. Thomas, K. Ellis, R. Hornsey, S. Jennings, Flight test evaluation of a prototype optical instrument for airborne sense-and-avoid applications, in: Proceedings of SPIE, Unmanned Systems Technology XIV, Baltimore, ML, USA, 2012, pp. 83870R1-14.
[29] B.C. Karhoff, J.I. Limb, S.W. Oravsky, A.D. Shephard, Eyes in the domestic sky: an assessment of sense and avoid technology for the Army's "Warrior" unmanned aerial vehicle, in: Proceedings of the IEEE Conference on Systems and Information Engineering Design Symposium, Charlottesville, VA, USA, 2006, pp. 36–42.
[30] T. Milkie, Passive Acoustic Non-cooperative Collision Alert System (PANCAS) For UAV Sense and Avoid, SARA Inc., Cypress, CA, USA, 2007.
[31] Case E.E., Zelnio A.M., Rigling B.D. Low-cost acoustic array for small UAV detection and tracking. In: Proceedings of IEEE National Aerospace and Electronics Conference, Dayton, OH, USA, 2008. p. 110-113.
[32] Finn A., Franklin S. Acoustic sense & avoid for UAV's. In: Proceedings of 7th International Conference on Intelligent Sensors, Sensor Networks and Information Processing, Adelaide, SA, Australia, 2011. p. 586-589.
[33] K.W. Lo, B.G. Ferguson, Y.J. Gao, A. Maguer, Aircraft flight parameter estimation using acoustic multipath delays, IEEE Trans. Aerosp. Electron. Syst. 39 (1) (2003) 259–268.
[34] R.W. Osborne, Y. Bar-Shalom, P. Willett, G. Baker, Design of an adaptive passive collision warning system for UAVs, IEEE Trans. Aerosp. Electron. Syst. 47 (3) (2011) 2169–2189.
[35] H. Sheng, H.Y. Chao, C. Coopmans, J. Han, M. McKee, Y.Q. Chen, Low-cost UAV-based thermal infrared remote sensing: platform, calibration and applications, in: Proceedings of the IEEE/ASME International Conference on Mechatronics and Embedded Systems and Applications, Qingdao, China, 2010, pp. 38–43.
[36] G. Gu, P.R. Chandler, C.J. Schumacher, A. Sparks, M. Pachter, Optimal cooperative sensing using a team of UAVs, IEEE Trans. Aerosp. Electron. Syst. 42 (4) (2006) 1446–1458.
[37] S. Oh, I. Hwang, S. Sastry, Distributed multitarget tracking and identity management, AIAA J. Guid. Control Dyn. 31 (1) (2008) 12–29.
[38] W. Wang, Q. Peng, J. Cai, Waveform-diversity-based millimeter-wave UAV SAR remote sensing, IEEE Trans. Geosci. Remote Sens. 47 (3) (2009) 691–700.
[39] M. Xing, X. Jiang, R. Wu, F. Zhou, Z. Bao, Motion compensation for UAV SAR based on raw radar data, IEEE Trans. Geosci. Remote Sens. 47 (8) (2009) 2870–2883.
[40] L. Zhang, Z. Qiao, M. Xing, L. Yang, Z. Bao, A robust motion compensation approach for UAV SAR imagery, IEEE Trans. Geosci. Remote Sens. 50 (8) (2012) 3202–3218.
[41] I. Hwang, H. Balakrishnan, K. Roy, C. Tomlin, Multiple-target tracking and identity management with application to aircraft tracking, AIAA J. Guid. Control Dyn. 30 (3) (2007) 641–653.
[42] L. Wallace, A. Lucieer, C.S. Watson, Evaluating tree detection and segmentation routines on very high resolution UAV LiDAR data, IEEE Trans. Geosci. Remote Sens. 52 (12) (2014) 7619–7628.
[43] G. Fasano, D. Accardo, A.E. Tirri, A. Moccia, E.D. Lellis, Morphological filtering and target tracking for vision-based UAS sense and avoid, in: Proceedings of the International Conference on Unmanned Aircraft Systems, Orlando, FL, USA, 2014, pp. 430–440.
[44] F. Dommermuth, J. Schiller, Estimating the trajectory of an accelerationless aircraft by means of a stationary acoustic sensor, J. Acoust Soc. Am. 76 (4) (1984) 1114–1122.
