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SURVEY

A Survey of Indoor and Outdoor UAV-Based Target Tracking Systems: Current Status, Challenges, Technologies, and Future Directions

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ABSTRACT Due to their distinctive features, unmanned aerial vehicles (UAVs) have been recently exploited to support a wide range of applications. The features include low maintenance cost, compact size, and excellent capability of maneuvering. In particular, UAVs have the potential capabilities to support different technologies such as Internet-of-things (IoT) devices, sensors, cameras, and systems, thus, performing civilian, target tracking, industrial, and military applications. Specifically, target tracking has been recently configured as one of the most attractive applications of UAVs. With this, UAVs estimate and detect the behavior or locate a moving or a stationary item. Accordingly, several research efforts have been conducted to investigate the promising capabilities of UAVs in target-tracking missions, including indoor and outdoor tracking missions. This paper surveys UAV-based target tracking and monitoring for indoor and outdoor environments, where the deployment scenarios of such UAV-based systems are characterized and investigated. Furthermore, we discuss a set of practical design challenges of UAV-based target tracking systems, and thus, we provide a set of potential solutions to deal with these challenges. Specifically, we present a set of recent enabling technologies that might be integrated into UAV target tracking systems, including machine learning (ML), cloud computing, and emerging fifth-generation (5G) technologies. We also demonstrate a use-case scenario in which ML is used to facilitate indoor target tracking and monitoring. Finally, future research directions are outlined that can help in improving the efficiency of the UAV-based target-tracking systems.

INDEX TERMS Target tracking systems, drones, uncertain movement, indoor/outdoor deployment, artificial intelligence (AI).

I. INTRODUCTION

Unmanned aerial vehicles (UAVs), popularly known as drones, have been recently nominated as promising solutions to support a wide set of agricultural and civilian

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applications [1]. In particular, an UAV is a type of aircraft that needs no pilots on board to operate and can be controlled either autonomously or by using portable or ground-based control equipment [2]. To be specific, the concept of UAVs is not new, as it was initially suggested for military purposes at the beginning of the 20th century [3]. However, due to the revolutionary development in UAVs' manufacturing [4], several distinctive features have been recently offered for UAVs, which thus, enable the further deployment of UAVs to facilitate our daily life activities. The features include a long service lifetime, small size, low maintenance and operation cost, excellent maneuvering capability, and the capability of flying at different altitudes [4]. In addition, UAVs can hoover under various degrees of autonomy while offering an appealing paradigm to exploit various technologies, i.e., sensors, global positioning systems (GPSs), and cameras [5]. Furthermore, the fact that UAVs can self-optimize and operate completely and independently makes this technology highly valuable for completing tasks in situations where human availability is impossible (inaccessible locations). Accordingly, UAVs can be used to support a broad range of applications, including agriculture monitoring [6], [7], rescue missions [8], military tasks [9], transportation [4], communication coverage, [10], and target tracking [11].

In particular, target tracking tasks include estimating and detecting the behavior of an object, predicting the object's future location, or locating a moving or stationary item [12], [13], [14]. Accordingly, target tracking is crucial in a wide range of applications and sectors where it is needed to observe and track the movement of items, people, or vehicles. Target tracking has a variety of uses, including surveillance and rescue applications [15], [16], tracking desired activity [4], traffic management, military operations [9], industrial automation [17], and human activities recognition [18]. It is important to note that traditional tracking techniques have a number of practical drawbacks, including limited mobility, limited access to difficult-to-reach areas, high cost, large number of required personnel and equipment and relatively higher response time. However, in UAV-based target tracking systems, the integration of computer vision, localization methods, and sensing devices with UAVs allows precise identification of the considered target and improves navigation/control. UAV-based systems can also provide efficient tracking solutions at a low-cost and high level of security and reliability [5]. Furthermore, UAVs have the ability to rapidly cover large and inaccessible areas, whether indoors or outdoors. As a result, UAV technology is seen as a promising option for autonomous surveillance and target tracking missions [4]. Accordingly, tracking and detecting targets using UAVs have been recently investigated in the literature as a promising technique to perform a wide range of tasks, namely, those involving stationary and dynamic target tracking tasks [10], [13]. In addition, UAVs are able to autonomously perform target tracking tasks with and without prior knowledge of the target's movement behavior. For example, substantial studies have been conducted on using UAVs to search and locate stationery items [15], [16], [19]. colorblackIn [10], it has been assumed that the UAV(s) should detect and track one or multiple stationary target(s) to aid personnel in reaching the target(s) promptly. Unlike stationary target tracking scenarios, a dynamic target tracking scenario has been considered in [20]. The targets are assumed to move continuously from one place to another under known/unknown probability distributions. On the other hand, employing multi-UAVs for target tracking tasks has also been investigated in [21].

While UAV-based target tracking can be exploited to support a wide set of applications, several issues should be considered. For instance, the unavailability of information regarding the target behavior is one of the major aspects that might restrict the capabilities of UAV-based tracking systems. This occurs when the target is mysterious and has uncertain and unknown movement behavior. Another difficulty faced by UAV-based tracking systems is the limited UAV battery capacity, which restricts flight time and the UAV's searching capabilities [22]. Furthermore, the expected delay between UAVs and ground stations is one of the primary obstacles encountered during target tracking using UAVs. Therefore, it is essential to propose efficient latency-aware communication protocols to facilitate timely information exchange in UAV-based target tracking systems [23], [24], [25]. To end with, target camouflage, localization [26], collision avoidance [6], UAV size [27], and weather conditions [28] are also key challenges associated with using UAVs for target tracking.

A. CONTRIBUTION

Although many interesting surveys have been recently published to overview existing UAV-based target tracking systems (e.g., [29], [30], [31], [32], [33], [34], [35]), most of them only cover a subset of the challenges related to the efficient deployment of such systems. Inspired by this fact and the rapid growth of UAV capabilities and AI technologies, in this paper, we shed light on the different system classifications of existing UAV-based tracking systems. In addition, we discuss the recent exploitation of UAVs in several target-tracking scenarios. Then, we highlight some potential state-of-the-art enabling technologies that can be utilized to improve the performance of UAV-based tracking systems. To be specific, we summarize the main contributions of this paper as follows:

- We provide a detailed overview of recent classifications of UAV-based target tracking based on various aspects.
- Then, we discuss the target tracking policies and techniques used in indoor and outdoor systems. Furthermore, we illustrate some of the main challenges facing efficient designs of UAV-based target tracking systems.
- We also provide a set of potential enabling technologies that can be used to deal with the discussed challenges and improve tracking performance.

