Journal Pre-proof

A review of current studies on the unmanned aerial vehicle-based moving target tracking methods

Binbin Yan, Yuxin Wei, Shuangxi Liu, Wei Huang, Ruizhe Feng, Xiaoqian Chen

PII: S2214-9147(25)00032-7

DOI: https://doi.org/10.1016/j.dt.2025.01.013

Reference: DT 1577

To appear in: *Defence Technology*

Received Date: 6 November 2024

Revised Date: 7 December 2024

Accepted Date: 15 January 2025

Please cite this article as: Yan B, Wei Y, Liu S, Huang W, Feng R, Chen X, A review of current studies on the unmanned aerial vehicle-based moving target tracking methods, *Defence Technology*, https://doi.org/10.1016/j.dt.2025.01.013.

A review of current studies on the unmanned aerial vehicle-based moving target tracking methods

Binbin Yan[a], Yuxin Wei[a], Shuangxi Liu[b,]*, Wei Huang[b], Ruizhe Feng[b], Xiaoqian Chen[c]

[a]School of Astronautics, Northwestern Polytechnical University, Xi'an 710072, China

[b]Hypersonic Technology Laboratory, National University of Defense Technology, Changsha 410073, China

[c]College of Aerospace Science and Engineering, National University of Defense Technology, Changsha 410073, China

*Corresponding author: lsxdouble@163.com

A review of current studies on the unmanned aerial vehicle-based moving target tracking methods

Abstract

Unmanned aerial vehicles (UAVs) have become crucial tools in moving target tracking due to their agility and ability to operate in complex, dynamic environments. UAVs must meet several requirements to achieve stable tracking, including maintaining continuous target visibility amidst occlusions, ensuring flight safety, and achieving smooth trajectory planning. This paper reviews the latest advancements in UAV-based target tracking, highlighting information prediction, tracking strategies, and swarm cooperation. To address challenges including target visibility and occlusion, real-time prediction and tracking in dynamic environments, flight safety and coordination, resource management and energy efficiency, the paper identifies future research directions aimed at improving the performance, reliability, and scalability of UAV tracking system.

Keywords: Unmanned Aerial Vehicle (UAV); Tracking methods; Moving targets; Information prediction; Tracking strategies; Swarm cooperation

1. Introduction

1.1. Background

In the current era of rapid technological advancement, the field of unmanned aerial vehicles (UAVs) has witnessed significant expansion and diversification [1–8]. A particularly intriguing and challenging application within this domain is the use of UAVs for tracking moving targets [9–14]. This shift in technological paradigms is driven by the pressing demand for surveillance solutions that are efficient, safe, and cost-effective. Such solutions are essential across a wide range of sectors, including both military operations and civilian applications.

As depicted in Fig. 1, the capability to accurately and continuously follow a moving target using a UAV has extensive implications in various sectors, such as the military [15,16], surveillance [17,18], environmental monitoring [19,20], and search-and-rescue operations [21,22][1].

---

[1] The source information for Fig. 1 is as follows:

https://unidir.org/event/in-the-crosshairs-addressing-military-drone-use-and-proliferation/

https://www.criminalsecurityintel.com.au/security-specialist-consulting/aerial-surveillance-security-patrol/

https://mapware.com/blog/drone-enabled-remote-sensing-and-environmental-monitoring/

