The Importance of Applying Artificial Intelligence on Unmanned Aerial Vehicle

Amine Mohammed Taberkit, Ahmed Kechida, and Abdelmalek Bouguettaya

Abstract Unmanned Aerial Vehicles (UAVs) are used in several applications and they are growing in popularity. Recent progress in unmanned aerial vehicles and artificial intelligence constitutes a new chance for an autonomous operation and flight. Nowadays, artificial intelligence and deep learning are driving the evolution of UAVs and fueling their autonomous future. Computer vision achieved very important progress in image classification and segmentation, and object detection, which make it very attractive research field when it is applied on unmanned aerial vehicle. Artificial intelligence is not only important and benefic, but can be rather, dangerous and serious matter since the UAVs learns through algorithms, and use that for future decision making. This work is a survey, where we present works, challenges and dangerous part of using artificial intelligence on UAVs.

Keywords UAV · Machine learning · Artificial intelligence · System · Drone

1 Introduction

An unmanned aerial vehicle (UAV) is defined as an aircraft, without any presence of a pilot on board. UAVs can be used to execute observation or detection (objects and/or persons) missions [1] through automatic or remote control. Taking aerial records have two main advantages, low cost and high movability. The reference standards developed by the UAV community are based on several parameters such as: flight altitude, endurance, speed, maximum payload and others [2]. The three main components of an UAV system are: the aircraft with common or other sensor features, Ground control station, and operator. There are a wide collection of UAV depending on their shapes, functionalities, configurations, and characteristics. Their hardware

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Fig. 1 Some quadcopter UAVs developed in CRTI research center

and software design can be modified with the task requirements. Quadcopter UAVs are one of the most favored kinds of small unmanned aerial vehicles because of their very simple mechanical construction and propulsion principle [3].

The civilian and military applications in several fields have got a drastic increase during the last years [4]. Some examples encompass the inspection of power line [5], wildlife conservation [6], building inspection [7], precision agriculture [8] and military surveillance [9].

In our research center we developed many Quadcopter UAVs, two among them were presented in the university Salah BOUBNIDER, Constantine 3 (Fig. 1).

2 Machine Learning

Machine Learning is defined as the capability allowing Artificial Intelligence (AI) systems to learn through data. A suitable definition for what learning covers is as follow: “A computer program is said to learn from experience E with respect to some of class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E” [4–10].

It can be defined as an evolving field of computational algorithms that are designed to mimic the human intelligence by learning through the surrounding environment [11]. This ability is the main key to develop successful machine learning.

Historically, the inception of machine learning can be traced to the seventeenth century. Pascal and Leibniz [12] developed machines that can emulate ability of add and subtract. Arthur Samuel, from IBM, invented the term “Machine Learning” and demonstrated the computer ability of playing checkers [13]. In 1958, Rosenblatt developed the perceptron and it was one of the early neural networks [14]. A great development was made in 1975 with the development of

Werbos multilayer perceptron (MLP) [15], and development of decision trees by Quinlan in 1986 [16]. Several works based on Machine learning algorithms have been proposed, including Adaboost [17] and random forests [18].

Deep learning (DL) in artificial intelligence (AI) has recently won a significant interest. Deep learning is applied in many fields such as autonomous systems, facial recognition, classification, and object detection. Among the most promising systems that can exploit deep learning are unmanned aerial vehicles (UAVs).

Convolutional Neural Networks (CNNs) is class of deep neural networks, and mostly applied to analyze visual imagery. CNN is considered as very good and powerful tool in the classification and object detection [19]. The structure of a CNN typically contains a feature extractor stage followed by a classifier [20].

Many object detectors have been proposed by the deep learning researchers, including R-CNN [21], R-FCN [22], YOLO [23] and SSD [24]. Many auspicious CNN architectures were recently proposed, such as CaffeNet [25] and GoogLeNet [26].

In Fig. 2, we represent the evolution of some object detectors over the years.

CNN architecture includes many layers of different types [27]:

- **Convolutional layers**, as their name indicates, they compute the convolution of the input image with the weights of the network [27].
- **Pooling layers**, the role of these layers is to diminish the size of the input layer using some local non-linear operations.
- **Normalization layers**, the aim of using those layers is to improve generalization of the CNN. Neurons used in these layers are sigmoid [28].
- **Fully-connected layers**, these layers are used in the last levels of the network [28].

