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Survey of RPAS Autonomous Control Systems Using Artificial Intelligence

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ABSTRACT In this survey, we look at the overall idea of Remotely Piloted Aircraft Systems (RPAS) and autonomous control, as well as RPAS infrastructure, levels of autonomy, and current benefits and difficulties in the field when utilizing Artificial Intelligence. While current remotely piloted aircraft systems have a manual pilot operator to provide double-layer security and safety, studies show that having RPAS with a fully autonomous vehicle at its centre could significantly improve decision-making and overall mission precision, accuracy, safety, and efficiency.

INDEX TERMS RPAS, UAV, AI, drones, control.

I. INTRODUCTION

Remotely Piloted Aircraft Systems (RPAS) capabilities have dramatically expanded in the last decade [1]. The continued development of autonomous systems and their integration into RPAS has been particularly groundbreaking. RPAS have practical applications across a multitude of industries, including military [2]–[7], commercial [8], and agriculture [9]. AI-driven RPAS offer the promise of efficient mission capabilities, system adaptability, accurate analysis, and comprehensive decision-making [10], and have captured the imagination of military and civilian communities alike [11]–[13], with an estimated 8% of polled US citizens owning an RPA [14].

Although the terms "autonomous" and "automatic" are often used interchangeably in common parlance, they are technologically distinct from one another, with autonomous capabilities still being developed and representing a futuristic end goal for the RPA industry. An autonomous system is an enhanced version of an automatic system, wherein the degree of human intervention in system management is significantly reduced. While an automated system merely executes pre-programmed solution algorithms, an autonomous system uses algorithms to process and learn from new data; in other words, autonomous systems possess a level of intelligence that allows them to craft dynamic solutions independently.

Autonomous unmanned systems incorporate various technologies, including communication, control, and security. They are increasingly integrated into the components of Remotely Piloted Aircraft Systems (RPAS), which include the Remotely Piloted Aircraft (RPA), referred to in some literature as drones or Unmanned Aerial Vehicles (UAV); a Ground Control Station (GCS); and a communication data link [12].

Recent advancements in AI and RPAS technologies have led to a higher level of onboard intelligence [15]. However, a fully autonomous and independent RPAS has yet to emerge: partly due to safety concerns, the vehicles continue to be primarily managed by humans through remote control systems, though both government and commercial use of RPAS would benefit from eliminating the need for an actively involved human pilot. A number of heuristics are used to assess RPAS autonomy, including a six-, and three-level classification. In this survey, we discuss both of them. Besides providing a roadmap for understanding the industry's progress towards complete autonomy, these categorizations also allow researchers to understand the trade-offs of automation for different purposes as they consider how best to utilize AI in an RPA control system.

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This paper also explores how rapidly advancing AI technology is increasingly applied to RPA control systems. The goal is to understand the potential efficiency of a fully autonomous system and its use in real-world situations. Introducing AI into RPAS poses several interesting and complex problems tethered to the level of autonomy. As RPAS become more ubiquitous and are put to practical use by industry and individuals alike, the airspace will likely become more crowded; the increased aircraft in the sky may present safety, ethics, and regulatory challenges related to air traffic [16], among other concerns.

The remainder of this paper is divided as follows: Section II motivates our survey. We then discuss various autonomous control levels of RPAS in Section III. The broad concept of RPAS and autonomous control, including RPAS infrastructure and levels of autonomy, is explored. Next, in Section IV, we discuss current benefits and challenges in the field; Section V discusses the desirable Autonomous Control Levels, while Section VI explores examples of current advances in AI applied to RPAS, including supervised, unsupervised, and reinforcement learning; Section VII presents future challenges and trends, followed by conclusions.

II. MOTIVATION FOR CONCEPT OF AUTONOMOUS CONTROL

One study of civil drone safety found that 70-80% of RPA accidents are due to human factors [17]. Particularly in unpremeditated descent scenarios, loss of control, and controlled flight into terrain [18], artificial intelligence is a potential avenue to reducing human error.

RPAS contain several sub-systems that comprise three key components: an RPA, a GCS, and the communication system [12], [19], as seen in Figure 1. Autonomous Control is achieved when an RPA is equipped with onboard computers [20] that allow RPAS to control navigation and decision-making processes under significant uncertainty with minimal or no human interference [21].

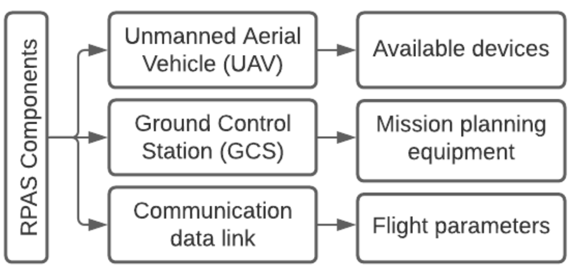

FIGURE 1. The main components of RPAS.

An RPA is a stand-alone remote-controlled or autonomous, fixed or rotary-wing aircraft that can complete missions [19]. RPAs differ from one another in size, structure, autonomy, and the goal they serve, and thus, for high-level discussions, are often classified based on a variety of factors, most commonly maximum take-off weight (MTOW), operational altitude, level of autonomy, launch method, ownership, and airspace class [22]. Other studies have classified RPAs based on MTOW, endurance, altitude, operational area radios, and usage [22], [23]. The fuel system (disposable or multi-aircraft) and wing system (fixed-wing, rotary-wing, blimps, and flapping-wing) are other standard classifications. In this survey, we present the classification of RPAs provided by the US army, as seen in Table 1.

