Journal of Systems Engineering and Electronics
Vol. 33, No. 5, October 2022, pp.1123 – 1134

Review on artificial intelligence techniques for improving representative air traffic management capability

TANG Jun[1], LIU Gang[2,*], and PAN Qingtao[1]

1. College of Systems Engineering, National University of Defense Technology, Changsha 410073, China; 2. School of Information Science and Engineering, Hunan Institute of Science and Technology, Yueyang 414000, China

Abstract: The use of artificial intelligence (AI) has increased since the middle of the 20th century, as evidenced by its applications to a wide range of engineering and science problems. Air traffic management (ATM) is becoming increasingly automated and autonomous, making it lucrative for AI applications. This paper presents a systematic review of studies that employ AI techniques for improving ATM capability. A brief account of the history, structure, and advantages of these methods is provided, followed by the description of their applications to several representative ATM tasks, such as air traffic services (ATS), airspace management (AM), air traffic flow management (ATFM), and flight operations (FO). The major contribution of the current review is the professional survey of the AI application to ATM alongside with the description of their specific advantages: (i) these methods provide alternative approaches to conventional physical modeling techniques, (ii) these methods do not require knowing relevant internal system parameters, (iii) these methods are computationally more efficient, and (iv) these methods offer compact solutions to multivariable problems. In addition, this review offers a fresh outlook on future research. One is providing a clear rationale for the model type and structure selection for a given ATM mission. Another is to understand what makes a specific architecture or algorithm effective for a given ATM mission. These are among the most important issues that will continue to attract the attention of the AI research community and ATM work teams in the future.

Keywords: artificial intelligence (AI), air traffic management (ATM), air traffic services (ATS), airspace management (AM), air traffic flow management (ATFM), flight operations (FO).

DOI: 10.23919/JSEE.2022.000109

1. Introduction

The modern field of artificial intelligence (AI) spans many sub-fields [1−4]. Most of these sub-fields handle issues pertaining to the understanding and abstraction of various human behavioral traits and patterns that are commonly considered as indications of intelligence [5−10], attempting to realize the same behavioral patterns in machines [11]. The term “AI” was coined during the Dartmouth College conferences in 1956 [12], which were organized for developing ideas about machines that could think. These conferences are widely considered as the headstream of the field. Recently, in the fields of air traffic management (ATM), attention has been focused on the development of AI methods for performing various air and ground functions, especially in air traffic services (ATS), airspace management (AM), air traffic flow management (ATFM), and flight operations (FO). These functions ensure the safe and efficient movement of aircraft during all phases of operations [13−16].

The AI technique is a novel technology continuously developed based on modern information technology. The basic principle is to use computers to simulate various ways of expressing human thoughts, thereby transforming them into various thinking processing modes used by traditional professional computers for information processing and simulation work [1]. AI mainly includes the following techniques [6−9]: machine learning, building data auto-discovery patterns and generally dealing with more data, the more accurate predictions will be; computer vision, applying image processing operations and machine learning technologies to decompose tasks to facilitate management; natural language processing, making computers have the ability to process text similar to humans; robotics, such as drones, medical robots, and working robots; biometric identification, using the inherent biological characteristics of the human body for personal identification.

This paper provides a systematic review of studies that employ AI techniques for improving ATM capability.

Manuscript received April 01, 2021.
*Corresponding author.
This work was supported by the National Natural Science Foundation of China (62073330), the Natural Science Foundation of Hunan Province (2020JJ4339) and the Scientific Research Fund of Hunan Province Education Department (20B272).

The remainder of the paper is structured as follows. Sections 2–6 discuss the applications of AI to ATM, ATS, AM, ATFM, and FO, respectively. Section 7 summarizes the conclusions and Section 8 discusses potential future research issues.

2. AI for ATM

Previously, AI techniques have been shown to outperform state-of-the-art calculation methods and models in several fields, with ATM being one of the most prominent cases. Several operational challenges underscore the requirements for increased automation for improving the level of ATM, and there seems to be little doubt that AI will be a key enabler of advanced functionality and increased automation in future ATM systems. Since the beginning of the 21st century, the Internet has promoted the continuous innovation and practical usage of AI methods, which has also promoted their application to the ATM field. Fig. 1 shows the search results of "AI applied for ATM" according to Google Scholar, for the time period of 2001 to 2020. The overall trend is upward and relatively flat. Starting in 2015, there has been a significant increase in the application of AI methods to ATM, which may be owing to the widespread emergence of open-source machine learning platforms such as Tensor Flow [17], continuous publication of AI achievements such as DeepMind papers [18], and a gradual outbreak of the remotely piloted aircraft (RPA) market [19,20]. The defeat of the Go champion by AlphaGo further stimulates the interest in AI applications [21−23].

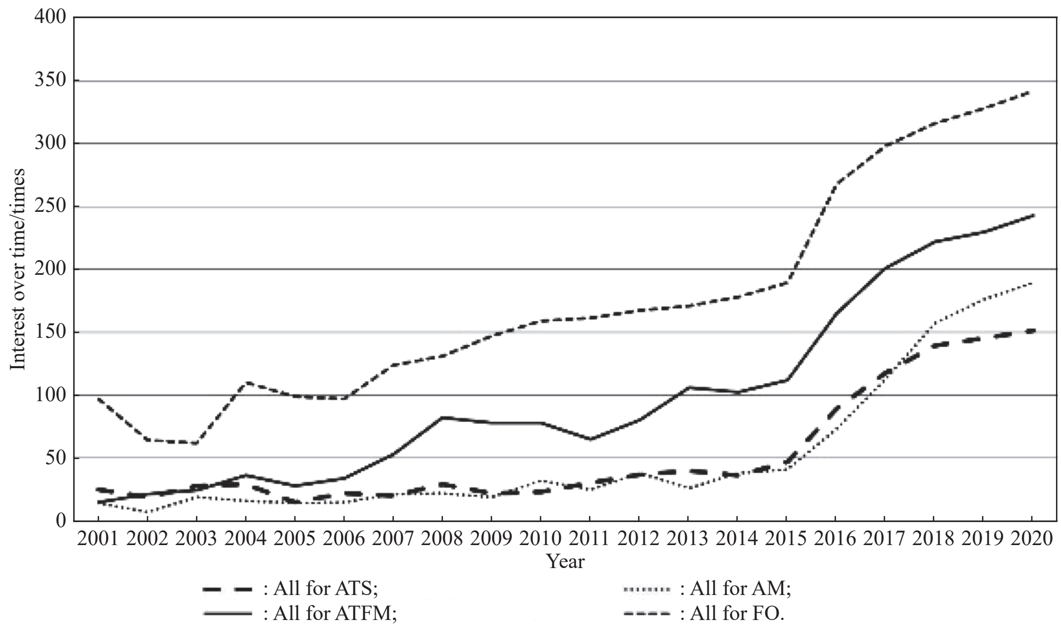

Fig. 1 Google trends indicator of AI for ATM from 2001 to 2020

In light of the above discussion, we focus on four most important vocational works, ATS/AM/ATFM/FO, with respect to their core function and applicability to ATM. The current coverage is by no means exhaustive. For example, although hardware plays an important role in ATM, it is not reviewed in this paper, because it is predominantly related to device management and quality. This review targets the community of AI algorithm developers and researchers, as well as the community of aviation specialists and general air traffic managers who are interested in the state-of-the-art AI methods for ATM tasks. Example areas of interest include flight-planning requirements, dynamic use of airspace, conflict detection and resolution, situational awareness, optimization of traffic flows, and pilot procedures. The advantages of using AI methods for ATM are as follows: (i) these methods provide alternative approaches to conventional physical modeling techniques, (ii) these methods do not require knowing relevant internal system parameters, (iii) these methods are computationally more efficient, and (iv) these methods offer compact solutions to multivariable problems.