https://dronetechguide.com/drone-search-and-rescue/

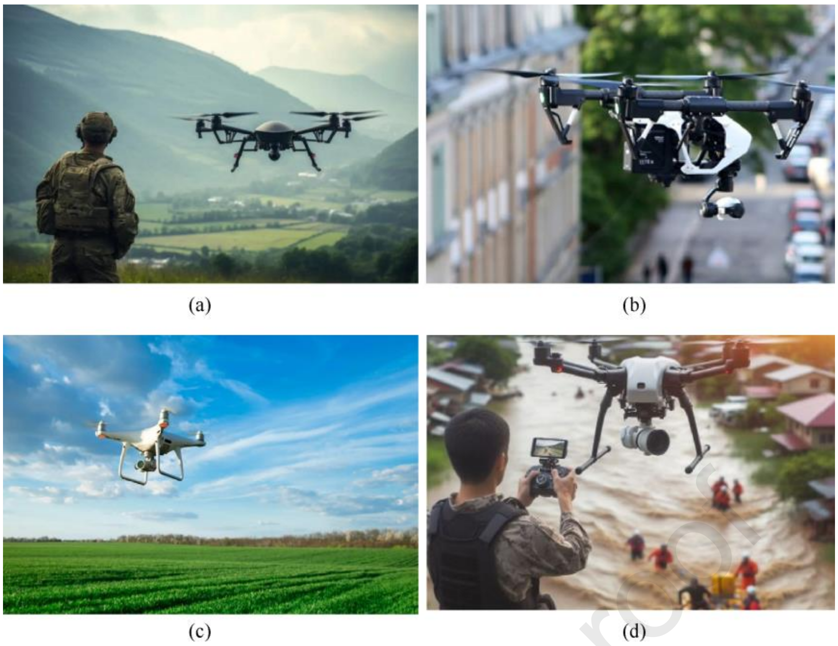


Fig. 1. Examples of utilizing a UAV to track moving targets: (a) Military; (b) Surveillance and security; (c) Environmental monitoring; (d) Search-and-rescue operations.

1.1.1. Military applications

In military scenarios, UAVs have become indispensable for tracking moving targets. Equipped with advanced tracking systems, these UAVs provide real-time data on the position, speed, and direction of potential targets, such as enemy vehicles, moving troops, or low-flying aircraft. This information is crucial for strategic decision-making, including planning airstrikes, ambushes, and monitoring enemy convoy movements. The stealth capabilities of certain UAVs, coupled with their ability to loiter over areas for extended periods, enable them to gather intelligence without easy detection. Consequently, this has revolutionized military reconnaissance and surveillance operations, facilitating more precise and timely responses to potential threats.

1.1.2. Surveillance and security

In urban environments, UAVs are effectively employed to monitor the movements of suspicious vehicles or individuals, thereby aiding criminal investigations. For instance, in the event of a high-profile theft or a potential terrorist threat, UAVs can be swiftly deployed to track suspects, providing law enforcement agencies with critical information regarding escape routes and potential hideouts. Furthermore, UAVs are instrumental at large-scale public events, such as sports games, concerts, or political rallies, where they monitor crowd dynamics and identify any abnormal behavior or potential security threats. This capability significantly contributes to maintaining public order and ensuring the safety of attendees.

1.1.3. Environmental monitoring

In the environmental domain, the use of UAVs for tracking moving targets has opened up new avenues for research and conservation efforts. In wildlife studies, UAVs are particularly valuable for monitoring the movements of migratory animals. By tracking herds of animals, such as wildebeests, during their annual migrations, researchers can gather critical data on migration patterns, preferred routes, and stopover points. This information is essential for understanding the ecological needs of these species and for developing effective conservation strategies. Similarly, UAVs equipped with sensors can be utilized in marine studies to monitor the movement of floating debris, marine mammals, or schools of fish. This capability aids in evaluating the health of marine ecosystems and understanding the impact of human activities, such as pollution and overfishing. Thus, UAVs serve as a powerful tool in both terrestrial and marine environments, enhancing our ability to conduct comprehensive ecological research and implement informed conservation measures.

1.1.4. Search-and-rescue operations

The ability of UAVs to track moving targets is a potentially life-saving asset during search and-rescue missions. In natural disasters such as earthquakes, floods, or hurricanes, survivors often move in search of safety. UAVs can be rapidly deployed to cover extensive areas, identifying the locations of these moving individuals. Additionally, UAVs enhance the coordination of rescue efforts by tracking the movements of rescue teams, ensuring efficient collaboration among different units. In maritime search-and-rescue operations, UAVs are invaluable for monitoring the drift of lifeboats or the movements of distressed vessels, thereby enabling rescuers to reach victims promptly.