[45] F. Dommermuth, The estimation of target motion parameters from CPA time measurements in a field of acoustic sensors, J. Acoust. Soc. Am. 83 (4) (1988) 1476–1480.
[46] K.W. Lo, B.G. Ferguson, Broadband passive acoustic technique for target motion parameter estimation, IEEE Trans. Aerosp. Electron. Syst. 36 (1) (2000) 163–175.
[47] T. Gandhi, M.T. Yang, R. Kasturi, O. Camps, L. Coraor, J. McCandless, Detection of obstacles in the flight path of an aircraft, IEEE Trans. Aerosp. Electron. Syst. 39 (1) (2003) 176–191.
[48] P. Narayan, P. Wu, D. Campbell, Unmanning UAVs – addressing challenges in on-board planning and decision making, in: Proceedings of the 1st International Conference on Humans Operating Unmanned Systems, Telecom Bretagne, Brest, France, 2008, pp. 159–171.
[49] M. Puterman, Markov Decision Processes: Discrete Stochastic Dynamic Programming, John Wiley & Sons, Hoboken, NJ, USA, 2005.
[50] A.G. Shem, T.A. Mazzuchi, S. Sarkani, Addressing uncertainty in UAV navigation decision-making, IEEE Trans. Aerosp. Electron. Syst. 44 (1) (2008) 295–313.
[51] B. Bethke, J.P. How, J. Vian, Group health management of UAV teams with applications to persistent surveillance, in: Proceedings of the American Control Conference, Seattle, WA, USA, 2008, pp. 3145–3150.
[52] L.F. Bertuccelli, A. Wu, J.P. How, Robust adaptive Markov decision processes: planning with model uncertainty, IEEE Control Syst. Mag. 32 (5) (2012) 96–109.
[53] T. Mikaelian, D.H. Rhodes, D.J. Nightingale, D.E. Hastings, A logical approach to real options indentification with application to UAV systems, IEEE Trans. Syst. Man Cybern. A 42 (1) (2012) 32–47.
[54] P. Hart, N. Nilsson, B. Rafael, A formal basis for the heuristic determination of minimum cost paths, IEEE Trans. Syst. Man Cybern. A 4 (2) (1968) 100–107.
[55] A. Bicchi, G. Canaline, C. Santiago, Planning shortest bounded-curvature paths for a class of nonholonomic vehicles among obstacles, J. Intell. Robot. Syst. 16 (4) (1996) 387–405.
[56] H. Erzberger, H.Q. Lee, Optimal horizontal guidance techniques for aircraft, J. Aircr. 8 (2) (1971) 95–101.
[57] I. Shapira, J.Z. Ben-Asher, Near-optimal horizontal trajectories for autonomous air vehicles, AIAA J. Guid. Control Dyn. 20 (4) (1997) 735–741.
[58] B.L. Pierson, S.Y. Ong, Minimum-fuel aircraft trajectories, Math. Comp. Model. Dyn. 12 (6) (1989) 925–934.
[59] J.W. Burrows, Fuel-optimal aircraft trajectories with fixed arrival times, AIAA J. Guid. Control Dyn. 6 (1) (1983) 14–19.
[60] J.L. Vian, J.R. Moore, Trajectory optimization with risk minimization for military aircraft, AIAA J. Guid. Control Dyn. 12 (3) (1989) 311–317.
[61] B.A. Kumar, D. Ghose, Radar-assisted collision avoidance/guidance strategy for planar flight, IEEE Trans. Aerosp. Electron. Syst. 37 (1) (2001) 77–89.
[62] C. Goerzen, Z. Kong, B. Mettler, A survey of motion planning algorithms from the perspective of autonomous UAV guidance, J. Intell. Robot. Syst. 57 (1–4) (2010) 65–100.
[63] A. Tsourdos, B. White, M. Shanmugavel, Cooperative Path Planning of Unmanned Aerial Vehicles, John Wiley & Sons, Chichester, UK, 2011.
[64] A. Atyabi, D.M.W. Powers, Review of classical and heuristic-based navigation and path planning appraoches, Int. J. Adv. Comput. Technol. 5 (4) (2013) 1–14.
[65] O. Souissi, R. Benatitallah, D. Duvivier, A. Artiba, N. Belanger, P. Feyzeau, Path planning: a 2013 survey, in: Proceedings of the 2013 International Conference on Industrial Engineering and Systems Management, Rabat, Morocco, 2013, pp. 1–8.