3. AI for ATS

ATS refers to managing and controlling the air activities of aircraft [24]. It includes air traffic control (ATC) services, flight information (FI) services, and alerting (AL) services. The ATC services aim to: (i) avoid collisions between aircraft and between aircraft and obstacles, and

(ii) accelerate and maintain safe and orderly operation of air traffic. FI services provide suggestions and information to aircraft in flight that is conducive to safe and effective implementation of flights. AL services give notices to relevant organizations to search and rescue aircraft, and coordinate organizations and/or the relevant work, according to the situational needs.

Traditionally, as the major component of ATS, ATC tasks have been performed by human air traffic controllers (ATCOs). According to the scheduled flight plan and the pilot's position report in flight, the controller can grasp the position and the altitude of the aircraft to ensure its orderly and safe flight [24]. After 1945, primary and secondary surveillance radars were introduced. Radar controllers determine the exact location of all aircraft in the radar wave coverage area, according to the radar display. However, the number of flights has been continuously increasing, which strains the system. As a result, the Federal Aviation Administration turned to computer-based equipment during the 1980s to help controllers in performing certain ATC functions. Automation has been introduced into air traffic control. Thus, the history of air traffic control can be divided into several periods, as shown in Table 1.

Table 1 History of air traffic control

Time	Control technology	Flight characteristic	Navigation characteristic
1929−1934	Visual flight rules	Fewer planes, shorter voyages and slower speeds	Flag and gun
1934−1945	Procedure control system	More aircraft, faster speed, mainly military flights	Air traffic control center, tower, terminal
1945−1980s	Radar control	Fast speed, long voyages, more flights	Primary radar, secondary surveillance radar
1980s−	Air-ground cooperative ATC	Airway/airport congestion, developed airborne equipment	Satellite technology

The development of computer technology and AI techniques positively affect ATC. Nguyen et al. [25] pioneered the application of AI techniques to ATC. Nguyen et al. tried to automate the function of the entire controller instead of focusing on one aspect of the controller's work. Cross [26] combined techniques from the fields of qualitative physics and AI research to develop an understanding of the effects of aircraft performance on the controller's ATC actions. Using AI methods for ATC can facilitate human-machine interaction. This resulted in the development of expert systems for ATC. Some research groups studied distributed expert systems for planning and control, such as the Lincoln Laboratory Group [27], and the Rand Corporation research team [28,29]. Gosling [30] developed an expert system and used it in aircraft gates for cost assignments. Gosling [30] pointed out that the using decision support systems with expert systems may be suitable for some problems relevant to the operation of airline stations. Li et al. [31] proposed an ATM expert system, serving as an accessory tool to help ATCOs with rescheduling. The use of AI methods in automated ATC systems has been promising. Krishnan [32] introduced entropy-based efficiency calculations and explored how these calculations, combined with AI methods, can be used for ATC. Modern ATC systems are intimately based on large distributed information technology (IT) applications and consist of many different components. Findler et al. [33] proposed distributed planning and problem solving as a reliable and effective ATC method. This includes design and implementation of a distributed planning system, that is, a location-centered collaborative planning system for a distributed ATC system. A runtime analysis and knowledge-based automated IT management method [34] was proposed and applied to ATC. Combining ontology and its inference ability in the Semantic Web with complex event-processing methods, a novel analysis method was proposed, which solves the problem of temporal modeling and state space explosion, without relying on the exclusive use of ontology.

When potential conflicts are detected, ATCOs must provide conflict resolution. Many mathematical models have been proposed for use as the ATCOs' conflict resolution tools [35−37]. Although these models have found several uses, they have some common limitations. For example, these mathematical models do not have good self-learning capabilities. Thus, some automated conflict resolution approaches were presented. Recently, AI has been widely proposed for supporting decision-making in ATC. Isaacson et al. [38] proposed a knowledge-based conflict resolution process that allows predictive conflicts to be resolved in a manner consistent with controller practices: including prioritization of resolution strategies and multiple degrees of freedom blending to achieve separation. Tran et al. [39] built an AI system as a digital assistant to support ATCOs in resolving potential conflicts. The proposed system consisted of two core components: one was an intelligent interaction conflict solution that acquired ATCOs' preferences, the other was an AI agent that used reinforcement learning (RL). The resulting system successfully proposed conflict resolution strategies. Kulkarni et al. [40] used artificial neural networks for ATC automation. Namely, a back-propagation network was used for making intelligent decisions. To solve the problem of the runway direction selection in airports, a self-enforcing network (SEN) [41] was proposed. The measured data for different time periods for forecasting wind conditions was given to the SEN, which provided suggestions for choosing suitable operation directions. Some researchers used multi-agent-based models to represent the tasks that had to be performed or physical resources for ATC (control centers, airports, and runways) [42]. The studies that applied AI techniques to ATC, and the applied techniques, are listed in Table 2.

Table 2 AI methods in ATC

Method	Expert system	Knowledge engineering	Agent-model	Machine learning/ deep learning	Mathematical	Others (distributed, IT, etc.)	Year
Gosling [30]	√	√	–	–	–	√	1990
Li et al. [31]	√	√	–	–	–	–	1997
Krishnan et al. [32]	–	–	–	√	–	√	2012
Findler et al. [33]	–	√	–	–	–	√	1991
Mever et al. [34]	–	√	–	–	–	√	2013
Kuchar et al. [35]	–	–	–	–	√	–	2000
Radanovic et al. [36]	–	–	–	–	√	–	2018
Jilkov et al. [37]	–	–	–	–	√	–	2018
Isaacson et al. [38]	√	√	–	–	–	√	2001
Tran et al. [39]	–	–	√	–	–	√	2019
Kulkani et al. [40]	–	–	–	√	–	√	2015
Klüver et al. [41]	–	–	–	√	–	√	2017

The current ATC system was developed over time to meet the users' needs with respect to modern technology, and it has performed remarkably well [43,44]. However, with the rapid increase in the number of flights and with increasing shortage of airspace resources, the demand for high-performance ATC systems has been increasing. Presently, the emergence of AI techniques has been very promising for rapid and efficient development of aviation technology. Using AI methods, we can build intelligent ATC systems that permit a richer analysis of existing air traffic problems. At the same time, AI techniques can help to develop intelligent conflict detection and resolution module systems for detection of flight conflicts, which will result in safer flights. However, AI techniques also put forward higher requirements on the input data of the ATC system, and require system users to have more professional domain knowledge.