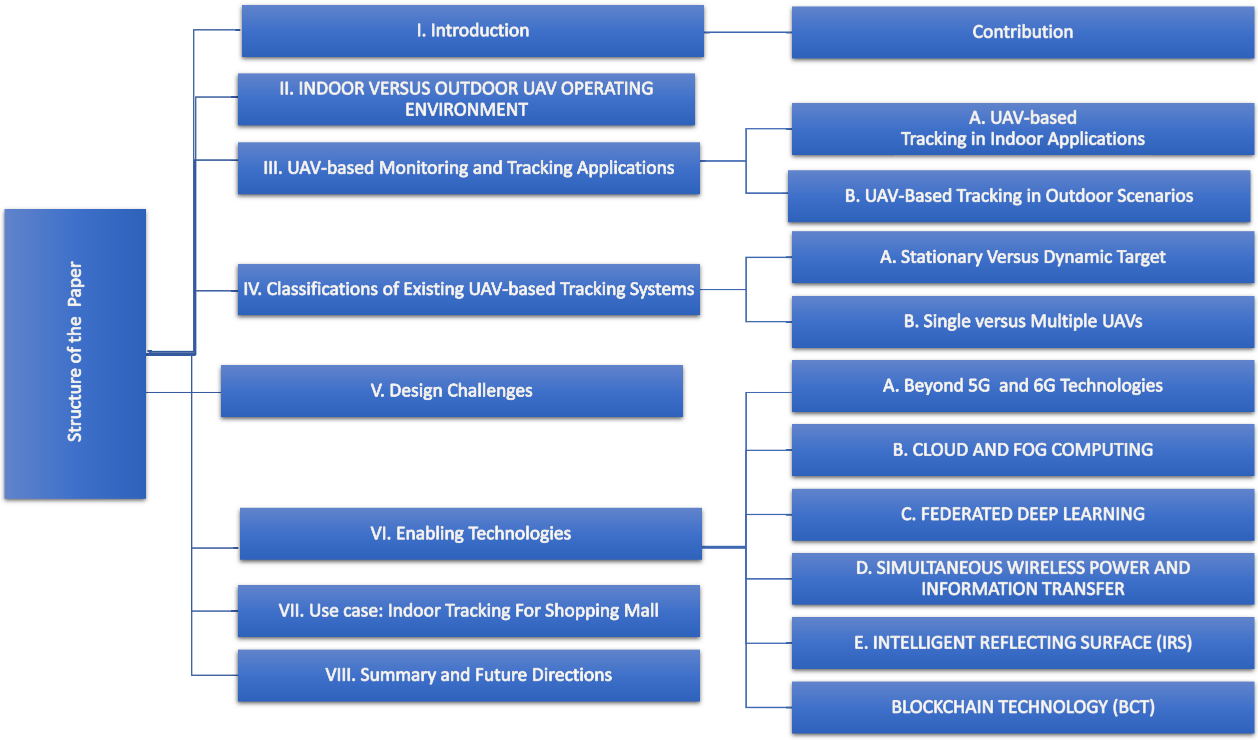


FIGURE 1. **Structure of the paper.**

- Finally, we provide a set of promising research directions for designing efficient UAV tracking systems.

The rest of this survey is organized as follows. Section II demonstrates the classification of UAVs based on indoor or outdoor tracking environments. Section III presents the applications of UAV-based target tracking systems. The tracking mechanisms and target categorization are discussed in Section IV. Section V addresses some design challenges that face UAV systems. Also, some enabling technologies that can be used in UAV systems are presented in Section VI. After that, we provide a use case for indoor tracking in Section VII. Finally, concluding remarks are provided in Section VIII. Fig. 1 depicts the structure of this survey.

II. INDOOR VERSUS OUTDOOR UAV OPERATING ENVIRONMENT

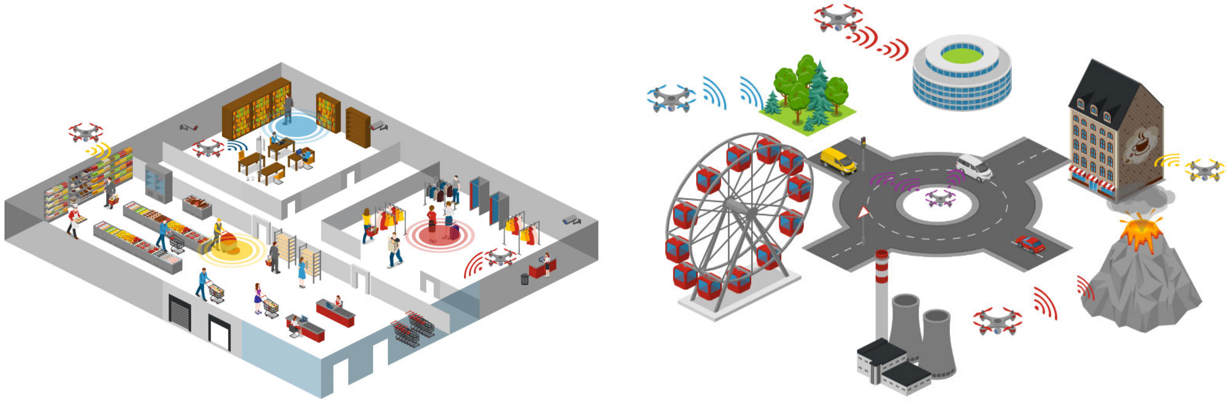
This section presents an overview of the classification of UAV-based target tracking systems depending on their operating environment, namely indoor and outdoor UAV-based systems. In the UAV-based indoor environment, UAVs are intended for use in enclosed spaces, where GPS signal is not available, or unreliable [26]. Indoor UAVs are small, light, and very maneuverable compared with outdoor UAVs, allowing them to fly in confined spaces and quickly change directions without endangering themselves or their surroundings [16]. In particular, altitude control is an important design factor in indoor scenarios as UAVs need to remain stationary in one location while performing inspection and surveillance tasks. Several indoor UAVs incorporate sensors and cameras to assist them in spotting obstructions and avoiding collisions [6]. However, outdoor UAVs are built to operate in open-air environments, where their designs are capable of covering larger areas with extended flight times [4]. To be specific, compared to indoor UAVs, outdoor UAVs are generally larger, more robust, and equipped with advanced sensors and cameras. Outdoor UAVs are often used for surveying, mapping, and monitoring large areas and inspecting infrastructure such as power lines and wind turbines [36]. In summary, indoor and outdoor UAV-based systems' operating environments, applications, advantages, and design challenges are fundamentally different. Each system offers particular benefits, support certain applications, and imposes unique constraints and design challenges.

III. UAV-BASED MONITORING AND TRACKING APPLICATIONS

UAV-based tracking systems can be deployed in both indoor and outdoor scenarios. Fig. 2(a) and Fig. 2(b) show scenarios for using indoor and outdoor UAV-based target tracking systems, respectively.