We distinguish three different categories: supervised, unsupervised, and reinforcement learning (Fig. 3).

The reinforcement learning (RL) methods allow an agent to learn suitable actions with little or without knowledge about its environment, and it can be used to adapt to randomly changing environmental conditions [29, 30]. Reinforcement learning is actually very used in Robotics [31]. Despite the fact that deep learning has been extremely successful in many applications; it has remained limited to applications in which useful features can be created manually [32] or applications with fully observed low dimensional state space. Volodymyr et al. [32] used deep neural network to develop a new artificial agent, termed a deep Q-network, this agent can learn successful policies from high-dimensional input. In this work they demonstrated that a single architecture with very essential prior knowledge such as pixels and the game score as inputs can successfully learn control policies at human-level control. Alejandro et al., developed a deep reinforcement learning strategy for UAV autonomous landing on a moving platform [33].

Compared to supervised learning, the amount of feedback the learning system obtains in reinforcement learning is much less [34]. We can measure the learning

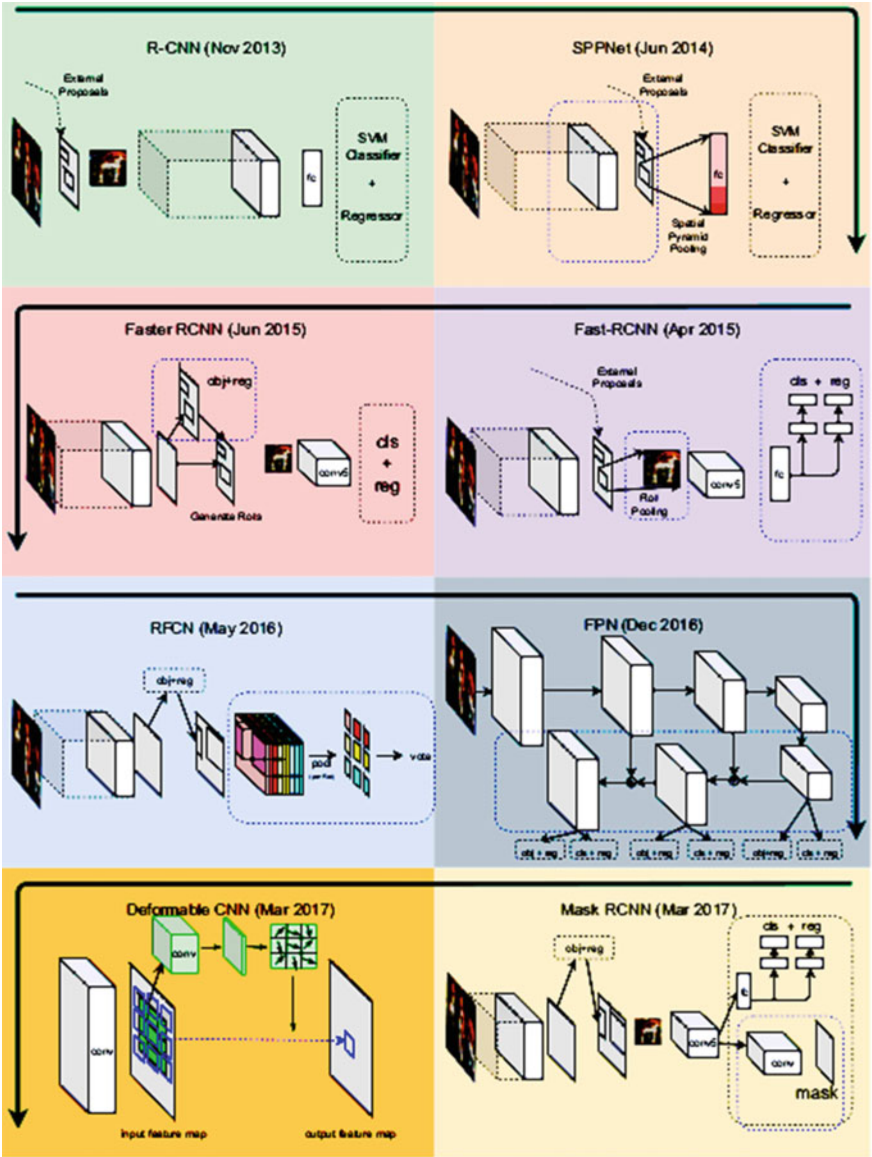

Fig. 2 Development of some objects detectors. Main developments in chronological order are: R-CNN, SPPNet, Fast-RCNN, Faster RCNN, RFCN, FPN, Mask RCNN [66]