4. AI for AM

AI aims to create intelligent machines that are likely to be very useful for different industrial applications; consequently, AI methods have become a very essential part of ATM. In the AM area, AI methods can be applied to performance trade-off, such as identifying the reasons underlying en-route flight inefficiencies. They can also be used for modeling airline route choices. In addition, AI methods are expected to be highly accurate for trajectory prediction. AI methods are also capable of providing low-cost solutions that can be adapted for speed recognition tools for use at other airports.

The studies that applied AI techniques to AM are listed in Table 3.

Table 3 AI methods in AM

Method	[Multi-agent, machine learning]	[Centralized, decentralized]	Collaboration with airspace users	Multi-objective optimization	[Time uncertainty, small training set]	Intelligent optimization algorithm	Multilevel grid spatiotemporal index	[Multi-agent, machine learning]	Year
Jarvis et al. [45]	[√, −]	[√, −]	√	−	[−, −]	√	−	[√, −]	2010
Schefers et al. [46]	[−, −]	[√, −]	−	√	[√, −]	−	−	[−, −]	2018
Wu et al. [47]	[−, −]	[√, −]	−	√	[−, −]	√	−	[−, −]	2018
Cao et al. [48]	[−,√]	[√, −]	−	−	[−,√]	−	−	[−,√]	2018
Miao et al. [49]	[−, −]	[√, −]	−	−	[−, −]	−	√	[−, −]	2019
Agogino et al. [50]	[√,√]	[−,√]	−	−	[−,−]	−	−	[√,√]	2012
McCrea et al. [51]	[−, −]	[√, −]	−	−	[−, −]	−	−	[−, −]	2008
Cruciol et al. [52]	[−,√]	[√, −]	−	−	[−, −]	−	−	[−,√]	2015
Yu et al. [53]	[−,√]	[−, −]	−	−	[−, −]	−	−	[−,√]	2019
Wang et al. [54]	[−,√]	[√, −]	−	−	[−, −]	−	−	[−,√]	2017
Schirmer et al. [55]	[−, −]	[√, −]	−	−	[−, −]	√	−	[−, −]	2018
Gerdes et al. [56]	[−, −]	[√, −]	−	−	[−, −]	√	−	[−, −]	2018
Insaurralde et al. [57]	[−, −]	[−, −]	−	−	[−, −]	√	−	[−, −]	2017
Kravaris et al. [58]	[−, √]	[√, −]	−	−	[−, −]	−	−	[−, √]	2017
Cai et al. [59]	[−, −]	[√, −]	−	−	[−, −]	√	−	[−, −]	2012

Jarvis et al. [45] proposed a method for resolving the demand and capacity imbalances in the US national airspace with close collaboration with airspace users. This method utilized a software negotiation framework, and achieved the safety standard with high user satisfaction. Schefers et al. [46] introduced a method that used constraint programming enabled by AI and fostered adherence of the airspace users' trajectory, and introduced a novel mechanism for improving flight departure scheduling under temporal uncertainty. Wu et al. [47] proposed a multi-objective optimization model for addressing the problem of collaborative optimization of global flight flows in the airspace sector network; their model utilized a dynamic adaptive non-dominated sorting genetic algorithm (NSGA). Cao et al. [48] proposed a framework for knowledge mining in small training sets; thus, their proposed system used a small training set and demonstrated promising performance on complexity evaluation. Miao et al. [49] presented a multi-level grid spatiotemporal index-based conflict detection method, which exhibited high computational efficiency. Agogino et al. [50] proposed a multi-agent algorithm that used RL for reducing congestion; the proposed method significantly improved the traffic flow, and provided adaptive and robust solutions to the flow management problem. Mccrea et al. [51] used k-means clustering to conduct an economic benefit analysis and applied it to a large-scale airspace environment management. Cruciol et al. [52] proposed a decision support system using multi-agent systems, to organize and optimize the solutions for handling traffic flows in the airspace. They modeled the air-holding problem using RL. Yu et al. [53] integrated the underlying physics of aircraft dynamic systems into machine learning models, to reduce training costs, and for accurate prediction of flight trajectories. Wang et al. [54] introduced a method that mapped the raw sensory data of unmanned aerial vehicle (UAV) into control signals, which enabled the UAVs to autonomously generate suitable trajectories in virtual large-scale complex environments. Schirmer et al. [55] introduced current certification practices in unmanned aviation, supported by autonomous systems and AI, and demonstrated that it is possible to use specific operation assessment as an enabler for hard-to-certify techniques. Gerdes et al. [56] used evolutionary algorithms for optimization of the airspace, which led to the flexible use of the airspace. Insaurralde et al. [57] discussed challenges and opportunities associated with implementation of knowledge technology solutions for the management of shared multi-aviation airspaces. Kravaris et al. [58] proposed collaborative RL methods for resolving demand-capacity imbalances under pre-tactical ATM, which is likely to be feasible even for extremely difficult scenarios. Cai et al. [59] used a memetic algorithm with a pull-push operator to solve the crossing waypoint's location problem.

In summary, it is necessary to further automate traffic management systems, as the number of air vehicles is continually increasing along with their level of automation. Automation is likely to help to offload certain tasks, thus allowing air traffic managers to focus on the airspace safety issues. However, most of the applications of the above-mentioned artificial intelligence technology in AM are centralized, and discretization is of more practical value; and the training data set is generally large in scale, and the scale and quality of data collection are relatively high. Therefore, significant amount of research is still needed to ensure that automated systems with AI can meet high safety standards and security requirements on aviation systems.

5. AI for ATFM

ATFM has several stakeholders, such as airlines, pilots, local flow administration centers, and the national flow administration center. Superior techniques and proficient traffic controllers are pertinent to ATFM [60,61]. Weather situations, aircraft operational restrictions, and controllers' skills have enormous implications on the proper functioning of ATFM systems.

In the domain of ATFM, the related work mostly falls into two different categories: (i) principles-based modeling performed by domain experts [62−65] and (ii) algorithmic approaches, pursued by the community of agents [66−68]. AI-based approaches mostly belong to the second category. A survey of recent literature on this topic reveals application of several AI methods to ATFM: automata theory, intelligent agent-based approaches, swarm theory methods, and multi-agent approach with RL. Indeed, the most mainstream direction is the multi-agent approach with RL. Table 4 lists the AI methods that have been used for ATFM.