1.2. Motivations

Tracking moving targets with UAVs presents several key challenges, primarily due to the dynamic nature of both the targets and the environments in which they operate. One of the most significant difficulties is maintaining continuous target visibility. In complex environments, obstacles such as buildings, trees, and weather conditions like fog or rain can obstruct the UAV's line of sight, causing sensor data interruptions. These occlusions can result in delays or even complete loss of track, making real-time tracking unreliable.

Ensuring UAV safety is another major concern. As UAVs follow highly mobile targets, they must continuously adjust their flight paths to avoid both environmental obstacles and other UAVs. External disturbances like wind or sudden weather changes can destabilize the UAV’s flight path, requiring advanced control mechanisms to ensure stable operation. This challenge becomes more pronounced when multiple UAVs are involved, as coordination between them is needed to maintain both safety and accuracy.

Trajectory smoothness is equally important. UAVs must quickly respond to sudden changes in target behavior, such as speed or direction alterations, while maintaining smooth and precise flight paths. Abrupt adjustments can lead to tracking errors or instability, making it essential to balance responsiveness with smooth, continuous trajectories.

These challenges are especially critical in real-time applications, where any processing delays or disruptions can compromise tracking performance. Overcoming these issues is vital for enhancing UAV-based tracking systems, which are increasingly applied in military, civilian, and environmental sectors. Tackling these issues will help improve the efficiency and reliability of UAV systems, making them more effective in dynamic, real-world scenarios.

The primary objective of this paper is to review advanced techniques and algorithms for UAV-based moving target tracking, addressing significant challenges in the field. This involves three methods: target information prediction, target information tracking and swarm cooperation strategy. The significance of this research extends across multiple domains. In the military sector, enhanced tracking precision and reliability are crucial for improving operational effectiveness and decision-making in both offensive and defensive scenarios. In the civilian sphere, advanced UAV-based tracking systems can enhance traffic management efficiency, reduce congestion, and improve road safety. Furthermore, during disasters, these systems aid in locating and rescuing survivors. In wildlife protection, they provide valuable data for understanding animal behavior and promoting habitat conservation. This paper has the potential to drive innovation in industries reliant on UAV-based moving target tracking.

2. Status of target information prediction method

Accurate prediction of a target's future position is essential for efficient and stable UAV target tracking. The prediction module is crucial as it infers future positions from historical motion data, guiding the UAV's trajectory and minimizing delay and tracking bias. In real-world scenarios, target movement patterns can be complex and variable, especially with nonlinear trajectories like those of crowds and vehicles, necessitating reliable prediction methods.

As illustrated in Fig. 2(a), the vehicle moves along a nonlinear trajectory with variable speed, making it easy for the UAV to lose track of the target[2]. As shown in Fig. 2(b), it is illustrated that individuals become obscured by trees in their environment, resulting in the failure of UAV tracking systems due to the loss of target visibility. The primary issue arises from the UAV’s inability to maintain continuous information about the target. To address this challenge, it is essential to develop a reliable method for target prediction, which ensures the accurate acquisition of target information.

(a) (b)

Fig. 2. UAV-based tracking of moving targets cases: (a) A UAV tracks a ground vehicle which can move around at

[2] The source information for Fig. 2(a) is as follows:
https://engineering.purdue.edu/Engr/AboutUs/News/Spotlights/2022/2022-0613-uav-competition

will; (b) A UAV is tracking an individual who is partially hidden by trees.

Currently, three main types of prediction strategies are widely employed: filter-based algorithms, deep learning-based algorithms, and regression-based algorithms. These methods capture the dynamic characteristics of targets to varying degrees, enhancing the UAV's tracking capabilities. By reducing deviations caused by rapid movements or sudden turns, they enable the UAV to adjust its path more smoothly, ensuring efficient and accurate tracking.