[66] J.T. Betts, Survey of numerical methods for trajectory optimization, AIAA J. Guid. Control Dyn. 21 (2) (1998) 193–207.
[67] T.G. McGee, J.K. Hedrick, Optimal path planning with a kinematic airplane model, AIAA J. Guid. Control Dyn. 30 (2) (2007) 629–632.
[68] L. Techy, C.A. Woolsey, Minimum-time path planning for unmanned aerial vehicles in steady uniform winds, AIAA J. Guid. Control Dyn. 32 (6) (2009) 1736–1746.
[69] N. Yokoyama, Y. Ochi, Path planning algorithms for skid-to-turn unmanned aerial vehicles, AIAA J. Guid. Control Dyn. 32 (5) (2009) 1531–1543.
[70] K.J. Obermeyer, P. Oberlin, S. Darbha, Sampling-based path planning for a visual reconnaissance unmanned air vehicle, AIAA J. Guid. Control Dyn. 35 (2012) 619–631.
[71] L. Paull, C. Thibault, A. Nagaty, M. Seto, H. Li, Sensor-driven area coverage for an autonomous fixed-wing unmanned aerial vehicle, IEEE Trans. Cybern. 44 (9) (2014) 1605–1618.
[72] S.M. LaValle, Rapidly-exploring random trees: a new tool for path planning, Technical Report 98-11, Iowa State University, Ames, IA, USA, 1998.
[73] E. Frazzoli, M.A. Dahleh, E. Feron, Real-time motion planning for agile autonomous vehicles, AIAA J. Guid. Control Dyn. 25 (1) (2002) 116–129.
[74] H. Yu, R. Beard, J. Byrne, Vision-based navigation frame mapping and planning for collision avoidance for miniature air vehicles, Control Eng. Pract. 18 (7) (2010) 824–836.
[75] M. Kothari, I. Postlethwaite, A probabilistically robust path planning algorithm for UAVs using rapidly-exploring random trees, J. Intell. Robot. Syst. 71 (2) (2013) 231–253.
[76] L. Lin, M.A. Goodrich, Hierarchical heuristic search using a Gaussian mixture model for UAV coverage planning, IEEE Trans. Cybern. 44 (12) (2014) 2532–2544.
[77] H.I. Yang, Y.J. Zhao, Trajectory planning for autonomous aerospace vehicles amid known obstacles and conflicts, AIAA J. Guid. Control Dyn. 27 (6) (2004) 997–1008.
[78] G. Vachtsevanos, L. Tang, G. Drozeski, L. Gutierrez, From mission planning to flight control of unmanned aerial vehicles: strategies and implementation tools, Annu. Rev. Control 29 (1) (2005) 101–115.
[79] Y. Kim, D.W. Gu, I. Postlethwaite, Real-time path planning with limited information for autonomous unmanned air vehicles, Automatica 44 (3) (2008) 696–712.
[80] J. Karelahti, K. Virtanen, J. Ostrom, Automated generation of realistic near-optimal aircraft trajectories, AIAA J. Guid. Control Dyn. 31 (3) (2008) 674–688.
[81] P. Ogren, M. Winstrand, Minimizing mission risk in fuel-contrained unmanned aerial vehicle path planning, AIAA J. Guid. Control Dyn. 31 (5) (2008) 1497–1499.
[82] A. Eele, A. Richards, Path-planning with avoidance using nonlinear branch-and-bound optimization, AIAA J. Guid. Control Dyn. 32 (2) (2009) 384–394.
[83] R. Dai Jr., JEC, . Path planning and state estimation for unmanned aerial vehicles in hostile environment, AIAA J. Guid. Control Dyn. 33 (2) (2010) 595–600.
[84] A. Chamseddine, Y.M. Zhang, C.A. Rabbath, Trajectory planning and replanning strategies applied to a quadrotor unmanned aerial vehicle, AIAA J. Guid. Control Dyn. 35 (5) (2012) 1667–1670.
[85] A. Chamseddine, Y.M. Zhang, C.A. Rabbath, C. Join, D. Theilliol, Flatness-based trajectory planning/replanning for a quad-rotor unmanned aerial vehicle,

IEEE Trans. Aerosp. Electron. Syst. 48 (4) (2012) 1667–1671.