Table 4 AI methods in ATFM

Method	Reinforcement learning	Automata theory	Intelligent agents	Swarm theory	[Environment, Human]	Capacity	Delay	Cost	Year
Pechoucek et al. [69]	√	−	−	−	[√, √]	−	−	−	2006
Tumer et al. [70]	√	−	−	−	[−, −]	√	−	−	2007
Wolfe et al. [71]	√	−	−	−	[−, √]	−	−	−	2009
Li et al. [72]	√	−	−	−	[√, −]	−	√	−	2010
Crespo et al. [73]	√	−	−	−	[−, −]	√	√	−	2017
Cruciol et al. [74]	√	−	−	−	[−, √]	√	−	−	2013
Bayen et al. [75]	−	√	−	−	[√, −]	√	√	−	2003
Wolfe et al. [76]	−	−	√	−	[−, −]	−	√	√	2007
Torres et al. [77]	−	−	−	√	[√, −]	−	√	√	2012

In the context of flow management of decision processes, pilots, central, and local controllers can be considered as agents in ATFM applications. An adaptive multi-agent approach is appropriate for modeling complex interactions between agents, such as collaboration, negotiation, and coordination. To assess the agents' learning performance, an appropriate reward mechanism is required for an adaptive multi-agent system. As a constituent multi-agent system, RL can implement this, capturing the experience and the level of knowledge of controllers. Furthermore, it could also support control activities. The reward function in RL plays a critical role in artificial intelligent ATFM systems. Intelligent agents use the reward function to assess the effect of a certain action on other agents, and generate ATFM actions/measures based on that reasoning. Different reward structures differentially affect the underlying system performance. Pechoucek et al. [69] proposed an agent-reward structure, which enables agents to learn how to act better and explore; the proposed system exhibited a good system-level performance in an indirect environment. Tumer et al. [70] proposed a multi-agent algorithm for optimization of traffic flow management. In this algorithm, an agent is related to a fix and its location includes setting required separation among multiple airplanes crossing that fix, where RL is applied to set the separation, following which the traffic is accelerated or decelerated to dispose of congestion. The study by Tumer used an air traffic flow simulator, FACET, to test the algorithm. Wolfe et al. [71] built an agent-based simulation system using Brahms, which is a modeling and simulation environment for studying human work practices and programming intelligent software agents with the purpose of supporting work practices in organizations. Li et al. [72] developed a distributed decision support system for tactical systems, for ATFM. Crespo et al. [73] presented an

ATFM method developed using computational agents based on RL, to determine delays upon departing schedules of aircraft taking off from some terminal areas. The goal was to reduce saturation and congestion in the air traffic control departments on account of a potential imbalance between capacity and demand. Cruciol et al. [74] adopted two reward functions for agent-based RL, for ATFM. The first function mostly concentrated on safety separation and equity among multiple commercial entities in the ground holding problem. The second function mostly focused on safety separation in the air holding problem. Real-case studies in Brazil showed that the two developed reward functions have satisfactory effectiveness and efficiency during the decision procedure of ATFM.

Other AI methods have been applied to ATFM. Bayen et al. [75] used the hybrid automata theory to develop a control theoretical model of sector-based air traffic flow, and used a Lagrangian model to model the attributes of the system along its tracks. A sub-model was used for analyzing and predicting the air traffic congestion: Firstly, the dynamic sector capacity was defined and derived. Then the model was applied to forecast the instance in which a certain portion of the airspace will become overloaded. Wolfe [76] proposed assistive agents to support better communication between collaboration parties, thus improving the decision-making process. A swarm intelligence-based approach was also appropriate for the level of complexity associated with ATFM. Advances in airborne technologies made swarm intelligence methods more practical. Since it is not practical to adopt technology of combinatorial optimization to deal with the multi-target traffic flow optimal problem, and a large number of variables and exceedingly large Pareto fronts related to the solution domain would lead to a combinational explosion, Torres [77] presented a different method for ATFM, which was based on the swarm theory methods. This method regarded pilots as goal-seeking agents, who separately searched for solutions to the optimization problem. The collective action of agents basically converged to the Pareto optimal condition as a result of emergent behavior. Several other complex air traffic problems have also adopted particle swarm optimization methods [78,79].

The main objectives here are to ensure safety, lower delays, reduced environmental effects, and to balance demand and capacity. In Table 4, different studies focus on different objectives. Most of them have the advantages that they can improve the capacity or decrease delays, while they do not contribute to the reduction of operating costs.

6. AI for FO

To ensure flight safety and to improve flight efficiency, it is necessary to monitor and manage the entire flight process, that is, the FO must be managed scientifically and reasonably [80]. FOs mainly include system-level communications, navigation, and surveillance (CNS), and application-level pilot procedures such as air traffic incident reporting, communication failure procedures, adequacy of distress, and emergency communication program. By integrating the operations of CNS and pilot procedures, it is possible to maintain ATC-specified separation to ensure aviation flight safety.

In the field of aviation, the use of AI-based systems is regarded as a viable solution to some problems, such as reducing the flight cost, optimizing the airspace usage, meeting ATC requirements, assisting the flight crew with decisions, improving data management, and assisting with maintenance. With the rapid development of information technology and AI technology, increasing attention has been paid to the prospect of intelligent avionics systems. The CNS system is the most important component of any avionics system. It is used primarily for aircraft taxiing, take-off, cruise, and landing [81]. The applications of AI to FO are listed in Table 5.

Table 5 AI methods in FO

Method	[Machine learning, neural network]	Agent	Data fusion	Others	Airplane	UAV	Year
Apiecionek et al. [84]	[−, −]	−	√	√	√	−	2015
Sanchez-Lopez et al. [85]	[−, −]	√	−	√	−	√	2016
Bouwmeester et al. [86]	[−, −]	−	√	−	√	√	2015
Sinopoli et al. [87]	[−, −]	−	√	−	−	√	2001
Khansari-Zadeh et al. [88]	[√, √]	−	√	−	√	−	2011
Wu et al. [89]	[−, −]	−	√	√	−	√	2005
Zhilenkov et al. [90]	[−, √]	−	√	−	−	√	2018
Popova et al. [91]	[−, −]	−	√	√	−	√	2016
Kochenderfer et al. [92]	[√, −]	−	−	−	√	−	2012
Durand et al. [93]	[−, √]	−	−	−	√	−	2000
Sislak et al. [94]	[−, −]	√	−	−	√	−	2011
Schetinin et al. [95]	[√, −]	−	−	√	√	−	2018

The communication system mainly transmits information from a transmitter to a recipient through a medium. Modern aviation interconnection technology can be mainly divided into air to ground communication [82] and satellite communication [83]. A practical implementation scheme of the communication system architecture for use on military airplanes was proposed in [84]. The proposed system continuously accesses information online using AI, which increases the pilots' situational awareness. UAVs have had a major impact on the aviation industry. In most cases, each UAV is controlled by the ground control station (GCS) at the same time. Some basic infrastructure-based swarm capabilities have been considered and are often conveniently available in the GCS software [85]. One advantage of infrastructure-based swarming is that the GCS can be optimized in real time using high-performance computers that can be reasonably operated on UAVs. Bouwmeester et al. [86] developed and in-silico tested a system that allows an RPA to autonomously communicate with ATCOs. With the rapid development of UAVs, in autonomous multi-UAV systems, the flight plan will change as the environment or mission changes, and traditional centralized control is no longer applicable.