TABLE 1. RPAs classification according to [24].

Category	Size	Maximum Gross Takeoff Weight (lbs)	Normal Operating Altitude (ft)	Airspeed (knots)
Group 1	Largest	>1320	>18,000	Any airspeed
Group 2	Larger	<1320	<18,000 MSL	Any airspeed
Group 3	Large	<1320	<18,000 MSL	<250
Group 4	Medium	21-25	<3,500	<250
Group 5	Small	0-20	<1,200 AGL	<100

The aerial platform of an RPA includes the airframe, the navigation system, the power system, and the payload. The airframe is the RPA's main physical structure. The navigation system ensures that RPAs can communicate with the control station to exchange real-time data. The power system is used to provide energy to the system and is chosen based on the RPA's airframe, with the most common options being Wankel rotary engines, fuel cells, electric and lithium polymer batteries. The payload consists of instruments or other equipment used to acquire specific data (e.g. RGB/multispectral camera, video camera, thermal or other sensors).

Ground Control Stations (GCS) are ground-based software applications that communicate with the RPA and govern the sensors, surveillance cameras, and other payloads installed on the aircraft. A GCS can display real-time data on RPA performance, action, and position [25], [26]. When human assistance is needed, human pilots use GCS to monitor and control the RPA sensors and decision-making patterns and send the RPA commands. Although RPAs are capable of autonomous flight through the use of a pre-defined flight plan, the current state of autonomous technology mandates that a pilot remain available, whether physically or remotely, in case of emergency, malfunction, or reaction to uncertainties [19]. Using real-time information about the RPA position, performance, and decision patterns provided by the GC, the pilot can take appropriate action, including overriding the flight path and pre-programmed procedures to take control manually. A remote pilot's presence will continue to be crucial to RPA performance and safety until such a time as fully autonomous systems can handle the enormous amount of real-time data generated during flight with high precision and accuracy.

The centrepiece of the RPA communication system is a radio connection between the airborne vehicle and the ground [19]. A continuous communication link must be maintained if an emergency requires the pilot to control the vehicle remotely.

While a manual pilot operator provides double-layer security and safety in current remotely piloted aircraft systems,

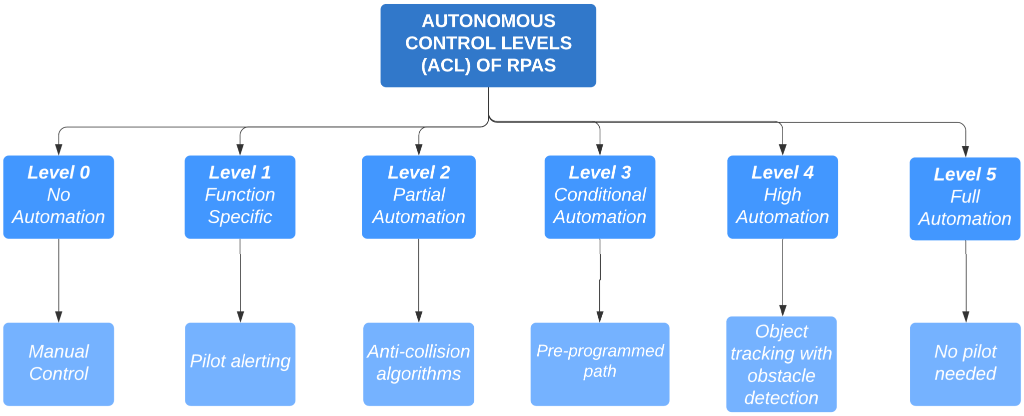

FIGURE 2. 6-level automation of RPAS.

having RPAS with a fully autonomous vehicle at the system's center could significantly improve decision-making and overall mission precision, accuracy, and efficiency. Artificial Intelligence, and more specifically, Machine Learning (ML) and Deep Learning (DL) techniques, play a significant role in the development of fully autonomous vehicles, with the primary objective of allowing intelligent decision-making and adaptation to environmental changes without human intervention by finding correlations within a set of data or past action sequences. Deep Learning enables network elements to monitor, learn from, and predict various communication-related parameters such as traffic patterns, collision patterns, user, and device location. Machine Learning and Deep Learning especially offer benefits in RPAS applications that act as a human proxy in completing high-risk, high uncertainty, or dangerous missions. Ultimately, the level of autonomy is determined by the extent to which RPAS can mimic or surpass human senses and decision-making capabilities to respond to uncertainties and avoid false action patterns effectively.

III. AUTONOMOUS CONTROL LEVELS (ACL) OF RPAS

All commercially and recreationally available drones map to the Sheridan Autonomy Scale [27], the standard scale for measuring autonomy in complex autonomous manufactured systems, or to the three predominant RPA-related scales for measuring autonomy: a ten-level system proposed by researchers in the Air Force Research Laboratory's Air Vehicles Directorate at the beginning of the civilian drone era [28], a modern six-level system [29], [30], and a three-level system that classifies autonomy across all mission planning stages [10]. This paper will explore the examples of current solutions classified as six- and three-level scales.