2.1. Filtering-based algorithms

Filtering-based algorithms are extensively employed in applications like target tracking, navigation, and signal processing due to their ability to dynamically estimate a target's true state [23–28]. These algorithms utilize statistical methods to integrate historical observation data with prior system information. The core principle of filtering-based algorithms is the establishment of a prediction-update cycle. Initially, the algorithm predicts the system's next state, then updates the current state estimate using new observations. This strategy effectively reduces the impact of uncertainties, including sensor noise and environmental interference.

Some studies combine filtering algorithms, such as Kalman filtering (KF), Extended Kalman filtering (EKF), and Unscented Kalman filtering (UKF), with other methods to predict the future motion states of targets. By integrating these prediction techniques with additional algorithms, researchers aim to improve the accuracy and robustness of target tracking and motion forecasting. In a related study, Zhao et al. [29] utilized KCF to track targets, identifying the pixel position of vehicles in each video frame. They introduced a passive geolocation method to compute the GPS coordinates of moving vehicles. Cheng et al. [30] utilized the You Only Look Once (YOLO) method to detect the moving target by defining it as a bounding box. They then employed the UKF technique to forecast the target's motion and subsequently tracked the target based on the estimated velocity. Bonatti et al. [31] integrated MobileNet [32] and Faster-RCNN [33] to enhance object detection capabilities. They utilized linear Kalman filtering to predict the target's motion state. Farahi et al. [34] introduced the Probabilistic Kalman Filter (PKF) algorithm, which examines the constructed probability graph to identify targets exhibiting unconventional behaviors. Hui et al. [35] proposed an RGB-D camera-based segmentation method to detect and locate the target, and used EKF to predict the target's motion state within a limited time frame. Similarly, Lin [36] employed the EKF to estimate the state of a moving target in visual inspection. Liu et al. [37] employed Deep Neural Networks (DNN) and kernelized correlation filters (KCF) for target recognition and localization within the pixel coordinate system using vision-based techniques. By integrating laser ranging data with an image-based distance estimation algorithm, they accurately determined the distance between the UAV and the target.

Several studies have focused on the development and improvement of filtering algorithms to address specific challenges in UAV target tracking. These advancements aim to enhance the accuracy and robustness of tracking systems in dynamic and complex environments. By refining traditional filtering techniques, researchers have proposed new algorithms that effectively mitigate noise, handle target appearance variations, and account for environmental disturbances, thereby improving the overall performance of UAV tracking. Gulay [38] introduced a KF approach specifically designed for collision avoidance and target tracking in autonomous aircraft. This method leverages motion-based tracking to effectively monitor multiple objects simultaneously. To detect moving objects, a background subtraction algorithm was employed, which is crucial for distinguishing these objects from their surroundings. Subsequently, corrective actions were implemented to minimize noise and accurately identify connected pixel groups that correspond to the detected objects. Deng et al. [39] developed an online tracking algorithm centered on discriminative correlation filter. This algorithm utilizes the alternating direction method of multipliers to simultaneously learn spatial and temporal regularization terms. This approach effectively mitigates environmental disturbances and leverages historical data to create a robust target appearance model. Li et al. [40] drew inspiration from keyframe simultaneous localization and mapping to propose a Keyfilter-Aware Object Tracker (KAOT) filter tailored for UAV tracking of targets. This filter intermittently learns context at a specific frequency and imposes a time constraint to prevent filter corruption over time, effectively reducing contextual noise. Fig. 3 presents the qualitative tracking results of KAOT in comparison to other excellent trackers across five challenging UAV image sequences. Lin et al. [41] developed a Bidirectional Incongruity-aware Correlation Filter (BiCF) aimed at enhancing UAV tracking capabilities. This innovative scheme addresses the challenges of appearance changes and inconsistent errors by incorporating response-based bidirectional incongruity errors. As depicted in Fig. 4, BiCF constructs these errors by leveraging sample information and filters from the previous frame, thereby optimizing the utilization of inter-frame information. This method stands in contrast to the traditional Discriminative Correlation Filter (DCF), which relies exclusively on samples from the current frame, making it more susceptible to appearance changes. Addressing the diversity and mobility of targets, Liu et al. [10] applied a single shot multiBox detector (SSD) algorithm to generate multiple candidate targets. They then employed a support vector machine-based method for target screening to identify the correct target. Furthermore, they developed the TLD-KCF tracker, which incorporates a conditional scale adaptive algorithm to improve the tracking performance of quadrotor UAVs in complex outdoor environments. Yeom [42] developed a method to track targets using an infrared thermal camera mounted on a UAV. This method employs two-point differencing initialization and either a Kalman filter or an interacting multiple model filter.