The aircraft navigation system determines the aircraft position and guides its flight according to a predetermined route. A machine vision-based UAV navigation system has been proposed previously [87]. Khansari-Zadeh et al. [88] developed a vision-based neural network-based estimation and navigation algorithm that was validated for a navigation distance as long as 1 800 m. Wu et al. [89] presented an extended Kalman filter approach for UAV visually aided inertial navigation using only an inertial measurement unit (IMU), camera, and magnetometer as navigation sensors. To realize autonomous navigation systems of UAVs in difficult rescue areas, Zhilenkov et al. [90] used an artificial convolutional neural network. Using image motion velocity fields (i.e., optical flow), navigation based on computing the camera path became highly demanded, especially for relatively small and even micro-scale UAVs. Popov et al. [91] proposed a method for integrating the optical flow and inertial navigation systems for UAV navigation.

Surveillance is necessary for safe flying and ATM. At present, the traditional airborne monitoring system mainly includes the traffic collision avoidance system (TCAS), the transponder, and the terrain avoidance and warning system discrete devices. Among them, the TCAS is widely used for effectively solving encounters, and it has also been shown to initiate collision threats in hectic air traffic. Recently, the aircraft collision avoidance problem has been described as a part of the observable Markov decision process, which promoted the development of aircraft collision avoidance systems [92]. Durand et al. [93] proposed a neural network based on unsupervised learning, which could calculate almost optimal trajectories, thus solving the problem of two aircraft collision avoidance with the highest reliability when calculating the headings with the resolution of a few milliseconds. Sislak et al. [94] presented two agent-based cooperative decentralized aircraft collision avoidance algorithms that worked with different levels of coordination autonomy, making realistic assumptions about the accuracy of flight execution (integrating required navigation performance), where planning interlaced with the planned execution phase. Because the uncertainty in the data and the model used for detection can lead to the TCAS alarm errors, Schetinin et al. [95] proposed an uncertainty estimation model for early warning systems based on Bayesian learning. More accurate results can be obtained using Bayesian model averaging, which estimates the predicted posterior probability distribution.

Considering the unpredictable outbreak in the use of air transport systems and the demand for higher levels of automated operation, the abovementioned research lacks attention to single-pilot operation which should require higher cognitive efforts. Through literature collection and sorting, we found that less relevant research discusses this topic. Liu et al. [96] proposed a novel cognitive pilot-aircraft interface concept, which uses knowledge-based adaptive systems that play an important role in helping individual pilots accomplish important missions and safety-critical tasks for modern commercial transport aircraft. An intelligent autopilot system (IAS) [97] was proposed, which learns piloting skills by imitating and observing human expert pilots. The IAS may allow to solve some common problems associated with flight uncertainties in automatic FO, and allows to manually establish a control model. Lungu et al. [98] presented an automatic structure that controls the aircraft's lateral-directional motion during its landing process. The system uses a classical controller and a radio-navigation system to control the lateral angular deviation of the aircraft's longitudinal axis relative to the runway.

7. Conclusions

ATM is widely studied in several different fields, owing to its complexity and criticality to a variety of stakeholders including passengers, airlines, regulatory agencies, and ATCOs. The last two decades have seen a dramatic increase in the development and proposal of various types of AI techniques for ATM. We present a solid review of applications of AI techniques for ATM, by discussing several carefully selected literature studies. The studies are classified into four main categories, i.e., ATS, AM, ATFM, and FO. The published studies discussed in the present review suggest that AI-based approaches have indeed exhibited superior performance for managing rapidly growing air traffic. This review also highlights several directions for future research.

Several literatures summarized in this paper provide examples of the usefulness of AI technology in the ATM field. In conclusion, despite the promising (and in some cases impressive) results that have been presented by the reviewed studies, significant challenges exist. One such challenge is in providing a clear rationale for the model type and structure selection for a given ATM mission. Another outstanding challenge is in understand what makes a specific architecture or algorithm effective for a given ATM mission. These are the main issues that will continue to attract the attention of the AI research community and ATM work teams in the future.

8. Future directions

AI methods are being developed and deployed worldwide in different fields, owing to the superior capability of AI to handle problems that are described by complex input-output relationships. Below, we list some topics (from auxiliary unit work to improving safety to reducing RPA impact) which we believe merit future research.

(i) Improving crew's working efficiency. Using AI techniques to construct the mission models, behavior models, error models, and workload models for the flight crew can help the crew break through their physiological and mental bounds and is likely to significantly reduce the associated workload. This is likely to become especially important in emergency situations, and is likely to improve flight safety.

(ii) Establishing decision support systems. Combined with stochastic models, AI methods are recommended for establishing decision support systems for aircraft rotation management, which contains schedule disruption management functionality that would allow to handle unexpected schedule perturbations.

(iii) Solving conflicts in high-density airspace. The multi-agent approach with RL is the most promising one for future ATFM. This method can solve the problem of conflicts between air intersections and junctions in high-density air traffic management. The future development of this field should seek to coordinate the actions of agents autonomously, reduce manual intervention, and introduce novel evaluation functions that will affect or be affected by restrictive measures in air traffic flow management procedures. Another important direction is to improve the prediction of real-time traffic movements, especially for identification and tracking of aircraft flows.

(iv) Realizing autonomous flight. With the rapid development of different aviation vehicles, it is necessary to increase research on flying ad hoc network systems. Mobile communication technology is essential for real-time interconnection of aircraft in the air, information interaction and task assignment. This will help realize autonomous flight for intelligent ATM.

(v) Reducing RPA impacts. The exponential growth of RPA is expected to pose its own challenges and have significant impacts on ATM, with clear consequences for both human-machine systems and infrastructure to support highly automated and trusted autonomous operations [99]. Considering the intelligent recognition characteristics of AI, a cybersecure intensive future RPA CNS architecture is required to support the RPA traffic management system in low-altitude airspace and the common airspace in which RPA coexist with manned aircraft.

References

[1] GHAHRAMANI Z. Probabilistic machine learning and artificial intelligence. Nature, 2015, 521: 452–459.

[2] LU H M, LI Y J, CHEN M, et al. Brain intelligence: go beyond artificial intelligence. Mobile Networks and Applications, 2018, 23(2): 368–375.