A. 6-LEVEL SCALE

First, we explore the 6-level scale of automation - the summary of it is presented in Figure 2.

1) LEVEL 0 (NO AUTOMATION)

RPAs are controlled manually and/or remotely using a human pilot. The performance range of RPAS that falls into this level is bound to receive commands and instructions from the GS monitored by a human pilot [31]. Having a remote control system or a steering wheel embedded with the RPA can effectively act as a safety pilot and overwrite any command that does not fit well with the risks of a mission ahead. A DJI Tello is one example of such RPA [32].

2) LEVEL 1 (PILOT ASSISTANCE/FUNCTION SPECIFIC)

This level indicates the lowest autonomy domain where an automated system is integrated into the RPA system and can assist in at least one vital function over a finite time. The pilot remains in control of the overall operation and safety of the vehicle. A level 1 RPA can use navigation sensors and algorithms to direct the vehicle. To accomplish an accurate navigation process, the RPA can be equipped with a Proportional Integral Derivative (PID) controller to be tuned for navigation sensor readings [33]. A PID is a tool that regulates temperature, pressure, speed, and other procedures using a temperature sensor (e.g. thermocouple) as an input, comparing the desired temperature to the actual temperature, and providing an output to the control system to perform attitude control.

A level 1 RPA uses a Global Navigation Satellite System (GNSS) receiver to perform basic commands (steering mode) and stabilize flights, a mission plan to perform automatic mission (autonomous mode), home location, and path saver to complete smart return to the home mission. This ranges from a simple recreational photo or video footage to high-end asset inspections in the industry. At this level, sense and avoid features are available to alert the pilot of the drone's proximity to obstacles – the avoid part is up to the manual input of the pilot. An instance of this is DJI Mavic Air, used to inspect oil pipelines by Microsoft and DJI. It can automatically detect cracks while the pilot retains control of its movement [34].

3) LEVEL 2 (PARTIAL AUTOMATION)

The vehicle can control both attitude and acceleration/deceleration, while the pilot is still responsible for the safety of the operation and ready to take over the control of navigation, altitude, and speed in the time of malfunction of a reaction to a condition. At this level, a pre-programmed flight path is uploaded to RPAS, and the vehicle can execute commands in time of need. Although the pilot is actively monitoring flight conditions, all anti-collision (front, back, sides) sensors are active at this level. The anti-collision modules embedded in the sensors can analyze the situation, calculate the maneuvers, and propose navigation advice to the vehicle. RPAS then either acknowledges or rejects the proposed maneuver and takes action respectively [33]. Examples include DJI Mavic Pro 2 or Autel Robotics EVO, which can perform mapping, surveying, spraying, and measuring [35].

4) LEVEL 3 (CONDITIONAL AUTOMATION)
The transition from level 2 to level 3 is significant; at level 3, vehicles have environmental detection capabilities, make informed decisions in uncertainties, and manage safety-critical functions [21]. However, the human pilot needs to remain alert to take over control if the vehicle requests pilot intervention or if the system cannot execute a command. As an example, a drone flies along a pre-programmed flight path when onboard sensors detect an obstacle. After the detection (e.g. a building in the flight path), an RPA will stop and send an alarm of an object close by to the pilot. The pilot then manually corrects the heading/altitude before the drone continues to fly along its pre-programmed path. Examples include obstacle avoidance while maintaining the pre-planned path by DJI Air2S [36].

5) LEVEL 4 (HIGH AUTOMATION)
A level 4 RPA can conduct the flight task and monitor the environment in most circumstances because RPAS contain a fixed set of rules that dictates the system's behaviour. The vehicle can intervene in case of an unexpected event or a system failure. However, a human pilot has the option to take over control if the condition falls out of the autonomous authorization limit of the vehicle. The vehicles at this level are expected to have a backup system so that if a system fails, the vehicle can still execute commands and operate. The system in level 4 is not equipped with an autonomous learning system [37], preventing the vehicle from learning new patterns. As an example, the drone senses obstacles in the flight path while recording and tracking target objects and, at the same time, actively avoids contact by changing heading and/or altitude. Examples include DJI Inspire 2 in cinematography [38].

6) LEVEL 5 (FULL AUTONOMY)
Level 5 vehicles meet or exceed all lower autonomy levels and can control and monitor the environment in all circumstances with no expectation of human intervention. However, a human pilot is optional, and remote controlling systems are embedded in most level 5 vehicles only for safety reasons. All levels are equipped with full-time automation sensors. Intelligence is enabled given the use of AI and deep learning embedded with the central system of the vehicle so that it can learn patterns and algorithms to generate new risk management and be ready for any potential uncertainties with minimum pilot assistance. Currently, fully autonomous RPAS are undergoing testing and are not available in the production stage [39].

B. 3-LEVEL SCALE
Overall, these six levels of autonomy can also be described in a more concise three-level classification system that discusses low-level autonomy, medium-level autonomy, and high-level autonomy, as seen in Figure 3. This three-level scale is distinct as it considers mission planning in its classification of autonomy [10].