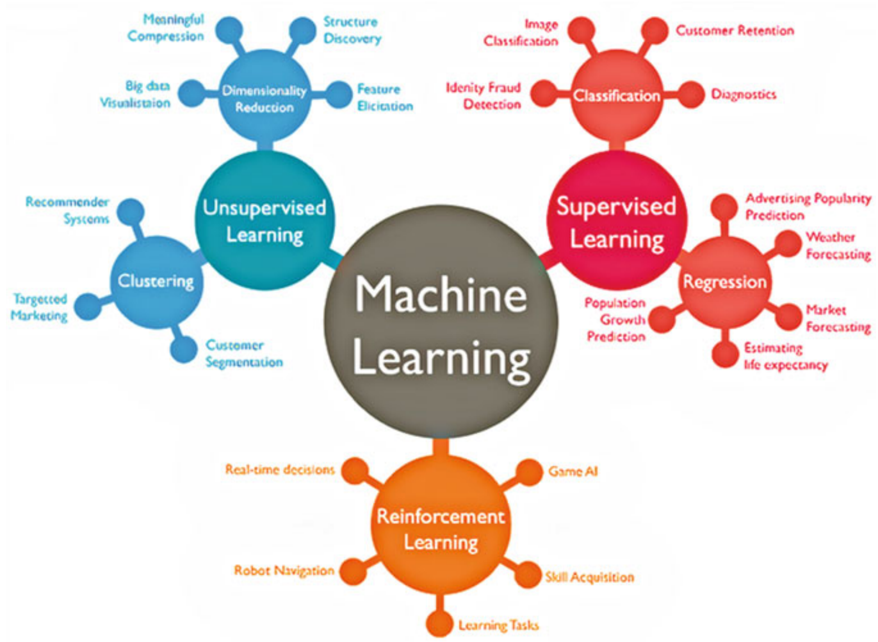

Fig. 3 Different fields and sub-fields of machine learning

performance by the number of correct answers, resulting in predictive accuracy. The difficulty comes from the possibility that learning can generalize new unclassified examples. In supervised and unsupervised learning, the data is usually considered static, and it is not the case in RL, where we notice a stochastic nature, this issue can be solved thought a constant interaction between evaluation and improvement of policies, and the use of learning rate adaption schemes [34]. Additionally, in front of some problems, it can be useful to provide agent with rewards for reaching intermediate sub-goals [34]. Christiano and et al., reported that we need to communicate complex goals to get sophisticated reinforcement learning systems, in their study they show that's possible to solve complex RL tasks without access to the reward function [35].

The most universally used machine learning methods are supervised learning methods, and we found them in several applications such as spam e-mail filtering, face recognition and identification, and medical helping diagnosis [36]. In supervised learning, the agent observes some input-output, and learns a map. The agent thought knowledge of the input; achieve the output labeling [37]. If the output is a discrete number of possible "classes", this is called a classification problems, if the output is continue it is called a regression [38]. In unsupervised learning, we haven't labeled output the agent focuses on observing patterns without labeled data. The aim is to search pattern structure and features embedded with data [39]. Clustering is an example of unsupervised learning. By eyeballing data, the agent will be able to discover the existence of many apparent clusters, then classify each data into the corresponding one [38].

3 Machine Learning Applied to UAVs for Autonomous Flight

UAV can be used in many different services, in the military context, the research are focused on enhancing the autonomy, with different kinds of missions [40]:

- Suppression of enemy air defense.
- Air-to-ground targeting scenario.
- Surveillance and reconnaissance.
- Avoidance of danger zones.