[86] A. Schrijver, Theory of Linear and Integer Programming, John Wiley & Sons, Hoboken, NJ, USA, 1998.
[87] S.E. Campbell, M.B. Bragg, N.A. Neogi, Fuel-optimal trajectory generation for persistent contrail mitigation, AIAA J. Guid. Control Dyn. 36 (6) (2013) 1741–1750.
[88] J. Israelsen, M. Beall, D. Bareiss, D. Stuart, E. Keeney, J.v.d. Berg, Automatic collision avoidance for manually tele-operated unmanned aerial vehicles, in: Proceedings of the IEEE International Conference on Robotics & Automation, Hong Kong, China, 2014, pp. 6638–6643.
[89] A.U. Raghunathan, V. Gopal, D. Subramanian, L.T. Biegler, T. Samad, Dynamic optimization strategies for three dimensional conflict resolution of multiple aircraft, AIAA J. Guid. Control Dyn. 27 (2004) 586–594.
[90] F. Borrelli, D. Subramanian, A.U. Raghunathan, L.T. Biegler, MILP and NLP techniques for centralized trajectory planning of multiple unmanned air vehicles, in: Proceedings of the American Control Conference, Piscataway, NJ, USA, 2006, pp. 1–6.
[91] S. Jain, P. Tsiotras, Trajectory optimization using multiresolution techniques, AIAA J. Guid. Control Dyn. 31 (5) (2008) 1424–1436.
[92] B.R. Geiger, J.F. Horn, G.L. Sinsley, J.A. Ross, L.N. Long, A.F. Niessner, Flight testing a real-time direct collocation path planner, AIAA J. Guid. Control Dyn. 31 (6) (2008) 1575–1586.
[93] P. Williams, Hermite–Legendre–Gauss–Lobatto direct transciption in trajectory optimization, AIAA J. Guid. Control Dyn. 32 (4) (2009) 1392–1395.
[94] Y. Ketema, Y.J. Zhao, Controllability and reachability for micro-aerial-vehicle trajectory planning in winds, AIAA J. Guid. Control Dyn. 33 (3) (2010) 1020–1023.
[95] J. Tisdale, Z. Kim, J.K. Hedrick, Autonomous UAV path planning and estimation, IEEE Robot. Autom. Mag. 16 (2) (2009) 35–42.
[96] R.B. Patel, P.J. Goulart, Trajectory generation for aircraft avoidance maneuvers using online optimization, AIAA J. Guid. Control Dyn. 34 (1) (2011) 218–230.
[97] T.R. Jorris, R.G. Cobb, Multiple method 2-D trajectory optimization satisfying waypoints and no-fly zone constraints, AIAA J. Guid. Control Dyn. 31 (2008) 543–553.
[98] N. Yokoyama, Path generation algorithm for turbulence avoidance using real-time optimization, AIAA J. Guid. Control Dyn. 36 (1) (2013) 250–262.
[99] D. Jung, P. Tsiotras, On-line path generation for unmanned aerial vehicles using B-spline path templates, AIAA J. Guid. Control Dyn. 36 (6) (2013) 1642–1653.
[100] A. Grancharova, E.I. Grotli, D.T. Ho, T.A. Johansen, UAVs trajectory planning by distributed MPC under radio communication path loss constraints, J. Intell. Robot. Syst. (2014) (10.1007/s10846-014-0090-1).
[101] B. Sridhar, H.K. Ng, N.Y. Chen, Aircraft trajectory optimization and contrails avoidance in the presence of winds, AIAA J. Guid. Control Dyn. 34 (2011) 1577–1583.
[102] G. Winter, Genetic Algorithms in Engineering and Computer Science, Wiley, Hoboken, NJ, 1999.
[103] I.K. Nikolos, K.P. Valavanis, N.C. Tsourveloudis, A.N. Kostaras, Evolutionary algorithm based offline/online path planner for UAV navigation, IEEE Trans. Syst. Man Cybern. B 33 (6) (2003) 898–912.
[104] I.K. Nikolos, N.C. Tsourvelouds, Path planning for cooperating unmanned vehicles over 3-D terrain, Inf. Control Autom. Robot. 24 (1) (2009) 153–168.
[105] Y.V. Pehlivanoglu, A new vibrational generic algorithm enhanced with a Voronoi diagram for path planning of autonomous UAV, Aerosp. Sci. Technol. 16 (1) (2012) 47–55.