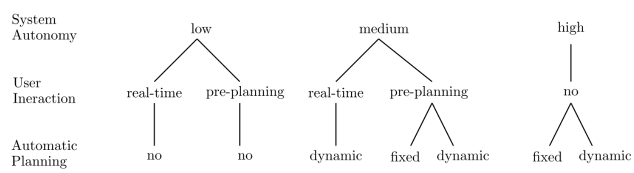

FIGURE 3. Proposed autonomous control levels (ACLs) in the context of a single mission stage [10].

Regardless of the classification system, the ideal level of autonomy is dictated by mission context and goals.

IV. BENEFITS AND CHALLENGES OF CURRENT ACL
Even at the current low or medium levels of autonomy, RPAS have been adopted or proposed as a solution across a number of industries, often with the result of making jobs less costly for humans, allowing humans to focus their specialized skills and energy elsewhere, or otherwise improving mission efficiency and outcomes. Among recent applications are rice seed sowing [40], parasite and pest management [41], monitoring soil moisture [42], and general crop surveillance [43] in agriculture; crime analysis [44] and highway surveillance [45] in policing; disaster relief and hunting hurricanes [46], radiological mapping and threat assessment [47], fire detection [48] and firefighting [49], [50], reforestation [51], and mountain search and rescue missions [52] in environmental risk and preservation; and assorted other tasks like 3D mapping [53], [54], product delivery, and transportation [55], surveillance [56], navigating and mapping indoor environments [57], cleaning buildings [50], aerial imaging, large-scale area surveying [58], [59].

While leaps forward in RPAS adoption and AI-driven autonomy have made these applications feasible and provided incalculable benefits, RPAS use also introduces several challenges across four major areas of concern: licensing, safety, ethics, and cost.

Regulating RPAs is an ongoing challenge that is likely to become more complex as RPAs become more intelligent. The Federal Aviation Administration (FAA) and Transport Canada (TC) have established specific rules for a small RPA that apply to commercial and recreational use. However, their ambiguities continue to be unexplored [60].

Safety concerns remain relevant to both piloted and autonomous aircraft, with the challenge of how best to ensure safety in all events of a collision or cyberattack [61] remaining a topic of debate. In extreme circumstances, an RPA with the currently available levels of automation does not possess sufficiently sophisticated pre-programmed commands to furnish it with the ability to decide an appropriate next course of action. A manual radio link may be used to regain human control of the aircraft temporarily; however, if data and radio links are not available, it may not be possible to re-establish human control. In the event of a loss of control and communication (i.e. C2 lost link), most RPA and ground control stations have one or more of the following fail-safe actions available. The most basic option is to hover in place for a pre-defined time and wait to re-establish the C2 link. Once the time runs out, the next option is to either return to home (RTH) or land. The return to home option can be along a direct path back to the take-off location or a smart RTH during which the RPA retraces its route back along with any pre-programmed waypoints it navigated through prior to loss of C2. An additional option is the inclusion of rally points which serve as alternate landing sites should, for example, the original home location be too far for the RPA to reach based on current battery levels.

RPAs pose a severe risk for planes in the sky [17], [23], [62]. This is the main reason why under the current regulatory framework, there is a strict requirement to maintain an unaided visual line of sight (VLOS) with the RPA at all times. This requirement can be waived under certain circumstances requiring a special flight operations certificate (SFOC) or temporary waiver. Upon loss of VLOS, the pilot must be able to manually maneuver the aircraft back into a position, enabling them to re-establish VLOS quickly and more safely. Some of the automated fail-safe systems described above (e.g. smart RTH) can help in this regard, but what if the pilot does not realize that they have lost sight of the aircraft? Perhaps future AI and ML systems can be taught to recognize situations that may lead to loss of VLOS and automatically warn the pilot and/or take corrective actions to ensure line of sight is maintained as per the current regulations.

Should the RPA pilot lose control of the vehicle and enter another aircraft's buffer zone, the RPA could collide with other aircraft and cause damage upon impact. This risk, among others, makes proactive traffic management a focal point of autonomous RPA development and AI as applied to RPAS. While regulatory agencies like the FAA and Canada's TC consider how best to regulate, writ large, possibly revolutionary changes in airway traffic, researchers turn to the question of how to deploy AI to provide onboard safety features in individual aircraft. One feature still being developed and optimized is collision avoidance.

Collision avoidance in RPAs [63], allows a moving autonomous body to navigate a space while avoiding static or dynamic objects in its path by interpreting data gleaned from a camera [64], ultrasonic or laser sensors, GPS data [65] and, recently, by monitoring air disturbance to predict object placement relative to the automaton [66]. Recent research into optimizing RPAs collision avoidance has considered many unique facets of the problem, ranging from the immediate low-quality high-speed image detection needs of drone racing enthusiasts [67], [68] to the maintenance of velocity for the sake of fuel or battery economy [69] to deploying RPAs indoors [70]; and has taken its cues from diverse approaches, including by building an RPA that intentionally crashes [71], learning from the complex ballistics of starlings [72] and considering advanced drone swarm dynamics [73], [74].