Fig. 3. Qualitative evaluation results in Ref. [40]. From top to bottom, they are respectively the sequences Chasing Drones, RcCar6, SnowBoarding2, Gull1, and wakeboard2.

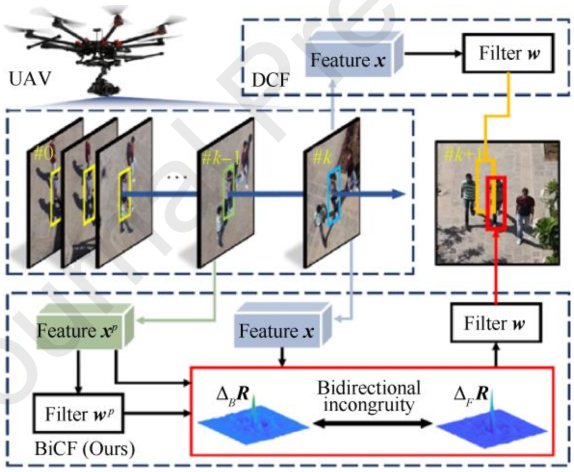


Fig. 4. Comparison of DCF and the designed BiCF tracker [41].

In summary, filtering algorithms play a crucial role in target information prediction, offering both significant advantages and notable disadvantages. These algorithms excel in real-time state estimation by efficiently integrating historical data with prior information, which helps to mitigate the impact of sensor noise and environmental disturbances. Their predictive capabilities allow for continuous updates, making them particularly suitable for applications that require dynamic tracking, such as in surveillance or inspection tasks, where the environment is less dynamic and the target's behavior is relatively stable. However, in more complex, dynamic environments, filtering-based algorithms face limitations. When targets exhibit erratic or non-linear motion, or when they are temporarily occluded, traditional filtering methods may struggle to maintain accurate tracking. In such cases, their reliance on predefined motion models can lead to tracking inaccuracies. To address these challenges, future research could focus on improving these algorithms' adaptability, enabling them to better handle sudden changes in target behavior, occlusions, or environmental disturbances. Additionally, incorporating machine learning and deep learning techniques could enhance their ability to model non-linear movements and appearance variations. Hybrid approaches that combine filtering with advanced object detection and tracking methods, such as convolutional neural networks (CNNs) or deep reinforcement learning (DRL), could further improve the robustness and accuracy of UAV-based tracking systems in unpredictable environments. Overall, while filtering methods are powerful tools for target tracking, their performance is highly dependent on the specific dynamics and context of the target.

2.2. Deep learning-based algorithms

The deep learning-based target prediction algorithm utilizes the robust feature learning capabilities of neural networks to improve the accuracy of target state predictions by automatically extracting valuable information from extensive datasets [43–45]. In object tracking tasks, these algorithms are trained on historical trajectory data to identify movement patterns and behavioral characteristics, thereby facilitating effective predictions in complex environments. To capture dynamic features and environmental information of the target, deep learning architectures such as long short-term memory networks (LSTMs), convolutional neural networks (CNNs), and graph neural networks (GNNs) are frequently employed [46–48]. To accurately describe the behavioral characteristics of the target, researchers must first collect extensive trajectory data. This data is then used to train model parameters through various methods, such as interacting multiple models (IMM) [49], Gaussian mixture models (GMM) [50], and hidden Markov models (HMM) [51]. Once the model is adequately trained, it can be employed to predict the target's trajectory effectively.