[106] H. Ergezer, L. Leblebicioglu, Path planning for UAVs for maximum information collection, IEEE Trans. Aerosp. Electron. Syst. 49 (1) (2013) 502–520.
[107] J. Kennedy, R.C. Eberhart, Particle swarm optimization, in: Proceedings of the IEEE International Conference on Neural Networks, Perth, WA, Australia, 1995, pp. 1942–1948.
[108] R. Poli, J. Kennedy, T. Blackwell, Particle swarm optimization, Swarm Intell. 1 (1) (2007) 33–57.
[109] J. Karimi, S.H. Pourtakdoust, Optimal maneuver-based motion planning over terrain and threats using a dynamic hybrid PSO algorithm, Aerosp. Sci. Technol. 26 (1) (2013) 60–71.
[110] Y. Fu, M. Ding, C. Zhou, Phase angle-encoded and quantum-behaved particle swarm optimization applied to three-dimensional route planning for UAV, IEEE Trans. Syst. Man Cybern. A 42 (2) (2012) 511–526.
[111] Y. Fu, M. Ding, C. Zhou, H. Hu, Route planning for unmanned aerial vehicle (UAV) on the sea using hybrid differential evolution and quantum-behaved particle swarm optimization, IEEE Trans. Syst. Man Cybern. A 43 (6) (2013) 1451–1465.
[112] D. Karaboga, B. Basturk, A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm, J. Glob. Optim. 39 (3) (2007) 459–471.
[113] C. Xu, H.B. Duan, F. Liu, Chaotic artifical bee colony approach to uninhabited combat air vehicle (UCAV) path planning, Aerosp. Sci. Technol. 18 (4) (2010) 535–541.
[114] D. Simon, Biogeography-based optimization, IEEE Trans. Evolut. Comput. 12 (6) (2008) 702–713.
[115] W. Zhu, H.B. Duan, Chaotic predator–prey biogeography-based optimization approach for UCAV path planning, Aerosp. Sci. Technol. 32 (1) (2014) 153–161.
[116] S.M. LaValle, Planning Algorithms, Cambridge University Press, Cambridge, UK, 2006.
[117] J.H. Chuang, N. Ahuja, An analytically tractable potential field model of free space and its application in obstacle avoidance, IEEE Trans. Syst. Man Cybern. B 28 (5) (1998) 729–736.
[118] A.A. Masoud, Motion planning with Gamma-Harmonic potential fields, IEEE Trans. Aerosp. Electron. Syst. 48 (4) (2012) 2786–2801.
[119] O. Cetin, I. Zagli, G. Yilmaz, Establishing obstacle and collision free communication relay for UAVs with artifical potential fields, J. Intell. Robot. Syst. 69 (1–4) (2013) 361–372.
[120] K. Subbarao, B.M. Shippey, Hybrid genetic algorithm collocation method for trajectory optimization, AIAA J. Guid. Control Dyn. 32 (4) (2009) 1396–1403.
[121] J.F. Horn, E.M. Schmidt, B.R. Geiger, M.P. DeAngelo, Neural network-based trajectory optimization for unmanned aerial vehicles, AIAA J. Guid. Control Dyn. 35 (2) (2012) 548–562.
[122] P. Ghosh, B.A. Conway, Numerical trajectory optimization with swarm intelligence and dynamic assignment of solution structure, AIAA J. Guid. Control Dyn. 35 (4) (2012) 1178–1191.
[123] P.B. Sujit, S. Saripalli, J.B. Sousa, Unmanned aerial vehicle path following: a survey and analysis of algorithms for fixed-wing unmanned aerial vehicles, IEEE Control Syst. Mag. 34 (1) (2014) 42–59.
[124] P. Martin, S. Devasia, B. Paden, A different look at output tracking: control of a VTOL aircraft, Automatica 32 (1) (1996) 101–107.
[125] L. Consolini, M. Tosques, On the VTOL exact tracking with bounded internal dynamics via a Poincare map approach, IEEE Trans. Autom. Control 52 (9) (2007) 1757–1762.
[126] X. Wang, J. Liu, K. Cai, Tracking control for a velocity-sensorless VTOL aircraft with delayed outputs, Automatica 45 (12) (2009) 2876–2882.
[127] L. Consolini, M. Maggiore, C. Nielsen, M. Tosques, Path following for the PVTOL aircraft, Automatica 46 (8) (2010) 1284–1296.