As RPAS are deployed as human proxies, particularly in monitoring and surveillance tasks, the ethics of using RPAs in policing or military missions has come into question. Although the public opinion of military RPA-strikes on foreign targets at the current level of autonomy is favourable, with 58% of polled Americans approving, and US military officials are beginning to consider deploying fully autonomous RPAS in combat situations rhetorically, ethicists and policymakers alike debate the use of an RPA in warfare both in terms of the targets and the pilots responsible for operating the RPAS [75]–[80].

Cost is an additional challenge. Deploying RPAS can be expensive in terms of the equipment required to integrate RPAS into a mission, the time cost of human training, and the potential technical issues that might occur. Designing a specialized RPAS for a specific mission or service can add costs since some RPAS features may need to be improved or enhanced to equip the vehicle for a given mission properly.

V. DESIRABLE ACL

The answer to these questions is not simple. It may seem obvious that a fully autonomous RPAS is the ultimate goal; however, we will need all levels of autonomous control to manage, monitor effectively, and coordinate the RPA maneuvers and the commands it receives. Earlier, some of the most critical current issues have been introduced. It is essential to note that reaching level 5 of ACL (fully autonomous) will not address these issues appropriately in some cases. It is most likely that the current challenges will escalate, as having a fully autonomous RPAS comes with uncertainties in terms of the level of intelligence, quality of pattern recognition, and accuracy of deep learning algorithms. Additionally, developing a fully autonomous RPAS is not feasible with sensitive sensors. To achieve level 5 of ACL, several challenges need to be addressed, such as ensuring that the software in RPAs is certified in terms of security and safety in decision-making and maneuver patterns, especially in adverse weather and collision avoidance strategies.

There is no consensus on the desired level of autonomy [81]; however, the ACL of an RPA should be defined by the context of its use [82]. Ideally, an RPA will have an ACL that allows it to complete its mission successfully. For example, Table 2 presents a roadmap for RPAs in the USA. 2020 has come and gone, yet class A has not yet been

TABLE 2. Autonomy (safety) class of drone and future roadmap (class A - E).

Class	Concept	Guidance	Navigation	Control	Scenarios
A 2020	Bio-inspired flight capable of flying to the destination only with vision.	Risk avoidance, real time route plan and re-plan, determination of event driven type, FTA (fault tree analysis) and crisis management capacity, and intelligent flight by AI learning.	Capable of momentarily recognizing change in three-dimensional environment including weather and radio wave, ability of momentarily recognizing three-dimensional environment with respect to real time mapping,and accurate localization momentary recognition.	Accurate, robust 3D trajectory tracking and optimization ability, wide range high speed visual SLAM standard equipment.	Capable of flying a long distance only using the ground support system (UTM), the camera and the like even without using GPS, and landing at the destination with high accuracy. Capable of flying like a bird with a landmark.
B 2019	Fault tolerance/ fail safe/flight that never crashes.	Capable of abnormality diagnosis during drone flight, and environment adaptivenes is present, Capable of determination whether to continue or stop the mission. Capable of SAA (Sense and Avoid).	Capable of recognizing the level of risk of the abnormal state of the drone itself at the time of occurrence of an abnormality, and changing the control structure and so forth.	A robust flight controller. Capable of reconstruction of make up for every failure or capable of adapting. Configure a control system that never crashes at worst.	Capable of analyzing the cause of the occurrence of a failure from the abnormality diagnosis result of the mulitcopter, and having an ability of autonomous determination of the presence and absence of flight continuation. Achievement of a drone that never crashes even though carrying out a crash landing using the parachute, airbag, and auto rotation autonomous startup ability.
C 2017	Autonomous flight (autonomous flight in a non GPS environment).	Capable of autonomous flight by an on-board camera and so on not using GPS regarding programmed flight of Class D.	Capable of all sensing and state estimation. Also partially capable of abnormality diagnosis function of drone during flight.	Regarding programmed flight of Class D, visual SLAM, optical flow standard equipment.	Capable of carrying out hovering, landing, and trajectory tracking flight by a camera without GPS, and reporting general failure such as communication failure, sensor failure, and propulsion system failure during flight.
D 2015	Autonomous flight (autonomous flight in a non GPS environment).	Capable of programmed flight such as waypoint flight and trajectory tracking flight. Flight plan, flight analysis, and guidance by a skilled person using the ground station.	Almost capable of sensing and state emission, and capable of abnormality presence and absence determination of a sample plane. All measurement and recognition by a skilled person.	The control command is calculated by an on-board micro-computer or a PC. The control is not intervened by an operator.	Capable of trajectory tracking control, take-off and landing, and hovering using GPS. In addition, also capable of detecting communication failure, GPS and electronic compass failure, battery power reduction, and so forth.
E 2013	Remotely operated.	All decision making (guidance function) are carried out by a skilled operator.	Almost measurement and recognition (navigation function) are carried out by a skilled operator.	All control (control including altitude control) are carries out by a skilled operator.	All control, hovering, take-off and landing, and target trajectory tracking are carried out by a skilled operator.

achieved, and even RPAs that can be considered class B are not guaranteed to be crash-safe.