A. UAV-BASED TRACKING IN INDOOR SCENARIOS

Recently, there has been an increase in the deployment of UAVs in various indoor applications, including monitoring and surveillance tasks in greenhouses, shopping malls, offices, and hospitals, among others [6]. Such various



(a) Indoor UAV-based tracking system (b) Outdoor UAV-based tracking system

FIGURE 2. Examples of possible UAVs tracking environments.

applications can be realized in indoor scenarios by equipping UAVs with HD cameras, communication units, motion detectors, and laser-range finders. We provide a detailed list of some applications for using UAV-based tracking systems in indoor environments:

- Indoor search and rescue (SAR) missions: SAR missions are carried out by emergency services to locate and detect someone who is in danger, lost, ill, or injured in remote or difficult-to-reach places [37]. SAR is considered one of the most important applications for using UAVs to save lives. Single-UAV or multi-UAV systems are viable options in this type of environment. Some tasks that can be executed in SAR missions include detecting and recognizing objects, exploring the mission area, and supplying essentials like medicine [27]. Locating and detecting people trapped inside a collapsed building can also be accomplished with the help of a small, lightweight, fast-moving multi-copter drone equipped with a thermographic camera [38].
- Health care and epidemic control: UAVs are valuable tools for achieving health and privacy objectives. UAV-based tracking systems have the potential to offer strategies for societal safety and security in populated spaces [39]. For instance, during times of widespread pandemics (e.g., COVID-19) [40], the UAVs can monitor the social distance between individuals and detect people with high temperatures in crowded areas (e.g., shopping malls). This can help in decreasing the spread of COVID-19 and other diseases [41], [42].
- Agriculture (e.g., greenhouse): Instead of using a large number of sensors in large greenhouses, UAVs can be considered good candidates to perform different tasks. Such tasks include visual inspections of plants and collection of the required information [6]. UAVs have surpassed wireless sensor networks (WSN) and mobile farm robots. Using UAVs, measurements can be taken from any point in the three-dimensional greenhouse space, improving the accuracy and convenience of climate control and crop monitoring [43], [44].
- Indoor surveillance and security: In this context, a mini UAV is given instructions on where to search for a specific target inside an indoor potentially hazardous environment [45]. colorblackDue to their sizes, various designs of mini UAVs are encouraged for indoor monitoring. UAVs can take the roles of humans during the daily routine of warehouse inspection, detect potentially hazardous situations, inspect difficult-to-reach indoor places, and detect potential criminal activity [17].

B. UAV-BASED TRACKING IN OUTDOOR SCENARIOS

Due to their high operating flexibility, UAVs can be effectively used for target tracking in different outdoor scenarios. Using UAVs in search and tracking systems can considerably increase search coverage and capabilities while accomplishing missions in a relatively short time [16]. Specifically, several UAV-based systems have been used for outdoor monitoring and tracking applications, which include:

- Target Tracking: UAVs are distinguished by their ability to take off and land reasonably, quickly, and smoothly. With such features, UAVs can be used in different outdoor environments. In particular, UAVs can also quickly and accurately provide targets' locations and images of their surroundings, allowing them to focus efforts and save time and resources in different missions. Systems for searching and tracking objects using UAVs can greatly expand their coverage, improve their effectiveness, and save expenses [16]. To overcome the challenge of tracking and finding small and fast-moving dynamic targets, we can employ a convolutional neural network (CNN), deep neural network (DNN), and YOLOv8 technique with a camera integrated into UAVs.

- SAR: UAVs are increasingly being used for exploratory navigation in outdoor regions due to their advanced sensing capabilities with a high degree of adaptability. In addition, UAVs can monitor and search environments that are unreachable or dangerous for humans. Due to the aforementioned features of UAVs, they have been proposed to accomplish several critical missions, including urban/outdoor SAR, and to find missing immobile humans or objects in unknown environments [15].
- Wildlife monitoring: Given the importance of wildlife in maintaining balance and stability to nature's processes, there are a number of attempts to conduct wildlife surveys in different environments. With the evolution of technologies, significant improvements have been seen in the methods used to collect data from different environments. UAV technology is one of the technologies with a significant footprint in monitoring and collecting data from different environments. This makes the UAV technology one of the most important tools for wildlife monitoring, replacing direct field investigations [28]. One of the primary features distinguishing UAVs from other wildlife monitoring technologies is their ability to cover large areas with high spatial and temporal accuracy. In addition, UAVs can also be used to explore potentially hazardous or inaccessible regions [46].
- Pollution monitoring: Air pollution monitoring with UAVs has recently received much attention from scientists. Accordingly, many different approaches have been suggested to address this problem. For example, small gas sensors can be installed on UAVs, allowing them to monitor a variety of pollutants in urban environments [47]. In addition, an aerobatic robotic (called an environmental drone) has been developed to learn more about climate change and air pollution [48].
- Smart Agriculture: The possibilities presented by the integration of UAVs in precision agriculture hold immense potential for addressing various challenges and improving agricultural practices worldwide. However, the price and simplicity of controlling UAVs for smart farming are crucial to encourage their use. The main benefits of using UAVs in agriculture are their portability, their ability to capture HD pictures, and their ability to analyze these pictures in real-time. Farmers can automate the irrigation process by remotely monitoring the crop field with various sensors attached to the UAVs. UAVs can also monitor crop quality and weed/animal attacks. Farmers and other stakeholders can remotely access UAV data from cloud-based platforms to evaluate crop yield, fertilizer, pesticide, etc. [49], [50].
- Border patrolling: Ensuring secure borders is a crucial necessity for safeguarding nations, necessitating continuous monitoring and control of these borders. The mission of monitoring and controlling borders might be difficult, especially when such borders extend thousands of kilometers with harsh terrains. In such cases, conventional solutions like installing domestic monitoring points at regular intervals would be inefficient and expensive. This inefficiency and costliness make the exploitation of UAVs for border protection feasible [9].

IV. CLASSIFICATIONS OF EXISTING UAV-BASED TARGET TRACKING SYSTEMS

In the previous discussions, UAV-based target tracking systems are classified based on their operational environments. However, this section provides a comprehensive overview of the UAV-based target tracking systems in terms of the target behavior (i.e., stationary or dynamic), number of used UAVs (single or multiple), target size, and target altitude.

A. STATIONARY VERSUS DYNAMIC MOVING TARGET

The locations of stationary targets remain fixed and can be identified more easily with the assistance of image processing and AI techniques. In the case of tracking and detecting stationary targets, the UAV(s) need to search for single or more targets located in fixed locations and maintain track of their locations [10]. On the other hand, for dynamic target tracking tasks, the UAV(s) are tasked with searching for and detecting one or more dynamic, uncertain targets. Specifically, for moving targets, the tracking task is divided into three processes: UAV launch, target detection, and successive tracking. With uncertain knowledge about the mission field and the behavior of the target, intelligent methods can be integrated into UAVs to substantially enhance tracking performance. These methods attempt to predict the target's mobility pattern by interacting with their surroundings, enabling the UAVs to make appropriate decisions during the mission [19], [51].