In the civilian context, UAVs could be used for purposes such as:

- Weather forecast/Disaster management [41, 42, 67].
- Urbane police surveillance.
- Agriculture production management [43].
- Border surveillance and inspection of infrastructures [44].
- Road Traffic Monitoring (RTM) [20].
- Emergency Response (ER) system [20].

Let us first cite what John Wyndham said: “The man and machine are naturally complementary” [45]. One of the current issues in AI is to make the link between heuristics used by human and programming. Another question is to know how to use the large data collected from various drone sensors. Many questions are pushing UAV research: how does a machine fly an aircraft like a human can, can a machine really “think” enough to fly autonomously? [46]. Beside those questions, UAVs have some challenges for control, real-time path planning and object recognition beneath uncertain environments [37]. To solve these problems, many approaches have been proposed such as negotiation approach, a heuristic approach, and graph theory [47]. Machine learning is an attractive approach to overcome these challenges for autonomous flight. It allows recognizing patterns or predicting from data [37].

Machine learning has contributed several fields of UAVs applications. Figure 4 shows the time-line of previous studies covered below [37].

Among the control strategies applied to an autonomous flight, we recognize the parameter tuning and real time path planning and navigation.

To compensate the limitations of the Proportional, Integral Derivative (PID) control systems technique, and operate in unpredictable and harsh environments, reinforcement learning (RL) is an active and successful area of research [48]. In reinforcements learning (RL) an agent is given a reward for every action it makes in

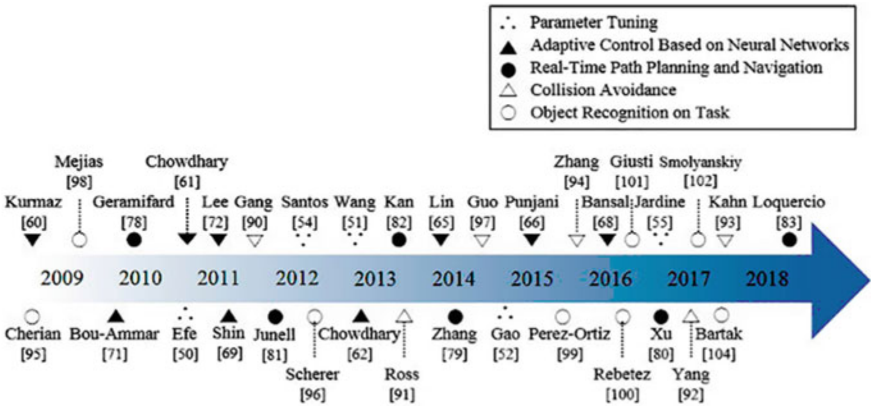

Fig. 4 Timeline of previous studies on machine learning applied on UAVs [37]

an environment with the objective to maximize the rewards. When we use reinforcement learning, it is possible to develop some optimal control policies for a UAV, and avoid making any assumptions about the aircraft dynamics [48].

Real-time path planning and navigation have been considered as elementary and required in UAVs for autonomous flight [37]. Many researchers have exploited and work on this area of research [49, 50, 68]. Loquerico et al. focused on civilian drones, because controlling the UAVs can become difficult when we work in urban areas, in those cases, the autonomous agent is not only expected to navigate while avoiding collisions, but to interact safely with other agents such as pedestrians or cars [51]. In this research they proposed a model that learns to navigate by initiating cars and bicycles and respecting the traffic rules.

Collision avoidance is also a very important research track, which can lead to new and very interesting technologies. Lei et al. [52] proposed a restructured Q-value learning algorithm based on reinforcement learning.

The autonomous navigation for large unmanned aerial vehicles (UAVs) is not problem; it is the micro and small UAVs, which fly at low altitude in crowded environments that meet many challenges in this area [53]. Ross et al., presented a small quadrirotor that navigates autonomously at low altitude through natural forest environments, They presented a MAV that autonomously fly at speeds of up to 1.5 m/s and altitudes of up to 4 m above the ground. They developed model based on the knowledge of a human pilot avowing collision with trees and they succeeded in more than 680 trees [53]. However, this method is limited when we need to perform longer flights and denser forests or any cluttered environments, The reactive method is limited in case of narrow field view, and causes most of time failures. Junell et al., proposed a high level reinforcement learning algorithm for UAVs to avoid collisions [54], they studied autonomous flight of UAV in unknown or uncertain environments, by taking pictures from disaster site. This method is efficient to solve the conflict between limited battery life and the big number of required iterations. However, it is limited in finding an efficient rout to the destination, and learning the best recharging point, in the aim of having the highest level of battery when it reaches the destination.