There are technological challenges that come with implementing just the right level of automation, but there are also moral and ethical issues that follow suit—using the example above with a vehicle with SAE level 5 autonomy. A car with no steering wheel or gas and brake pedals seems innovative; however, how viable is it in a real-world system? There are guaranteed to be some people who are opposed to the idea. No system that is ever designed is fault-proof. What happens when the system glitches and there are problems that happen on the road? Who is held accountable? These are the kind of questions that are raised when a new system is brought into play. This goes without saying that when there are negatives, there are also positives. An automatic system that drives cars around also eliminates the possibility of human error on the road. It negates the problem that people could run red lights or drive too fast and cause crashes. The points brought up here all help design a system that is just perfect for the situation. A level 5 ACL is not always the correct choice when designing a system at this wide scale.

VI. ARTIFICIAL INTELLIGENCE APPLICATION FOR AUTONOMOUS RPAs

To automate the use of RPAS while increasing the control system security and thus decreasing the need for a remote pilot intervention, specific advanced AI strategies can be integrated. There are four main categories of automation tasks currently, shown in Figure 4. The first one is path planning. The primary purpose is to find a safe flight path with minimum energy consumption on the premise of completing RPAS mission. The second task is collision avoidance. It allows to autonomously sense obstacles and avoid collisions during drone missions using sensors and AI-based software. The third one is take-off and landing. As the name suggests - these tasks are related to all procedures involving the start and end of the flight. Finally, we have Simultaneous Localization and Mapping (SLAM). It allows RPAS to build a map of its surroundings and then plan a path or trajectory to where it is going.

Moreover, machine learning algorithms can be classified into three categories of supervised, unsupervised, and reinforcement learning [83], and the application of each method towards the above-mentioned aspects to achieve autonomous RPAS is discussed in subsections below and summarized in Table 3.

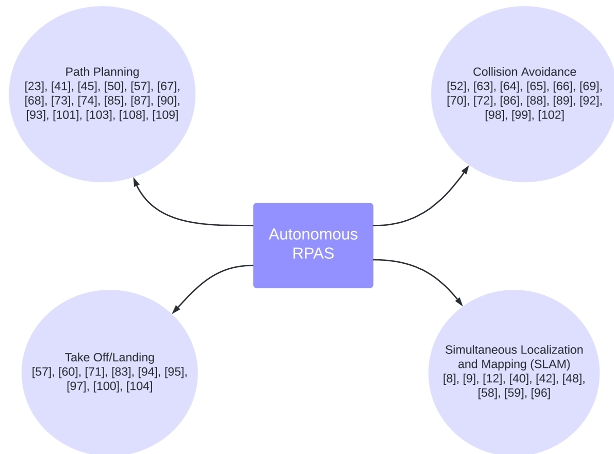

FIGURE 4. Autonomous RPAS based on four main tasks - path planning, SLAM, collision avoidance and autonomous take off/landing. The literature examples related to these features are indicated in the bubbles.

A. SUPERVISED LEARNING

Supervised learning algorithms train the machine using labelled training data to predict the outcomes for unforeseen data. In other words, the objective of a supervised learning model is to predict the correct label for newly presented input data [84]. There are two types of supervised learning algorithms - regression and classification. Supervised learning algorithms are now used in many domains; however, they are not without their limitations. Specific datasets are required for training classifiers, and decision boundaries can be overtrained without suitable examples.

Let us discuss some examples of supervised learning towards autonomous RPAS. Boussemart *et al.* [85] used a classic supervised learning method for autonomous path planning. For each hidden state in the learning paradigm, an emission probability function was analyzed to determine the set of most likely observables. The supervised learning model then used the pre-defined state labels to learn the most

TABLE 3. Summary of AI techniques applied to various tasks.

Technique	Reference	Task	Level of Automation	Application
Supervised learning	[85]	Path planning	Level 4	Autonomous path planning
	[86]	Collision avoidance	Level 4	Optimal trajectory of avoidance maneuver
	[87]	Path planning	Level 4	Autonomous decision-making based on natural hazards
	[88]	Collision avoidance	Level 3	Remote sensing
	[89]	Collision avoidance	Level 3	Obstacle avoidance
	[90]	Path planning	Level 3	Multi-RPAs coverage path planning
Unsupervised learning	[92]	Collision avoidance	Level 2	Post flight analysis
	[93]	Path planning	Level 3	Planning the number of target points in the cruising area
	[94]	Take off/landing	Level 2	Delivery planning
	[95]	Take off/landing	Level 3	Autonomous delivery
	[96]	SLAM	Level 3	Accurate digital terrain model
Reinforcement learning	[97]	Take off/landing	Level 4	Autonomous delivery
	[98]	Collision avoidance	Level 4	Autonomous navigation
	[100]	Take off/landing	Level 3	Landing on a moving platform
	[101]	Path planning	Level 3	Multi-RPAs path planning
	[102]	Collision avoidance	Level 4	Multi-RPAs collision avoidance
	[103]	Path planning	Level 3	Autonomous surveillance
	[104]	Take off/landing	Level 2	Optimized take off/landing

likely path to be used by the RPA. Majka [86] aimed to determine an optimal trajectory of avoidance maneuver of an RPA and minimize the time of performance when avoiding an aircraft flying at a much higher speed. The RPA was supposed to be capable of detecting a potential mid-air collision and performing avoidance maneuvres. The authors of [87] used RPAs to collect images of different natural hazards such as landslides, floods and earthquakes. Then they proposed a methodological framework for immediate assessment of the events based on supervised learning to allow autonomous decision-making for an RPA. Niu *et al.* [88] used an RPA resolution and waveband aware design with supervised learning to collect remote sensing aerial images with drones optimally. On the other hand, [89] compared the performance of the genetic algorithm to a supervised neural network with the goal of obstacle avoidance while flying in a 3D digital map simulator. Finally, [90] discussed the opportunities related to supervised learning and multi-RPAs coverage path planning.