B. SINGLE VERSUS MULTIPLE UAVS

In target detection and tracking missions, target tracking can be accomplished by exploiting single or multiple UAVs. While utilizing a single UAV can simplify the tracking system design and reduce the administrative cost, relying on a single UAV for tracking poses time constraints regarding the frequent need for battery recharge [52]. Additionally, employing a single drone can result in a single point of failure and can negatively impact the system's performance. Thus, multiple UAVs have been utilized to enhance tracking performance (e.g., [53], [54]) by mitigating the delay and energy limitations associated with the single-drone systems. Specifically, employing a group of UAVs allows for more extensive temporal and spatial data collection than relying on one UAV, enabling the successful execution of various missions. In addition, if one of the UAVs cannot perform its mission, the remaining UAVs can adapt the mission as needed, leading to a more resilient system [55]. Thus, using a group of UAVs enhances the system's reliability and reduces the time needed to accomplish tracking missions [56]. However, designing target tracking systems with multiple

UAVs imposes several design challenges related to UAV coordination, UAV route planning, and UAV-to-UAV communication.

Accordingly, UAV-based tracking systems can be categorized into eight groups based on the number of used UAVs, nature of the target movement, and number of targets:

- **SDSST:** Single-drone single-stationary target tracking systems (e.g., [15]).
- **MDSST:** Multi-drones single-stationary target tracking systems ([54]).
- **SDMST:** Single-drone multi-stationary target tracking systems (e.g., [57]).
- **MDMST:** Multi-drones multi-stationary target tracking systems (e.g., [54], [58]).
- **SDSDT**: Single-drone single-dynamic target tracking systems(e.g., [20], [21], [59]).
- **SDMDT**: Single-drone multi-dynamic target tracking systems (e.g., [20], [21], [59]).
- **MDSDT:** Multi-drones single-dynamic target tracking systems (e.g., [51], [60]).
- **MDMDT:** Multi-drones multi-dynamic targets tracking systems (e.g., [56], [61]).

Figure 3 provides an overview of the primary categorization of current indoor and outdoor target tracking systems. Table 1 compares a number of existing indoor and outdoor UAV-based tracking systems in terms of the number of used UAVs, type of target, number of targets, type of environment, and the use of AI.

C. LARGE SIZE VERSUS SMALL SIZE TARGETS

The targets can be further classified based on their size and their proximity to the UAV tracking system as large and small targets. The small size of the target makes it difficult to identify and track, especially in crowded scenarios. This makes small target tracking challenging. Tracking different size targets poses unique difficulties due to the requirement for long-range tracking of targets with different sizes and shapes [62]. To identify and track targets of varying sizes in situations with poor visibility, specialized sensors are required. These sensors can include infrared or acoustic sensors. Additionally, advanced AI algorithms are necessary to enhance target detection accuracy. Such AI algorithms need to be designed to work effectively regardless of the target size [63], [64]. We note that YOLOv8 (You Only Look Once v8) technique with an HD camera can be utilized to detect targets of different sizes and shapes. YOLOv8 is considered a state-of-the-art robust object detection platform. It can be utilized as an effective AI-based vision solution to identify, in real-time, a wide range of complex objects of different sizes (e.g., small objects in crowded indoor spaces). YOLOv8 introduces improvements over its previous YOLO versions for better performance, accuracy, and flexibility. YOLOv8 is expected to be widely implemented in various target detection and tracking systems [65].

D. HIGH-ALTITUDE VERSUS LOW-ALTITUDE DYNAMIC TARGETS

Based on their flying altitude, dynamic targets can be classified as high-altitude (within a few kilometers) and low-altitude targets (within 100's meters) [66]. Tracking objects flying at different altitudes is a challenging task due to the need for high precision, real-time response, and the presence of signaling error and noise [67]. Specifically, the task of achieving high precision and real-time performance involves several key factors. Effective algorithms for target identification, tracking, and prediction are crucial. Additionally, reliable sensor systems are required to provide accurate and timely measurements of the target's location, velocity, and other essential data [68]. Thus, target tracking systems should combine several sensors, AI algorithms, and advanced signal-processing techniques to provide reliable tracking solutions for targets flying at different altitudes [69].

V. DESIGN CHALLENGES FOR EFFICIENT UAV-BASED TRACKING SYSTEMS

Although the utilization of UAVs for tracking and monitoring missions has a number of features, there is a set of challenges corresponding with such UAV-based systems. In this section, we discuss some of these challenges and introduce a set of solutions to deal with them.

- Indoor navigation and collision avoidance: The use of UAVs in indoor environments has a number of technical difficulties. These difficulties include the numerous barriers that make hoovering more difficult, the GPS-denied operating environment, and the possibility of UAV failures and collisions with indoor obstacles [17]. Accurate localization and navigation without relying on GPS are essential in indoor operations. For autonomous UAVs navigating in unknown indoor scenarios, a number of unaided methods have been suggested in recent years. These methods rely on simultaneous localization and mapping, artificial landmarks, stereo vision sensors, DNN with image processing and laser range-finders [75], [76], [77], [78], [79]. On the other hand, collision avoidance methods are essential for UAV tracking systems in both indoor and outdoor environments. However, indoor environments are more crowded, which as a result, limiting maneuverability and enforcing precise control requirements [6], [27]. Most methods for indoor collision avoidance are based on either reactive or proactive planning [4], [80]. To be specific, reactive planning involves utilizing the UAV's onboard sensors to obtain information regarding its operating surroundings and respond immediately to existing obstacles. On the contrary, proactive planning allows the UAV to utilize its sensors to generate a map of the operating surrounding and accordingly allows for obstacle-aware UAV navigation [80].
- Battery capacity: UAVs face a major challenge with regard to battery capacity, which is considered one of the

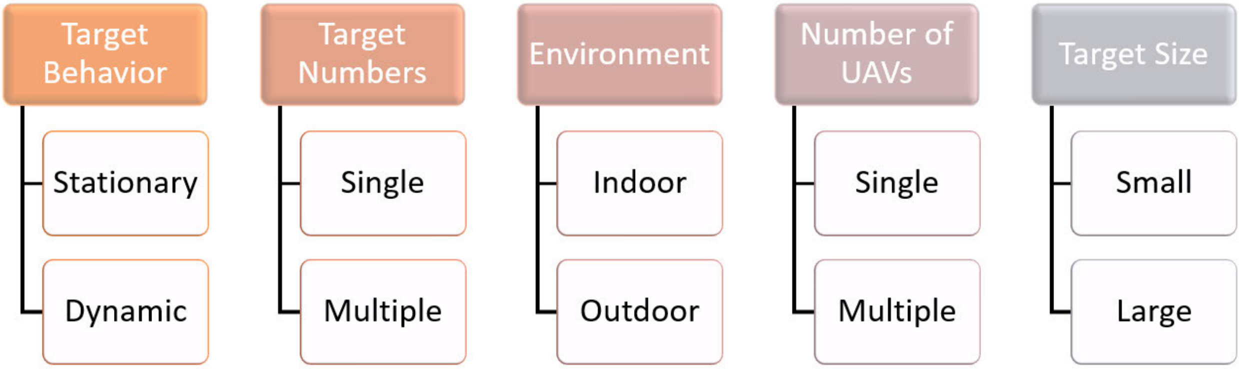


FIGURE 3. UAV-based Target Tracking system classification based on target mobility, the number of used drones, number of targets, mission environment, and UAV size.