[3] ZANG Y P, ZHANG F J, DI C A, et al. Advances of flexible pressure sensors toward artificial intelligence and health care applications. Materials Horizons, 2015, 2(2): 140–156.

[4] HAMET P, TREMBLAY J. Artificial intelligence in medicine. Metabolism, 2017, 69: S36–S40.

[5] TANG J, LAO S, WAN Y. Systematic review of collision-avoidance approaches for unmanned aerial vehicles. IEEE Systems Journal, 2021. DOI: 10.1109/JSYST.2021.3101283.

[6] HUANG M H, RUST R T. Artificial intelligence in service. Journal of Service Research, 2018, 21(2): 155–172.

[7] LEE J, DAVARI H, SINGH J, et al. Industrial artificial intelligence for industry 4.0-based manufacturing systems. Manufacturing Letters, 2018, 18: 20–23.

[8] PREVEDELLO L M, ERDAL B S, RYU J L, et al. Automated critical test findings identification and online notification system using artificial intelligence in imaging. Radiology, 2017, 285(3): 923–931.

[9] YASEEN Z M, EL-SHAFIE A, JAAFAR O, et al. Artificial intelligence based models for stream-flow forecasting: 2000-2015. Journal of Hydrology, 2015, 530: 829–844.

[10] TANG J, LIU G, PAN Q T. A review on representative swarm intelligence algorithms for solving optimization problems: applications and trends. IEEE/CAA Journal of Automatica Sinica, 2021, 8(10): 1627–1643.

[11] DUNJKO V, BRIEGEL H J. Machine learning & artificial intelligence in the quantum domain: a review of recent progress. Reports on Progress in Physics, 2018, 81(7): 074001.

[12] RUSSELL S J, NORVIG P. Artificial intelligence: a modern approach. Malaysia: Pearson Education Limited, 2016.

[13] BOLIC T, RAVENHILL P. SESAR: the past, present, and future of european air traffic management research. Engineering, 2021, 7(4): 448–451.

[14] TANG J. Conflict detection and resolution for civil aviation: a literature survey. IEEE Aerospace and Electronic Systems Magazine, 2019, 34(10): 20–35.

[15] TANG J, PIERA M A, GUASCH T. Coloured Petri net-

based traffic collision avoidance system encounter model for the analysis of potential induced collisions. Transportation Research Part C: Emerging Technologies, 2016, 67: 357–377.

[16] TANG J, ZHU F, PIERA M A. A causal encounter model of traffic collision avoidance system operations for safety assessment and advisory optimization in high-density airspace. Transportation Research Part C: Emerging Technologies, 2018, 96: 347–365.

[17] ABADI M, BARHAM P, CHEN J, et al. Tensorflow: a system for large-scale machine learning. Proc. of the 12th USENIX Symposium on Operating Systems Design and Implementation, 2016: 265–283.

[18] GIBNEY E. DeepMind algorithm beats people at classic video games. Nature, 2015, 518: 465–466.

[19] CLOTHIER R A, WILLIAMS B P, HAYHURST K J. Modelling the risks remotely piloted aircraft pose to people on the ground. Safety Science, 2018, 101: 33–47.

[20] GIORDAN D, HAYAKAWA Y S, NEX F et al. Preface: the use of remotely piloted aircraft systems (RPAS) in monitoring applications and management of natural hazards. Natural Hazards and Earth System Sciences, 2018, 18(11): 3085–3087.

[21] GIBNEY E. Google AI algorithm masters ancient game of Go. Nature, 2016, 529(7587): 445–446.

[22] WANG F Y, ZHANG J J, ZHENG X, et al. Where does AlphaGo go: from church-turing thesis to AlphaGo thesis and beyond. ACTA Automactica Sinica, 2016, 3(2): 113–120.

[23] SILVER D, SCHRITTWIESER J, SIMONYAN K, et al. Mastering the game of Go without human knowledge. Nature, 2017, 550(7676): 354–359.

[24] International Civil Ariation Organization. Air traffic management (16th edition). Montreal: International Civil Aviation Organization, 2016.

[25] NGUYEN T, LIM C P, NGUYEN N D, et al. A review of situation awareness assessment approaches in aviation environments. IEEE Systems Journal, 2019, 13(3): 3590–3603.

[26] CROSS S E. Qualitative reasoning in an expert system framework. https://www.ideals.illinois.edu/handle/2142/69273.

[27] TANG J. Analysis and improvement of traffic alert and collision avoidance system. IEEE Access, 2017, 5: 21419–21429.

[28] STEEB R, MCARTHUR D, CAMMARATA S, et al. Distributed problem solving for air fleet control: framework and implementations. https://www.rand.org/pubs/reports/R2728.html.

[29] THORNDYKE P W, MCARTHUR D, CAMMARATA S. Autopilot: a distributed planner for air fleet control. RAND CORP SANTA MONICA CA, 1981.

[30] GOSLING G D. Design of an expert system for aircraft gate assignment. Transportation Research Part A: General, 1990, 24(1): 59–69.

[31] LI W G, ALVES C J P, OMAR N. An expert system for air traffic flow management. Journal of Advanced Transportation, 1997, 31(3): 343–361.

[32] KRISHNAN G. Self learning automated ATC using AI technique and entropy approach. Journal of Computer Science and Technology, 2012, 3(5): 5190−5194.

[33] FINDLER N V, LO R. Distributed artificial intelligence approach to air traffic control. IEE Proceedings D (Control Theory and Applications), 1991, 138(6): 515–524.

[34] MEYER F, KROEGER R, HEIDGER R, et al. An approach for knowledge-based IT management of air traffic control systems. Proc. of the 9th International Conference on Network and Service Management, 2013: 345–349.

[35] KUCHAR J K, YANG L C. A review of conflict detection and resolution modeling methods. IEEE Trans. on Intelligent Transportation Systems, 2000, 1(4): 179–189.

[36] RADANOVIC M, EROLES M A P, KOCA T, et al. Surrounding traffic complexity analysis for efficient and stable conflict resolution. Transportation Research Part C: Emerging Technologies, 2018, 95: 105–124.

[37] JILKOV V P, LEDET J H, LI X R. Multiple model method for aircraft conflict detection and resolution in intent and weather uncertainty. IEEE Trans. on Aerospace and Electronic Systems, 2018, 55(2): 1004–1020.

[38] ISAACSON D, ROBINSO J. A knowledge-based conflict resolution algorithm for terminal area air traffic control advisory generation. Proc. of the AIAA Guidance, Navigation, and Control Conference and Exhibit, 2001: 4116.

[39] TRAN N P, PHAM D T, GOH S K, et al. An intelligent interactive conflict solver incorporating air traffic controllers' preferences using reinforcement learning. Proc. of the Integrated Communications, Navigation and Surveillance Conference, 2019. DOI: 10.1109/ICNSURV.2019.8735168.