Deep learning methods are increasingly being applied to improve the accuracy of target trajectory prediction and tracking performance. These approaches leverage the powerful feature extraction capabilities of neural networks to address challenges such as trajectory forecasting, aspect ratio changes, and environmental factors like low-light conditions. Alahi et al. [52] regarded the problem of trajectory prediction as a problem of position sequence generation, and employed the LTSM method to build a prediction model that can encode the observed target trajectory and generate the target's future trajectory. Zhang et al. [53] introduced a coarse-to-fine deep learning framework aimed at addressing the aspect ratio change challenge in vision-based aerial tracking. This framework is bifurcated into two distinct components: coarse trackers, which are tasked with generating initial estimates for the target object and managing the movement and scale changes of the bounding box as a whole; and fine trackers, which concentrate on the refinement of the bounding box boundaries. The fine trackers learn a sequence of actions designed to meticulously adjust the four edges of the bounding box. These two tracker components are collaboratively trained by leveraging a shared perception network within an end-to-end reinforcement learning architecture. Ye et al. [54] introduced a low-light image intensifier designed to alleviate the impact of illumination and ambient noise on target tracking. This approach leverages a lightweight map estimation network, ME-Net, which is adept at jointly estimating both the light map and the noise map, thereby enhancing tracking performance under challenging lighting conditions. Fig. 5 shows some tracking screenshots of the trackers with DarkLighter enabled or not, DarkLighter raises the tracking reliability of the trackers in these low-light scenes. Wang et al. [55] presented a UAV tracking method that capitalizes on manual features within a filtered tracking framework. In this method, a peak signal-to-noise ratio (PSR) stability metric is employed to assess the quality of tracking results and to determine the fusion weights. This strategy significantly bolsters the robustness of the tracking process.

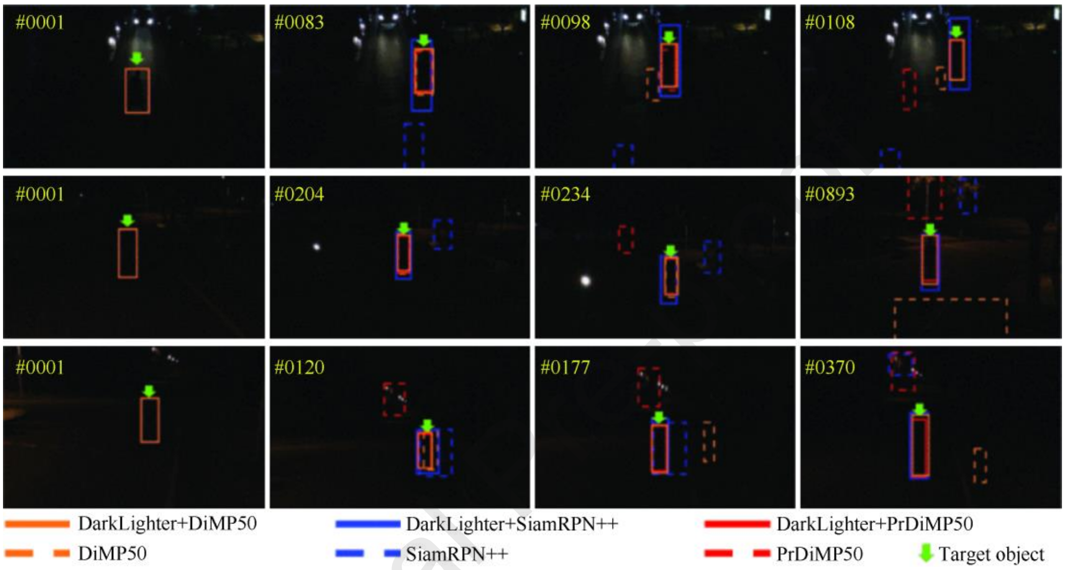


Fig. 5. Some qualitative evaluation results of trackers when DarkLighter is enabled (represented by solid line boxes) or not (indicated by dashed line boxes) presented in [54]. From top to bottom, the sequences are pedestrian3, person12 2, and person12 3 from UAVDark135. In the absence of DarkLighter's assistance, the involved trackers are unable to maintain robust tracking under these low-light conditions.