TABLE 1. Comparison of existing UAV-based target tracking systems.

The UAV system	Indoor	Outdoor	Single target	Multi targets	Single UAV	Multi UAVs	Stationary target	Dynamic target
[21]		✓	✓		✓			✓
[70]		✓		✓		✓	✓	
[61]		✓		✓		✓		✓
[71]		✓	✓			✓		✓
[51]	✓		✓			✓		✓
[59]	✓		✓		✓			✓
[72]		✓		✓	✓			✓
[57]		✓		✓	✓		✓	
[58]		✓		✓		✓	✓	
[54]	✓			✓		✓	✓	
[15]	✓		✓		✓		✓	
[16]		✓	✓		✓		✓	
[19]	✓		✓		✓		✓	
[20]	✓		✓		✓			✓
[73]	✓		✓		✓			✓
[60]		✓	✓			✓		✓
[53]	✓		✓			✓	✓	
[74]		✓		✓			✓	
[56]	✓		✓	✓		✓		✓

most critical design factors in providing efficient UAV deployment. In particular, the limited battery capacity of a typical small UAV restricts the amount of time the UAV can fly. For this reason, there are ongoing efforts to increase the traveling time of UAVs. Several suggested solutions can be exploited to increase flight time, such as expanding battery capacity, intermittent charging, and using optimization algorithms to optimize flight trajectories [22], [81]. Meanwhile, expanding battery capacity is challenging with current technologies, where increasing the battery capacity requires using heavy-weight batteries [22], [82]. The second alternative is intermittent charging, either through wired or wireless methods. Wired methods are intricate and can restrict the UAV's mobility while being charged, while wireless options provide more freedom but with reduced efficiency [82]. Finally, several studies have identified that optimizing the flying path and communication parameters can provide energy-efficient UAV deployment [83].

- Limited UAV computational resource: Achieving a totally autonomous mission in an indoor environment with small aerial robotics poses an implementation challenge due to their limited payload and computational capabilities. Therefore, when UAVs are designed for autonomous tasks without human supervision, the development of advanced decision-making algorithms becomes crucial. These algorithms need to strike a balance between mission performance and the computational resources available onboard the UAVs [27].
- Target recognition: The traditional recognition methods involve the drone capturing an image and sending it to a ground station for detection. The ground station then transmits back commands to the drone to control its actions. However, this approach is limited in responsiveness due to issues related to the network latency and high bandwidth requirements [25]. One of the recent attractive solutions to deal with this challenge is to deploy deep learning algorithms for image detection and recognition using deep learning [84]. Such algorithms have attracted much interest since they are able to offer promising performance. Specifically, the embedded system loaded on the UAV usually utilizes CNN (or region-based CNN)-based methods for image

analysis and pattern recognition, which can result in decreasing the needed bandwidth and response time [85].

- Communication protocols: Communication and data exchange is necessary to manage and support UAV trip control operations. High-performance, reliable communication plays an essential role in meeting the design challenges related to operating a swarm of UAVs [1], [86]. The key challenges in designing efficient data communication and routing protocols for UAV networks are the mobility of UAVs, network partitioning, intermittent links, scarce resources, high bit-error-rate links, and varying QoS requirements [23]. Due to the UAV's unique operating environment, existing communication protocols designed for conventional mobile ad hoc routing networks are not applicable to UAV networks. New data communication protocols that can adapt to the UAV's high mobility and dynamic topology are needed [87]. Such protocols should be designed to enable efficient UAV-to-UAV coordination, mission planning, and secured data/control exchange [24].
- Communication Security: UAV systems, in general, suffer from security attacks, including jamming attacks and ghost-control scenarios, where unauthorized agents attempt to take control of UAVs through spoofed navigation and control signals [88]. On the other hand, due to their restricted operational height and proximity to eavesdroppers, physical attacks might also affect the UAV-based target tracking systems, especially in indoor scenarios. Consequently, in addition to standard software-security measures, the implementation of distinct physical-level security protocols becomes necessary for UAV communications. This presents new challenges and research opportunities, including the need for AI-based proactive network management to detect and prevent real-time physical attacks.

While the aforementioned challenges restrict all UAV-based target tracking missions, the degree of importance of each challenge varies upon the classification of UAV-based target tracking systems. For example, the challenge of the limited battery capacity has a considerable impact when considering the outdoor tracking mission, while such a challenge is of less importance when considering indoor tracking missions. On the other hand, unlike the outdoor scenarios, due to the crowded nature of the indoor target tracking scenarios, proposing efficient collision avoidance protocols becomes of vital importance. Fig. 4 highlights the importance of the various design challenges with respect to the various tracking classifications.

VI. ENABLING TECHNOLOGIES

Over the past few years, several enabling technologies have been proposed to address the design challenges of deploying UAVs in target-tracking missions. Next, we shed some light on a set of such technologies, where we also demonstrate the potential roles of such technologies in handling the design challenges of UAV-based target tracking systems.

A. BEYOND 5G AND 6G TECHNOLOGIES

As demonstrated in the previous section, successful UAV-based target-tracking missions cannot be accomplished without developing efficient and reliable communication protocols. Accordingly, the recent advances of B5G and 6G are expected to facilitate the widespread deployment of UAV technology in target tracking missions while fulfilling the demanding communication requirements (in terms of rate and latency) of such systems [89]. Specifically, the provision of wireless connectivity that is dependable, risk-free, and efficient in terms of cost is necessary for the practical support of such a massive deployment of UAVs. In particular, UAVs are considered flying user equipment, and thus, serving them by cellular networks is a critical issue. Even though the existing cellular networks offer promising connectivity solutions for UAVs, allowing reliable UAV operations still present many challenges [90], [91]. The capabilities and advanced features of 5G make it possible to provide practical support for UAV communications. Some examples of these capabilities and features include spectrum flexibility, advanced antenna technologies, and network slicing [92]. The use of 5G drones presents a number of difficulties, including limited range, interference, bandwidth restrictions, and latency. These issues can hinder drones' ability to communicate with ground stations and other drones at greater distances, cause connectivity and control loss, and make it challenging to control multiple drones in the same space. The transition to 6G technology is crucial for a number of reasons, including better connectivity, increased range, improved security, and more effective spectrum use [93]. At the same time, 6G technology claims to provide 5G with better encryption and security features, faster speeds, lower latency, and increased capacity. This might make ground stations and drones' communications more reliable, expand the applications available, reduce the chance of hacking or other cyberattacks, and lessen interference from drones flying in the same area. In general, the transition to 6G technology is critical for the growth and development of drone technology, which has the potential to change a variety of industries completely [94].