[40] KULKARNI V B. Intelligent air traffic controller simulation using artificial neural networks. Proc. of the International Conference on Industrial Instrumentation and Control, 2015: 1027–1031.

[41] KLUVER C, KLUVER J, ZINKHAN D. A self-enforcing neural network as decision support system for air traffic control based on probabilistic weather forecasts. Proc. of the International Joint Conference on Neural Networks, 2017: 729–736.

[42] YANG J, ZHANG J, WANG H. Urban traffic control in software defined internet of things via a multi-agent deep reinforcement learning approach. IEEE Trans. on Intelligent Transportation Systems, 2020, 22(6): 3742–3754.

[43] YLINIEMI L, AGOGINO A K, TUMER K, et al. Simulation of the introduction of new technologies in air traffic management. Connection Science, 2015, 27(3): 269–287.

[44] ARICO P, BORGHINI G, DI FLUMERI G, et al. Human factors and neurophysiological metrics in air traffic control: a critical review. IEEE Reviews in Biomedical Engineering, 2017, 10: 250–263.

[45] JARVIS P A, WOLFE S R, ENOMOTO F Y, et al. A centralized multi-agent negotiation approach to collaborative air traffic resource management planning. Proc. of the 22nd Innovative Applications of Artifical Intelligence Conference, 2010: 1787–1792.

[46] SCHEFERS N, GONZALEZ J J R, FOLCH P, et al. A constraint programming model with time uncertainty for cooperative flight departures. Transportation Research Part C: Emerging Technologies, 2018, 96: 170–191.

[47] WU W H, ZHANG X J, CAI K Q, et al. A dynamic adaptive NSGA-II algorithm for sector network flight flow optimization. Proc. of the Integrated Communications, Navigation, Surveillance Conference, 2018: 3F2–1.

[48] CAO X B, ZHU X, TIAN Z C, et al. A knowledge-transfer-based learning framework for airspace operation complexity evaluation. Transportation Research Part C: Emerging Technologies, 2018, 95: 61–81.

[49] MIAO S, CHENG C Q, ZHAI W X, et al. A low-altitude flight conflict detection algorithm based on a multilevel grid spatiotemporal index. ISPRS International Journal of Geo-Information, 2019, 8(6): 289. DOI: 10.3390/ijgi8060289.

[50] AGOGINO A K, TUMER K. A multiagent approach to managing air traffic flow. Autonomous Agents and Multi-Agent

Systems, 2012, 24(1): 1–25.
[51] MCCREA M V, SHERALI H D, TRANI A A. A probabilistic framework for weather-based rerouting and delay estimations within an airspace planning model. Transportation Research Part C: Emerging Technologies, 2008, 16(4): 410–431.
[52] CRUCIOL L, LI W, BARROS A D. Air holding problem solving with reinforcement learning to reduce airspace congestion. Journal of Advanced Transportation, 2015, 49(5): 616–633.
[53] YU Y, YAO H P, LIU Y M. Aircraft dynamics simulation using a novel physics-based learning method. Aerospace Science and Technology, 2019(87): 254–264.
[54] WANG C, WANG J, ZHANG X D. Autonomous navigation of UAV in large-scale unknown complex environment with deep reinforcement learning. Proc. of the Global Conference on Signal and Information Processing, 2017: 858−862.
[55] SCHIRMER S, TORENS C, NIKODEM F. Considerations of artificial intelligence safety engineering for unmanned aircraft. Proc. of the International Conference on Computer Safety, Reliability, and Security, 2018: 465–472.
[56] GERDES I, TEMME A, SCHULTZ M. Dynamic airspace sectorisation for flight-centric operations. Transportation Research Part C: Emerging Technologies, 2018, 95: 460–480.
[57] INSAURRALDE C C, POLISHCHUK V. Multi-aviation airspace: insights into knowledge technologies for comprehensive air navigation. Proc. of the IEEE/AIAA Digital Avionics Systems Conference, 2017. DOI: 10.1109/DASC.2017.8102107.
[58] KRAVARIS T, VOUROS G A, SPATHARIS C. Learning policies for resolving demand-capacity imbalances during pre-tactical air traffic management. Proc. of the German Conference on Multiagent System Technologies, 2017: 238−255.
[59] CAI K Q, ZHANG J, CHI Z. Using computational intelligence for large scale air route networks design. Applied Soft Computing, 2012, 12(9): 2790–2800.
[60] BOLIC T, CASTELLI L, COROLLI L, et al. Reducing ATFM delays through strategic flight planning. Transportation Research Part E: Logistics and Transportation Review, 2017, 98: 42–59.
[61] SANDAMALI G G N, SU R, SUDHEERA K L K, et al. A safety-aware real-time air traffic flow management model under demand and capacity uncertainties. IEEE Trans. on Intelligent Transportation Systems, 2021, 23(7): 8615−8627.
[62] OZGUR M, CAVCAR A. 0–1 integer programming model for procedural separation of aircraft by ground holding in ATFM. Aerospace Science and Technology, 2014, 33(1): 1–8.
[63] HEYMSFIELD S B, PETERSON C M, BOURGEOIS B, et al. Human energy expenditure: advances in organ-tissue prediction models. Obesity Reviews, 2018, 19(9): 1177–1188.
[64] BERTSIMAS D, GUPTA S. Fairness and collaboration in network air traffic flow management: an optimization approach. Transportation Science, 2016, 50(1): 57–76.
[65] CHEN J, CHEN L, SUN D. Air traffic flow management under uncertainty using chance-constrained optimization. Transportation Research Part B: Methodological, 2017, 102: 124–141.
[66] CAI K Q, ZHANG J, XIAO M M, et al. Simultaneous optimization of airspace congestion and flight delay in air traffic network flow management. IEEE Trans. on Intelligent Transportation Systems, 2017, 18(11): 3072–3082.
[67] BREIL R, DELAHAYE D, LAPASSET L, et al. Multi-agent systems to help managing air traffic structure. Journal of Aerospace Operations, 2017, 5(1/2): 119–148.
[68] DAL SASSO V, FOMENI F D, LULLI G, et al. Planning efficient 4D trajectories in air traffic flow management. European Journal of Operational Research, 2019, 276(2): 676–687.
[69] PECHOUCEK M, SISLAK D, PAVLICEK D. Autonomous agents for air-traffic deconfliction. Proc. of the 5th International Joint Conference on Autonomous Agents and Multiagent Systems, 2006: 493−512.
[70] TUMER K, AGOGINO A K. Distributed agent-based air traffic flow management. Proc. of the 6th International Joint Conference on Autonomous Agents and Multiagent Systems, 2007: 342–349.
[71] WOLFE S R, JARVIS P A, ENOMOTO F Y. A multi-agent simulation of collaborative air traffic flow management. USA: IGI Global Press, 2009.
[72] LI W, DIB M V P, ALVES D P. Intelligent computing methods in air traffic flow management. Transportation Research Part C: Emerging Technologies, 2010, 18(5): 781–793.
[73] CRESPO A, LI W, BARROS A. Reinforcement learning agents to tactical air traffic flow management. International Journal of Aviation Management, 2017, 1(3): 145–161.
[74] CRUCIOL L, ARRUDA A C D, LI W. Reward functions for learning to control in air traffic flow management. Transportation Research Part C: Emerging Technologies, 2013, 35: 141–155.
[75] BAYEN A, GRIEDER P, MEYER G. Lagrangian delay predictive model for sector-based air traffic flow. Journal of Guidance Control & Dynamics, 2003, 28(5): 1015–1026.
[76] WOLFE S R. Supporting air traffic flow management with agents (Technical Report No. SS-07-04). http://aaai.org/Papers/Symposia/Spring/2007/SS-07-04/SS07-04-027.pdf.
[77] TORRES S. Swarm theory applied to air traffic flow management. Procedia Computer Science, 2012, 12: 463–470.
[78] LI W, LEITE A F, RIBEIRO V F, et al. Towards intelligent system wide information management for air traffic management. Proc. of the International Conference on Security, Privacy and Anonymity in Computation, Communication and Storage, 2017: 584–593.
[79] OZMEN E P, PEKEL E. Estimation of number of flight using particle swarm optimization and artificial neural network. Advances in Distributed Computing and Artificial Intelligence Journal, 2019, 8(3): 27–33.
[80] LU X, KOGA T. System wide information management for heterogeneous information sharing and interoperability. Proc. of the IEEE 13th International Symposium on Autonomous Decentralized System, 2017: 199–204.
[81] NARINS M. A holistic approach to the provision of communications, navigation, and surveillance for the 21st century national airspace system. Proc. of the Integrated Communication, Navigation, and Surveillance Conference, 2015. DOI: 10.1109/ICNSURV.2015.7121995.
[82] OSECHAS O, MOSTAFA M, GRAUPL T, et al. Addressing vulnerabilities of the CNS infrastructure to targeted radio interference. IEEE Aerospace and Electronic Systems Magazine, 2017, 32(11): 34–42.
[83] LI J T, HAN S, TAI X X, et al. Physical layer security enhancement for satellite communication among similar channels: relay selection and power allocation. IEEE Systems Journal, 2019, 14(1): 433–444.
[84] APIECIONEK L, MAKOWSKI W, BIERNAT D, et al. Practical implementation of AI for military airplane battlefield support system. Proc. of the International Conference on