Researchers have been combining deep learning models with traditional tracking algorithms to enhance the robustness and accuracy of object tracking systems. These hybrid approaches integrate methods like CNNs and novel loss functions to optimize tracking in complex environments, including dynamic obstacle detection and ground target tracking. Panetsos et al. [56] integrated a CNN with a KCF tracker to achieve uninterrupted detection of ground targets. Their approach harnesses the strengths of both CNNs and KCF to maintain a high level of tracking accuracy. Zhou et al. [57] proposed a dynamic obstacle position estimation method that utilizes learning-based MDE (Monocular Depth Estimation) and a monocular camera. This method addresses the scale ambiguity problem by integrating object detection and height-based depth estimation algorithms, thereby enhancing the accuracy of the estimation. Building upon the SiamCAR framework [58], Jin et al. [59] developed the RB-SiamCAR tracker. This tracker employs a ranking-based filter pruning technique and introduces a classification sorting loss and an IoU-guided sorting loss. These losses, in conjunction with the ECA (Efficient Channel Attention) module, facilitate the consistent optimization of both classification and positioning tasks. The result is a tracker that offers improved accuracy and robustness in target tracking. Giusti et al. [60] studied the problem of perceiving forest or mountain trails from a single monocular image, proposing a different approach based on a deep neural network used as a supervised image classifier. By operating on the whole image at once, their system outputs the main direction of the trail compared to the viewing direction, bypassing the challenging problem of determining trail characteristics. Paul et al. [61] proposed Siam R-CNN, a Siamese re-detection architecture that uses convolutional neural networks to model the appearance of objects, and combines it with a novel tracklet-based dynamic programming algorithm to track objects through re-detection. As shown in Fig. 6, the framework primarily consists of two simple sub-networks: a Siamese network for feature extraction and a classification and regression network for bounding box prediction.

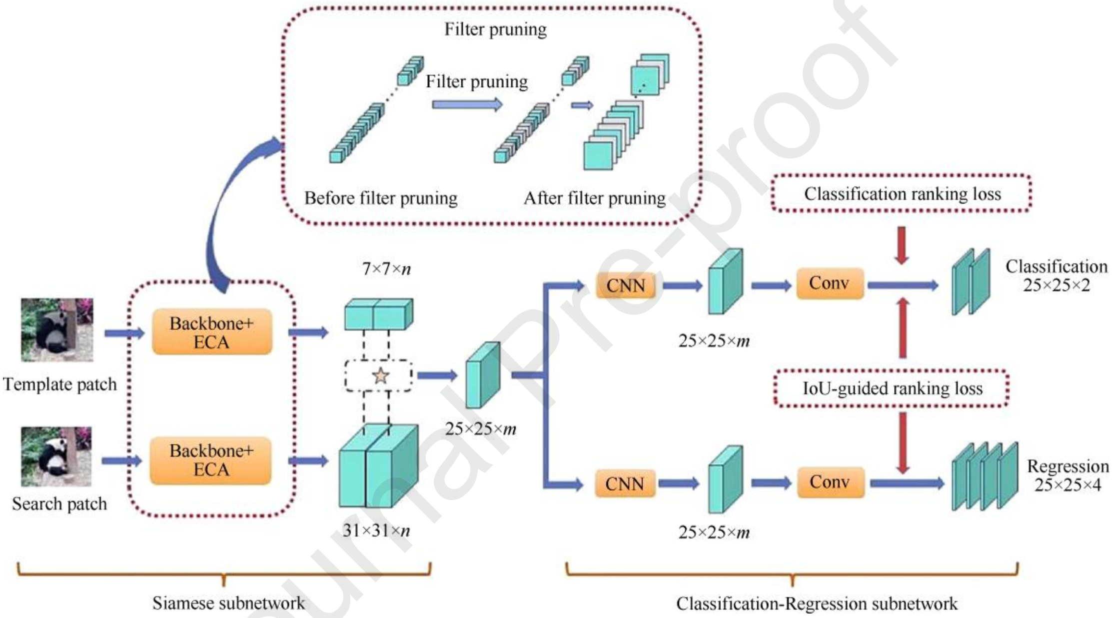


Fig. 6. Ranking-based SiamCAR framework of Ref. [61].