B. CLOUD AND FOG COMPUTING

Connecting the UAVs to cloud and fog computing platforms can open up a wide range of applications, such as a cloud-enabled system for intelligent risk-aware navigation in urban scenarios [95]. It was proposed that a cloud-based system could be used for monitoring unmanned air traffic within cities. This system offers services for the administration and control of traffic, making it possible to maintain safety and avoid collisions [96]. The use of cloud computing can improve UAVs in a number of ways. For example, UAV operators may be given a platform by cloud computing to store and process large amounts of data produced by the UAVs,

Classification / Challenges	Target Behavior		Number of Targets		Number of UAVs		Size of the Target	
	Stationary	Dynamic	Single	Single	Multiple	Multiple	Small	Large
Indoor navigation and Collision avoidance	-	-	-	-	✓	✓✓	-	-
Computational resources	✓	✓✓	✓	✓✓	✓	✓✓	✓✓	✓
Battery capacity	✓	✓✓	✓	✓✓	✓✓	✓✓	-	-
Target recognition	✓	✓✓	✓	✓✓	✓✓	✓	✓✓	✓
Communication protocols	-	-	-	-	✓	✓✓	-	-
Security Issues	-	-	-	-	✓✓	✓✓	-	-

FIGURE 4. The importance of the different design challenges with respect to the different UAV-based tracking system classifications (✓ being important and ✓✓ being most important).

enabling real-time analysis and decision-making. Cloud computing can give users access to sophisticated mission planning tools, such as 3D maps and weather information, which can aid operators in more efficient mission planning [97]. Additionally, cloud computing can enhance ground stations' and UAVs' interactions, fostering more effective mission execution. To protect UAVs from cyber threats, cloud computing can offer sophisticated cyber-security features [98]. In general, cloud computing can improve UAV capabilities, allowing for more effective, efficient, and secure operation in various applications [99]. On the opposite side, cloud computing is currently impractical due to bandwidth and latency constraints. The processing capabilities of UAVs can be increased by placing fog nodes closer to the event we want to monitor. In UAV systems, fog computing can solve latency, bandwidth, and energy consumption problems. By utilizing fog computing, UAVs can reduce the amount of data that should be sent back to the cloud for processing by offloading computation and storage tasks to edge devices like gateways, drones, and other Internet-of-things (IoT) devices [100]. UAVs can make more precise and timely decisions with the help of fog computing, which can facilitate more effective and responsive data analysis. In addition, fog computing can give UAVs more dependable and secure connectivity by enabling direct communication between UAVs and nearby edge devices rather than relying on cloud-based communication. Also, by allowing ML and other advanced algorithms to run at the edge, closer to the data source, fog computing can improve UAV autonomy and intelligence [101]. Integrating fog and cloud computing with UAVs might be challenging, even though both can provide several benefits to facilitate UAV operations and usage. Middleware can facilitate the smooth and efficient combination of UAV applications for smart cities with cloud and fog resources. To facilitate this type of amalgamation, the service-oriented middle-ware SmartCityWare was created [102]. In summary, cloud computing can be utilized to address the security and limited UAV computational/storage challenges by offering huge cloud-based computational/storage capabilities. However, fog computing can yield benefits such as decreased latency, enhanced communication reliability/security, and improved resource utilization by positioning the computational and storage resources closer to the UAVs.

C. FEDERATED DEEP LEARNING

To guarantee the efficiency of tracking tasks, UAVs can be outfitted with intelligent capabilities that allow them to comprehend the operation in the environment and take the appropriate actions as the mission progresses. A wide variety of AI and ML-based methods were developed and integrated for further enhancement of the UAV's capabilities for accomplishing various types of tasks in different environments. This can be achieved by employing AI and ML methods such as reinforcement learning (RL), which enable UAVs to fly autonomously and accomplish different tasks autonomously. RL will allow UAVs to learn in an unknown environment and gradually improve their performance over time [15], [19], [103]. Recent developments at Google have led the company to introduce the decentralized, federated deep learning (FDL) concept. In FDL, wireless devices utilize their local data to construct local DL models cooperatively and then send the local models and the associated weights to an FDL server for aggregation. As a result, FDL makes it possible to maintain the confidentiality of sensitive data in the exact location in which it was created while also training distributed deep learning models. In addition, FDL dramatically reduces the overhead of the network by eliminating the need to send data to a centralized location. Therefore, compared to the centralized ML scheme, the bandwidth requirements of FDL are significantly lower [104]. Furthermore, it was also shown that FDL is better suited for ultra-low latency applications because it allows wireless devices to learn a sharable prediction model concurrently while maintaining all training data locally [105]. This treatment suggested that, compared to the centralized cloud-centric frameworks, FDL could be an enabling technology for future UAV-based wireless networks for learning approaches. To this end, the FDL concept is better suited for UAV-based wireless networks than centralized deep learning schemes, which UAVs cannot independently support due to power, computing limitations, and limited available bandwidth. UAVs could use the FDL concept to create a learning model that is then used in UAV-based networks. In addition to protecting the privacy of UAV data, this will also make better use of UAV resources like power and processing speed. FDL protects the privacy of data collected by UAVs and decreases network overhead and latency. Also, FDL can be used by wireless networks supporting UAVs to overcome these obstacles [106]. In summary, FDL can be utilized by UAV tracking systems to mainly address the security, communication reliability, and limited UAV computational resource (i.e., resources needed for target recognition and collision avoidance) challenges.

D. SIMULTANEOUS WIRELESS POWER AND INFORMATION TRANSFER

Simultaneous wireless power and information transfer (SWIPT) has been recently categorized as an appealing solution to overcome the energy constraints of wireless communication systems. With SWIPT, a communication node should be able to harvest energy from the radio frequency (RF) wave while simultaneously decoding information. Such an energy-harvesting approach aligns with the mobile nature of UAVs and, thus, can play a major role in extending the flight's duration of a UAV while securing an appropriate communication exchange. Specifically, due to the limited battery capacity of UAVs, charging them with conventional resources has an undesirable impact on the flight's duration. This, as a result, limits the potential capabilities of deploying UAVs in target-tracking applications, especially those related to outdoor applications. With this, SWIPT can be identified as an appealing solution to deal with UAV's battery challenge [107]. On the one hand, employing SWIPT for UAVs extends the flight times, thus, enabling UAVs to carry out difficult target-tracking tasks. On the other hand, deploying SWIPT with UAVs improves the energy efficiency of such UAV-based systems, while also reducing the CO_2 emission. Furthermore, SWIPT can also reduce the weight and size of UAV batteries, thereby increasing the payload capacity of the UAVs. This allows for the integration of additional sensors, cameras, or other equipment, further expanding the potential applications of UAVs [108], [109]. It is worth mentioning that SWIPT can be performed by splitting the received signal, either in time or power, as a part of an RF signal is dedicated to harvesting energy, while another part is utilized to decode information. Despite the potential benefits of SWIPT for UAVs, its implementation faces various technical challenges, including optimizing power and data transmission protocols, designing efficient rectenna circuits, and addressing interference from other wireless devices. Nonetheless, SWIPT technology is still promising for improving the performance and capabilities of UAVs [110].