B. UNSUPERVISED LEARNING

Unsupervised learning is a machine learning technique that draws an inference from the datasets without human intervention and does not require previous knowledge of data. It is helpful in scenarios where we do not have access to labelled or purely standard data and let the machine work independently to learn. The first step to the method is the selection of a model that will determine the number of hidden states it should maintain [85]. The model is made to find its structure from the input data and discover groups with similar examples within the data. This algorithm plays a significant role when patterns for a situation are unknown and performs complex processing tasks. It helps to collect data in real-time, and thus all the input data is analyzed and labelled in the presence of the learners. Unsupervised learning is also used in fault detection, which was introduced to identify safe states and classify any patterns that were considered abnormal as fault states [91].

Ahn *et al.* [92] described anomaly detection in an RPA using K-means clustering, which is an unsupervised learning algorithm wherein observed data is divided into clusters using information about the distance between the data points. The flight data was collected for testing in advance and/or in real-time to find anomalies using a set of training data. When the model is trained, it is then tested, verified, and finally used as an anomaly detection scheme for either post-flight analysis or online anomaly monitoring.

Yue and Zhang [93] used a model decomposition technique to plan the number of target points in the cruising area. This is based on RPAs and uses the K-means algorithm to find the number of target points planned in the cruise area. A simulated annealing algorithm is then used to track the path of each RPA cruise area. Ferrandez *et al.* [94] investigated the effectiveness of using RPAs in delivery networks. An optimization algorithm is designed to determine an optimal number of launch sites. The algorithm also computes the minimal delivery time, and K-means clustering is used to find launch locations for the RPAs. Chang and Lee [95] proposed a new approach for drone delivery system since, in the previous approaches, routing of the drone was a significant concern. An effective delivery route was discovered by shifting weights that, in turn, moved the center of the clusters in the K-means algorithm. Callow, May and Leopold [96] found a solution for poorly represented conventional records of a tropical cyclone, tsunamis and other events. Images of the overwash fans (costal deposits) are collected using RPAs and Structure-from-Motion (SfM) with the K-means technique to remove the vegetation. This will help create a high resolution and accurate digital terrain model (DTM) of the overwash.

C. REINFORCEMENT LEARNING

Reinforcement Learning (RL) is a subcategory of machine learning that allows machines to learn from their actions, similar to the way humans learn from past experiences. This method is a practical approach because it allows an RPAS or RPAS team to learn and navigate [97] through a changing environment without a model for the environment [98]. Although RL has been around for some time, it is now prevalent to combine it with deep learning techniques. The word ''deep'' refers to multiple layers of an artificial neural network model that replicates the structure of a human brain by processing a large amount of training data and significant computing power. Deep reinforcement learning uses a trial and error approach, which generates rewards and penalties as a drone moves forward on its mission [99]. Rodriguez-Ramos [100] used a DRL framework wherein a learning agent can receive experience vectors and rewards from the environment. These are used to find the optimum action to take in each step.

Pham *et al.* [98] used a DRL algorithm implemented in an RPA to accomplish tasks in an unknown environment. This model is an agent-environment interaction wherein an agent builds up knowledge of its surrounding environment by accumulating experience through interacting with the environment. Maza *et al.* [101] used the Cooperative and Geometric Learning Algorithm (CGLA) as their principal DRL method. This approach is used to help multi-agent RPAS navigate through uncertain environments. The path-planning algorithm generates a cost metric for each state in the map, which the RPA then uses to navigate through the lowest-cost path towards its target. Wang *et al.* [102] used a two-stage reinforcement approach for collision avoidance in a multi-RPAs framework. The first step is a pre-training stage wherein the RPA interacts with a noisy environment and gets all the observations and rewards at a given time interval. These data are then fed into a shared policy to compute all control commands of different robots. The results are then used in the second stage, which is the unsupervised training stage using a deep deterministic policy gradient algorithm. Lee and Cha [103] implemented a reinforcement algorithm to optimize the flight path of autonomous surveillance drones. The authors used a simulation with a single surveillance drone, which used a reinforcement learning algorithm in an unknown grid area to find the optimized path autonomously. Finally, authors of [104] used GPU-based reinforcement learning to allow RPAS for autonomous take-off and landing in a variety of scenarios.