Human System Interactions, 2015: 249−253.
[85] SANCHEZ-LOPEZ J L, SUAREZ F R A, BAVLE H, et al. AEROSTACK: an architecture and open-source software framework for aerial robotics. Proc. of the International Conference on Unmanned Aircraft Systems, 2016: 332–341.
[86] BOUWMEESTER L, CLOTHIER R, SABATINI R, et al. Autonomous communication between air traffic control and remotely piloted aircraft. Proc. of the 16th Australian International Aerospace Congress, 2015: 48–87.
[87] SINOPOLI B, MICHELI M, DONATO G, et al. Vision based navigation for an unmanned aerial vehicle. Proc. of the IEEE International Conference on Robotics and Automation, 2001, 2: 1757–1764.
[88] KHANSARI-ZADEH S M, SAGHAFI F. Vision-based navigation in autonomous close proximity operations using neural networks. IEEE Trans. on Aerospace and Electronic Systems, 2011, 47(2): 864–883.
[89] WU A D, JOHNSON E N, PROCTOR A A. Vision-aided inertial navigation for flight control. Journal of Aerospace Computing, Information, and Communication, 2005, 2(9): 348–360.
[90] ZHILENKOV A A, EPIFANTSEV I R. Problems of a trajectory planning in autonomous navigation systems based on technical vision and AI. Proc. of the IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering, 2018: 1032–1035.
[91] POPOV A, MILLER A, MILLER B, et al. Optical flow and inertial navigation system fusion in the UAV navigation. Proc. of the SPIE-Unmanned/Unattended Sensors and Sensor Networks XII, 2016: 29−44.
[92] KOCHENDERFER M J, HOLLAND J E, CHRYSSANTHACOPOULOS J P. Next-generation airborne collision avoidance system. Lincoln Lab Journal, 2012, 19(1): 17–33.
[93] DURAND N, ALLIOT J M, MEDIONI F. Neural nets trained by genetic algorithms for collision avoidance. Applied Intelligence, 2000, 13(3): 205–213.
[94] SISLAK D, VOLF P, PECHOUCEK M. Agent-based cooperative decentralized airplane-collision avoidance. IEEE Trans. on Intelligent Transportation Systems, 2011, 12(1): 36–46.
[95] SCHETININ V, JAKAITE L, KRZANOWSKI W. Bayesian learning of models for estimating uncertainty in alert systems: application to air traffic conflict avoidance. Integrated Computer-Aided Engineering, 2018, 25(3): 229–245.
[96] LIU J, GARDI A, RAMASAMY S, et al. Cognitive pilot-aircraft interface for single-pilot operations. Knowledge-Based Systems, 2016, 112: 37–53.
[97] BAOMAR H, BENTLEY P J. An intelligent autopilot system that learns piloting skills from human pilots by imitation. Proc. of the International Conference on Unmanned Aircraft Systems, 2016: 1023–1031.
[98] LUNGU M H, LUNGU R. Automatic control of aircraft lateral-directional motion during landing using neural networks and radio-technical subsystems. Neurocomputing, 2016, 171: 471–481.
[99] KISTAN T, GARDI A, SABATINI R. Machine learning and cognitive ergonomics in air traffic management: recent developments and considerations for certification. Aerospace, 2018, 5(4): 1−18.

Biographies

TANG Jun was born in 1988. He received his Ph.D. degree from the Engineering School of the Autonomous University of Barcelona in 2015. He was dedicated to the Ph.D. studies in the technical innovation cluster on aeronautical management at the Universitat Autonoma de Barcelona, Sabadell, Spain. He is currently an associate professor with the College of Systems Engineering, National University of Defense Technology, China. His research interests include CPNs, state space, and air traffic management.
E-mail: tangjun06@nudt.edu.cn

LIU Gang was born in 1983. He received his B.S. and M.S. degrees from Naval Arms Command Institute, China in 2005 and 2008, respectively, and Ph.D. degree from National University of Defense Technology, China, in 2013. His research interests include intelligent information processing, optimization and path planning.
E-mail: liugang@hnist.edu.cn

PAN Qingtao was born in 1996. He received his B.S. degree from Ocean University of China in 2020. He is currently a researcher in the Science and Technology on Information Systems Engineering Laboratory, National University of Defense Technology, majoring in control science and engineering. His research interests include intelligent optimization algorithm, system simulation and cluster control.
E-mail: panqingtao@nudt.edu.cn