E. INTELLIGENT REFLECTING SURFACE (IRS)

Recently, intelligent reflecting surface (IRS) has been investigated as a promising candidate to enhance and control the propagation of electromagnetic waves, thus, improving the QoS of a communication system [111]. Specifically, IRS consists of passive reflecting elements that can smartly steer the reflected signals toward the intended users. In fact, establishing reliable communication links between BS and UAVs has been considered a restrictive requirement for successful target-tracking tasks. This requirement becomes of vital importance in crowded environments, i.e., indoor tracking applications. To deal with such circumstances, IRS can be viewed as a potential solution to improve the communication channel between the BS and UAVs. On the one hand, due to their light weights and ease of deployment, IRS units can be installed in difficult-to-reach locations, and, thus, can help to initiate a line-of-sight (LoS) link when such a link cannot be achieved due to the possible severe blockage [111]. On the other hand, IRS can be used to decrease the amount of power required for communication, extending the battery life of UAVs. Longer UAV flights and greater mission capabilities can be achieved by reducing the power consumption of the UAV communication system and enhancing the signal quality and strength [112]. To end with, the deployment of IRS technology in UAV-based networks can greatly improve the performance and capabilities of UAVs, increasing their dependability, effectiveness, and flexibility to meet a variety of needs. However, several key design challenges towards the practical deployment of IRS UAV-based networks should be addressed. For example, determining the optimal phase shift matrix of the IRS and designing appropriate IRS units that can be placed on UAVs.

F. BLOCKCHAIN TECHNOLOGY (BCT)

UAVs have a variety of sensors that depend on the specific application being used and contribute to the completion of various tasks. These tasks in the UAVs are controlled and monitored via a communication system, either directly or remotely. The BCT can be considered an excellent candidate to reduce the dangers associated with UAV data maintenance and improve security and privacy in the transmission data process [113]. Due to the distributive nature and architecture of UAVs, when they communicate with devices on the ground level or flying objects, it is necessary to use an anonymous mechanism such as BCT to ensure the safety of the communicating data. In summary, utilizing BCT technology in UAV tracking systems can achieve better security, data integrity, and decentralized communication. Thus, BCT can effectively be utilized by UAV-based tracking systems to address the security and communication challenges [114].

Figure 5 illustrates the application of the various enabling technologies in addressing the various challenges encountered in designing efficient UAV-based tracking systems.

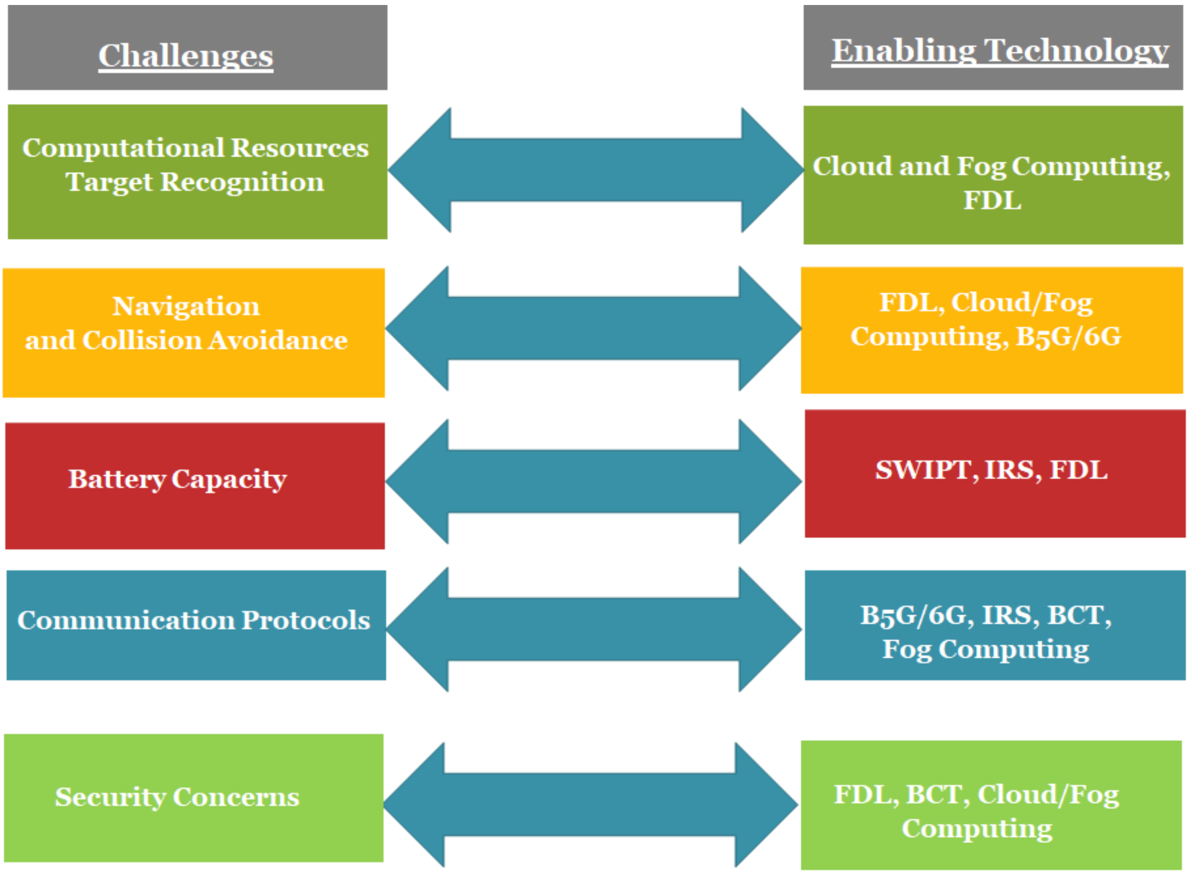
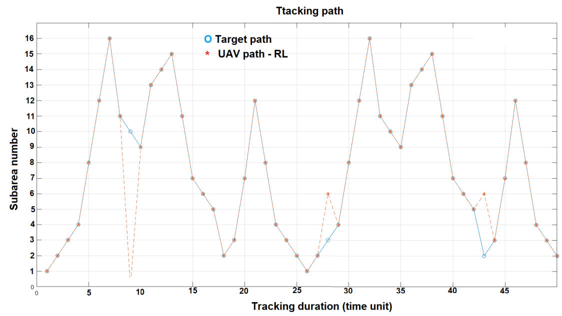


FIGURE 5. Linking enabling technologies with design challenges.