VII. FUTURE CHALLENGES AND TRENDS

Undoubtedly there will be more commercial applications of Remotely Piloted Aircraft Systems in the future. In September 2020, Amazon publicly announced its flying Ring camera, its first commercial smart drone that can launch itself if someone invades a home. Along with Wing Aviation and Flight Forward, developed by Google and UPS respectively, Prime Air, a drone delivery service also developed by Amazon, is expected to deliver the items to their customers within 30 minutes after they check out the orders online. This will enhance the supply chain in the economy without exacerbating the vehicle traffic system or pollution issues. This will also create an avenue for developing a public or private transportation system for autonomous aircraft in the future. This advancement will be supported by the expansion of AI/ML cloud platforms. For instance, Google, Azure IoT or AWS, will also play a critical role in drone development. AirMap, supported by Microsoft [105], is already an example of a traffic management platform for drones in the public and private sectors. Another interesting advancement of RPAS is its integration with other autonomous systems, such as underwater drones whose propellers can be used to fly in the sky or to push the system forward underwater. By the same token, RPAS can have wheels or chassis so that it can travel on the ground. These designs could make RPAS more adaptive to operate under various conditions in the future.

With the emergence of modern Internet of Things (IoT) sensors, such as RealSense technologies, lightweight yet powerful scanners with built-in LIDAR and depth sensors developed by EverDrone, a Swedish-based company, developing autonomous drone system to save people from cardiac arrest [106], there is no shortage of new applications on the horizon. RPAS are expected to transform the daily tasks of collecting and analyzing data in real-time, followed by improving many predictive models in research and business operations.

In parallel with the rapid growth of RPAS applications, new challenges will also come to light. One example of this is the authorization of RPAS for flight through national and international airspace [107]. The Specific Operations Risk Assessment (SORA) is a risk-based tool developed by the Joint Authorities on Rulemaking for Unmanned Systems (JARUS). This tool is used to determine the objectives required to gain authorization to fly in a given environment. The JARUS SORA tool considers the stakeholders on the ground (civilians) and in the air (aircraft) to evaluate the mission profile against the existing airspace infrastructure. The authorization of flight through international and national airspace also brings up the concern of airworthiness. Airworthiness is defined as ''the property of a particular air system configuration to attain, sustain, and terminate flight safely'' [108]. As RPAS attain greater levels of autonomy, it becomes more complex to certify their airworthiness. Although these vehicles have obtained the ability to conduct and complete a mission without any operational commands or a control link, their airworthiness will be challenging to certify using traditional techniques. An alternative to the traditional airworthiness certification process, concepts of operations can be evaluated and used to assess risk.

Another challenge is the relatively short lifespan of current battery systems, which remains one of the top issues followed by public safety concerns. In the event that RPAS loses battery power during the flight, even a lightweight drone could cause critical injuries to anyone that it impacts. A possible mitigation for this is a small parachute that deploys automatically when the aircraft departs its standard flight envelope helping the drone land safely on the ground while reducing kinetic energy. Providing that RPAS could land safely with a dead battery, it is worth designing a built-in self-recharging system so that it could maintain a GPS signal or even fly back home. For instance, a small solar panel [109], [110] on top of RPAS can help it recharge itself, possibly to the extent of preventing an accident.

Beyond the safety issues, there are privacy concerns associated with RPAS technologies used in surveillance activities. In early 2019, Autel Robotics announced their new EVO II equipped with an 8K video and 42MP camera, which could capture high-quality images from even distant aerial positions. As a consequence, this technology could be used to secretly violate personal privacy since the victim could be recorded through a window of a sky-high building. Acknowledging all of the potential benefits of RPAS also comes with some undesirable consequences such as the privacy issue, high-pitched noise, the risk of injury due to critical system failure and cyber security attacks. All of these factors will surely trickle down to an update in the regulations governing the use of RPAS.

Last but not least, the military applications of RPAS are not new, as autonomous aircraft systems have been deployed to conduct military attacks or for reconnaissance [44]. The advanced algorithms in object detection, such as You Only Look Once (YOLO) [111] or Single Shot Detector (SSD) [112], allow RPAS to become more intelligent in identifying the target of interest. On the one hand, this could prevent friendly-fire incidents, while on the other hand, the malicious uses of RPAS in terrorism and criminal activities are not beyond our imagination [113], [114].

VIII. CONCLUSION

This paper summarizes recent advancements in AI and RPAS technologies that have led to an increased level of onboard intelligence. With up to 80% of RPA accidents attributed to human error, implementing higher levels of artificial intelligence into RPAS control systems is a potential avenue to reducing accidents and increasing safety.

Currently, none of the commercially available RPAS offer level 5 (full autonomy) on the six-level scale of ACL or High on the three-level scale. Thus, RPAS that fly entirely on their own and learn along the way are still a thing of the (near) future.

The main challenges facing fully autonomous RPAS that rely mainly (or solely) on AI/ML algorithms to complete a task more safely and/or efficiently than human operators include: regulations and a clear definition of airworthiness, relatively short battery life, privacy concerns, C2 lost link behaviour, automated/assisted loss of VLOS recovery, and lack of a comprehensive sense and avoid system.

Thus, for now, at least, a remote pilot's presence will continue to be crucial to RPAS performance and safety until such a time as fully autonomous systems can handle the enormous amount of real-time data generated during a typical flight with the necessary precision and accuracy. In parallel to the required technology advance, the regulatory framework on a global scale also needs to be modernized to allow for fully autonomous RPAS operations.

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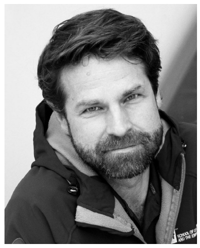

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