[128] D. Cabecinhas, R. Cunha, C. Silvestre, A nonlinear quadrotor trajectory tracking controller with disturbance rejection, Control Eng. Pract. 26 (1) (2014) 1–10.
[129] G.V. Raffo, M.G. Ortega, F.R. Rubio, Path tracking of a UAV via an underactuated $H\infty$ control strategy, Eur. J. Control 17 (2) (2011) 194–213.
[130] S.A. Al-Hiddabi, N.H. McClamroch, Tracking and maneuver regulation control for nonlinear nonminimum phase systems: application to flight control, IEEE Trans. Control Syst. Technol. 10 (6) (2002) 780–792.
[131] S. Park, J. Deyst, J.P. How, Performance and Lyapunov stability of a nonlinear path-following guidance method, AIAA J. Guid. Control Dyn. 30 (6) (2007) 1718–1728.
[132] K.D. Do, Z.P. Jiang, J. Pan, On global tracking control of a VTOL aircraft without velocity measurements, IEEE Trans. Autom. Control 48 (12) (2003) 2212–2217.
[133] A.P. Aguiar, J.P. Hespanha, Trajectory-tracking and path-following of underactuated autonomous vehicles with parametric modeling uncertainty, IEEE Trans. Autom. Control 52 (8) (2007) 1362–1397.
[134] J. Cayero, B. Morcego, F. Nejjari, Modelling and adaptive backstepping control for TX-1570 UAV path tracking, Aerosp. Sci. Technol. 39 (12) (2014) 342–351.
[135] M. Innocenti, L. Pollini, Guidance of UAVs based on fuzzy sets and fixed waypoints, AIAA J. Guid. Control Dyn. 27 (2004) 715–720.
[136] T.S. No, B.M. Min, R.H. Stone, K.C. Wong, Control and simulation of arbitrary flight trajectory-tracking, Control Eng. Pract. 13 (5) (2005) 601–612.
[137] S. Shehab, L. Rodrigues, Preliminary results on UAV path following using piecewise-affine control, in: Proceedings of the 49th IEEE Conference on Control Applications, Toronto, ON, Canada, 2005, pp. 358–363.
[138] D.R. Nelson, D.B. Barber, T.W. McLain, R.W. Beard, Vector field path following for miniature air vehicles, IEEE Trans. Robot. 23 (3) (2007) 519–529.
[139] H. Oh, S. Kim, A. Tsourdos, B.A. White, Decentralized standoff tracking of moving targets using adaptive sliding mode control for UAVs, J. Intell. Robot. Syst. 76 (1) (2014) 169–173.
[140] C. Cao, N. Hovakimyan, Design and analysis of a novel L1 adaptive control architecture with guaranteed transient performance, IEEE Trans. Autom. Control 53 (2) (2008) 586–591.
[141] I. Kaminer, A. Pascoal, E. Xargay, N. Hovakimyan, C. Cao, V. Dobrokhodov, Path following for unmanned aerial vehicles using L1 adaptive augmentation of commerical autopilots. AIAA, J. Guid. Control Dyn. 33 (2) (2010) 550–564.
[142] A. Fradkov, B. Andrievsky, Combined adaptive controller for UAV guidance, Eur. J. Control 11 (2005) 71–79.
[143] N. Dadkhah, B. Mettler, Control system design and evaluation for robust autonomous rotorcraft guidance, Control Eng. Pract. 21 (11) (2013) 1488–1506.
[144] R.W. Beard, J. Ferrin, J. Humpherys, Fixed wing UAV path following in wind with input constraints, IEEE Trans. Control Syst. Technol. 22 (6) (2014) 2103–2117.
[145] I. Prodan, S. Olaru, R. Bencatel, J.Bd Sousa, C. Stoica, S.I. Niculescu, Receding horizon flight control for trajectory tracking of autonomous aerial vehicles, Control Eng. Pract. 21 (10) (2013) 1334–1349.
[146] Y. Zhao, P. Tsiotras, Time-optimal path following for fixed-wing aircraft, AIAA J. Guid. Control Dyn. 36 (1) (2013) 83–95.
[147] T.H. Cheng, Z. Kan, J.A. Rosenfeld, W.E. Dixon, Decentralized formation control with connectivity maintenance and collision avoidance under limited and intermittent sensing, in: Proceedings of the American Control Conference, Portland, Oregon, USA, 2014, pp. 3201–3206.