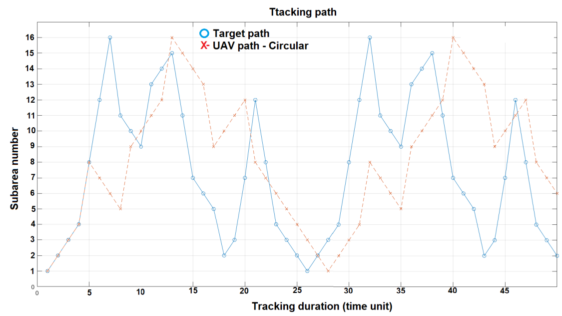
VII. USE CASE: INDOOR TRACKING FOR SHOPPING MALL

The use of real-time tracking systems yields numerous benefits across many fields. Applications range from Indoor Navigation to Real-Time Tracking, Motion Profile Analysis, and more. Indoor tracking is frequently used in crowded public spaces like airports and shopping centers. Once we know the behaviors of customers inside the shopping center, the quality of customer service can be enhanced even further. You can set alerts to go off whenever a customer enters a certain area, for instance, notifications of newly released films or ticket sales when they are near a theater. Indoor tracking and monitoring technology can also be useful for management. Tracking can provide information about customer journeys. We can find out more information about how users navigate the mall, which areas are the busiest, and even how long they spend in various stores; all of this information can help the mall make important decisions.

To give more insights about UAV-based indoor target tracking, we consider a shopping market of 40m $\times$ 40m $\times$ 5m area that is split into 16 uniform shops. Accordingly, we employ a single UAV equipped with a microprocessor for finding and tracking the behaviors of a 5 people group. This group moves according to the following pattern of unknown certain movement { 1, 2, 3, 4, 8, 12, 16, 11, 10, 9, 13, 14, 15, 11, 7, 6, 5, 2, 3, 7, 12, 8, 4, 3, 2, …}, and repeats its behavior every 25 transitions. Here, we present the suggested RL algorithm for an intelligent UAV that would be used to identify people's movement patterns inside a mall. The convergence-based algorithm serves as the exploration technique for the RL algorithm [115]. To calculate the value function and assess the used policy, state-action-reward-state-action is adopted. The UAV is also assumed to fly at a constant speed and fixed height. In contrast, the UAV is equipped with a lithium-ion battery along with ultrasonic sensors to keep it from colliding with obstacles. Furthermore, the UAV is equipped with an internal map of the shopping center to help the UAV in the navigation process and a camera to recognize objects. Fig. 6 compares the trajectory path for both the RL algorithm and a circular technique for 50-time units. To assess the tracking performance, we use a qualitative method that involves plotting the UAV and target trajectories on the environment map. The trajectory plots represent the target and UAV paths after sufficient training. It can be easily observed that the great superiority of the RL algorithm and how the UAV can understand and predict the target movement pattern. On the other hand, Fig. 7 plots the commutative discount return in the shopping center for both the RL algorithm and circular path. As we can see, the RL algorithm performs better than



(a) RL algorithm



(b) Circular path technique

FIGURE 6. **Trajectories of the UAV and the target.**

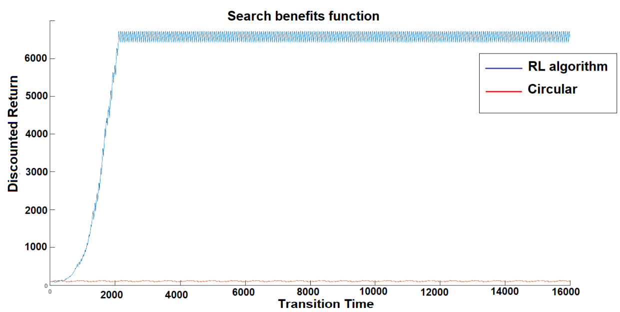


FIGURE 7. **Search benefits function.**

the circular path. Target movement patterns can be predicted in less time and with fewer samples than with the circular path. This is because it uses a learning strategy that tries to accurately evaluate various actions in different states to find an appropriate policy and use it to catch the target quickly. Finally, Fig. 8 shows the comparison between the developed RL algorithm and the circular technique according to the target percentage detection. This chart illustrates the typical success rate in catching the target in RL and circular. We look into how well the RL algorithm works. This graph demonstrates how the RL-based algorithm outperforms the circular method. To support this statement, the RL-based algorithm can acquire a statistical model of the target's movement over time, enabling it to navigate to specific subareas where the target is more likely to be located. The circular algorithm doesn't have a good result because it does not learn from past

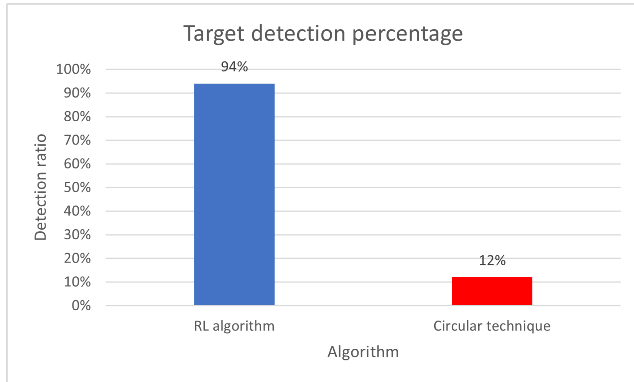


FIGURE 8. **Detection percentage.**

mistakes when it tries and takes advantage of the different possible actions.

VIII. SUMMARY AND FUTURE DIRECTIONS

UAVs possess various characteristics that make them suitable for diverse applications, such as hovering capability, compact size, low maintenance cost, and the ability to integrate sensors, cameras, and other tools. We can classify tracking and monitoring missions using UAVs into two main categories according to the nature of the mission environment: indoor or outdoor. Recently, there has been an increase in utilizing UAVs in indoor environments. Target tracking, search and surveillance, and plant monitoring tasks in greenhouses are examples of applications where UAVs can be used indoors. On the other hand, outdoor UAV systems can also perform different missions in outdoor environments, such as pollution monitoring, outdoor tracking, outdoor SAR, and border patrol. Deploying UAVs in indoor environments can be challenging as it requires addressing different UAV design and application considerations. These considerations include obstacles' height, high worker/machine density, GPS-denial, and the UAV size. Hence, non-GPS-based location solutions, such as fiducial markers, can be a viable option for accurately locating UAVs in complex indoor spaces.

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