Nusrsultan.I and al, achieved experimental study of autonomous navigation by using real-time model based reinforcement learning [29], which solved some limitations of the previous method [54]. Moreover, deep learning contributed in many applications, such as construction of database for aerial image classification in emergency response, and development of suitable CNN training strategy with low-computational and low-cost low-power [55]. Dmitriy et al., worked also on emergency response, but this time was about wildfires detection using unmanned aerial vehicles and they compared several methods in term of speed and accuracy [56].

Cherian et al. proposed a semi-supervised machine learning (SSL) algorithm to estimate the altitude of UAVs using top down aerial images [57]. The basic idea of this study is to learn mapping between the texture information contained in an image with a possible altitude. However this approach is only suited for low altitudes and low speeds. Manjia Wu et al., proposed an approach to detect intruding drones in sensitive areas, in real time using deep learning [58].

Most of cited studies are based on supervised learning, which control known problems; it is suggested to aim researches on unsupervised learning methods [37]. Reducing time spent on classification is another issue, Gonzalo-Martin et al., proposed a strategy to reduce the time spent on the classification trough another method called "superpixel" segmentation. The results evince that while the classification accuracy was identical to the results generated by pixel-based approach, the time spent is dramatically decreased [28]. In the work of Gonzalo et al. [28], we didn't notice the tests of this method on unmanned aerial vehicle unlike the work of Taro Suzuki et al. [59] who used this method in vegetation classification.

In classification approach based on CNN, training is achieved using big dataset [29], which require high performance equipment for processing.

None of actual commercial drones, own sufficient control autonomy to achieve missions without human skills, which makes the missions slow, dangerous and not scalable [60].

In an interview with BBC, Bill Gates discussed AI and he told: "I am in the camp that is concerned about super intelligence … That should be positive if we manage it well. A few decades that thought the intelligence is strong enough to be a concern."

Tesla's Elon Musk believes that we should be very concerned when it comes to AI. According to Stephen Hawking AI could be harmful to humans: "I think the development of full artificial intelligence could spell the end of the human race".

Legal regulation should give to autonomous flight, great attention to eliminate the danger for people and things [61]. The existence of moving obstacles push the researchers to equip the drone with additional sensors such as: "Sonars" and "Passive infrared sensors" [61]. At the same level of concern, drones damages during flight couldn't be acceptable, and a check of components state and weather conditions should be performed. A mistake and danger come from flights under bridges, inside tunnels, or near high-voltage power lines, which could lead to GPS data errors, and by result drone flight errors [62].

In the other hand, the scope of permissible self-help in defending the privacy should be broad-ranging [63]. The worst scenario is when a drone escapes with intrusive recordings that can be a major harm. Another issue concerns the images of detectable individuals captured by aerial surveillance which should not be retained or shared except if it contains criminal suspicion activity [2]. Froomkin and Colangelo, suggested measures including forbidding weaponized robots, and mandating RFID chips and serial numbers, in the aim of identifying the robot's owner [63]. The United States has had a monopoly over the use of drones, but cannot maintain that much more [64]. These new weapons will not transform the international system, as did the fast increase of nuclear weapons and ballistic missiles, they still be highly dangerous and deadly [64]. In USA, the Federal Aviation Administration (FAA) predicted that 30,000 drones could be flying in sky in the next 20 years [65]. When the numbers of UAVs increase, many accidents can happen in the sky, that is why several models was proposed to make the process easy and safe [65].

4 Conclusion

UAVs are expected to be more used, as there is considerable demand in all sectors (private and public). UAVs have the potential to be used in huge number of applications. Many solutions are suggested such as: adding sensors, enhancements of data processing and others can expand their use. Artificial intelligence is the most important solution, to boost their performances and allowing them to be autonomous. However, the privacy, security and cognitive aspect should not be ignored. In this work we presented the UAVs, their application, than we presented machine learning and its application on UAVs, finally we spoke about the aspects of security and privacy which are solvable.

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