[148] I. Kaminer, A. Pascoal, E. Hallberg, C. Silvestre, Trajectory tracking for autonomous vehicles: an integrated approach to guidance and control, AIAA J. Guid. Control Dyn. 21 (1) (1998) 29–38.
[149] M. Levy, T. Shima, S. Gutman, Linear quadratic integrated versus separated autopilot-guidance design, AIAA J. Guid. Control Dyn. 36 (6) (2013) 1722–1730.

[150] A.S. Matveev, H. Teimoori, A.V. Savkin, A method for guidance and control of an autonomous vehicle in problems of border patrolling and obstacle avoidance, Automatica 47 (3) (2011) 515–524.
[151] T. Yamasaki, S.N. Balakrishnan, H. Takano, Separate-channel integrated guidance and autopilot for automatic path-following, AIAA J. Guid. Control Dyn. 36 (1) (2013) 25–34.
[152] A.D. Zeitlin, Sense & avoid capability development challenges, IEEE Aerosp. Electron. Syst. Mag. 25 (10) (2010) 27–32.
[153] A. Farooq, Limebeer DJN. Optimal trajectory regulation for radar imaging guidance, AIAA J. Guid. Control Dyn. 31 (4) (2008) 1076–1092.
[154] O. Meister, N. Frietsch, G.F. Trommer, Adaptive path planning for VTOL-UAVs, IEEE Aerosp. Electron. Syst. Mag. 24 (7) (2009) 36–41.
[155] B. Zhang, W. Liu, Z. Mao, J. Liu, L. Shen, Cooperative and geometric learning algorithm for path planning of UAVs with limited information, Automatica 50 (3) (2014) 809–820.
[156] D. Sislak, P. Volf, M. Pechoucek, Agent-based cooperative decentralized airplane-collision avoidance, IEEE Trans. Intell. Transp. 12 (1) (2011) 36–46.
[157] M. Prandini, J. Hu, J. Lygeros, S. Sastry, A probabilistic approach to aircraft conflict detection, IEEE Trans. Intell. Transp. 1 (4) (2000) 199–220.
[158] J.K. Kuchar, L.C. Yang, A review of conflict detection and resolution modeling methods, IEEE Ttans. Intell. Transp. 1 (4) (2000) 179–189.
[159] W. Liu, I. Hwang, Probabilistic trajectory prediction and conflict detection for air traffic control, AIAA J. Guid. Control Dyn. 34 (6) (2011) 1779–1789.
[160] H. Chen, K. Chang, C.S. Agate, UAV path planning with Tagent-plus-Lyapunov vector field guidance and obstacle avoidance, IEEE Trans. Aerosp. Electron. Syst. 49 (2) (2013) 840–852.
[161] J.W. Adaska, K. Obermeyer, E. Schmidt, Robust probabilistic conflict prediction for sense and avoid, in: Proceedings of the American Control Conference, Portland, Oregon, USA, 2014, pp. 1198–1203.
[162] M. Melega, S. Lazarus, A. Savvaris, A. Tsourdos, Multiple threats sense and avoid algorithm for static and dynamic obstacles, J. Intell. Robot. Syst. 77 (1) (2015) 215–228.
[163] J. Ordaz, S. Salazar, S. Mondie, H. Romero, R. Lozano, Predictor-based position control of a quad-rotor with delays in GPS and vision measurements, J. Intell. Robot. Syst. 70 (1–4) (2013) 13–26.
[164] Y.M. Zhang, J. Jiang, Bibliographical review on reconfigurable fault-tolerant control systems, Annu. Rev. Control 32 (2) (2008) 229–252.
[165] X. Prats, L. Delgado, J. Ramirez, P. Royo, E. Pastor, Requirements, issues, and challenges for sense and avoid in unmanned aircraft systems, AIAA J. Aircr. 49 (3) (2012) 677–687.
[166] AIA, Unmanned Aircraft Systems: Perceptions and Potential, Aerospace Industries Association, Arlington, VA, USA, 2013.
[167] FAA, Integration of Civil Unmanned Aircraft Systems (UAS) in the National Airspace System (NAS) Roadmap, U.S. Department of Transportation, Federal Aviation Administration, Washington, D.C., USA, 2013.