In summary, deep learning-based target prediction algorithms leverage the robust feature extraction capabilities of neural networks to enhance prediction accuracy by automatically extracting information from large datasets. These algorithms effectively capture dynamic features and environmental information through architectures such as LSTM, CNN, and GNN. By training on historical trajectory data, they learn complex motion patterns and behavioral characteristics, which enables accurate predictions even in challenging environments. Furthermore, advancements such as end-to-end reinforcement learning frameworks and lightweight networks enhance their robustness and adaptability. However, these deep learning methods typically require extensive data collection and training to optimize model parameters, a process that can be resource-intensive. They are also susceptible to overfitting, especially in situations with limited data diversity. Additionally, their dependence on large computational resources may hinder real-time implementation, and their performance can degrade in scenarios involving rapid changes or unexpected target behaviors.

To address these limitations, future advancements could incorporate emerging technologies such as edge computing, which would allow for faster data processing and real-time decision-making without the need for powerful centralized servers. Additionally, the integration of advanced multi-modal sensing technologies, like LiDAR or 3D vision, could improve robustness in tracking under difficult environmental conditions. Moreover, newer model optimization techniques, such as lightweight neural networks or the use of neuromorphic computing, could further enhance the speed and adaptability of deep learning-based trackers, making them more effective in real-world applications. Overall, while deep learning algorithms show significant promise for target prediction, their effectiveness is contingent upon data quality, model training, and computational capacity.

2.3. Regression-based algorithms

Regression-based target prediction algorithms aim to forecast a target's future location by constructing a mathematical model based on historical data. These algorithms typically utilize methods such as linear or polynomial regression to establish a relationship between time and location, drawing on the target's positional information at various time points. A key strength of the regression model lies in its ability to effectively capture movement trends, thereby facilitating accurate position predictions. The implementation process places significant emphasis on feature engineering, where the model's predictive capabilities are often enhanced by extracting dynamic features like velocity and acceleration. Despite their relative simplicity and lower computational demands, regression algorithms may struggle with complex motion patterns and noisy environments, where deep learning methods often excel. However, in scenarios characterized by linear or straightforward motion patterns, regression-based algorithms can still deliver precise and efficient predictions. Consequently, they are widely applied in fields such as target tracking and motion analysis.

Several studies in target trajectory prediction utilize analytical and polynomial approaches to model and forecast the motion of targets. These methods rely on historical data and dynamic constraints, with some models addressing uncertainties, collision avoidance, and smoothness in the target's future trajectory. Cui et al. [62] used Bernstein basis polynomials, considering the distribution of obstacles around the target, to predict the target's future movement, assuming it aims to avoid obstacles. Wang et al. [63] utilized polynomial trajectories to approximate historical path-points to forecast the future trajectory of the target over time. Then, the initial tracking trajectory is generated as which is topologically equivalent to the target prediction trajectory, and the b-spline is employed to represent the tracking trajectory while taking into account the smoothness, collision and dynamic feasibility. Li et al. [64] employed observational regression based polynomial values to extend the polynomials to future times to rapidly predict the future motion of the target after obtaining the observed values for the target. Considering the effects of observation errors and noise, the predicted target trajectory might intersect with the position of the obstacle. To avoid the above situation, the target trajectory is corrected through using the breadth-first search (BFS) method to guarantee that the modified target trajectory is safe. Lee et al. [65] considered the UAV camera sensor, position, velocity and covariance of its estimation error, and also the size (radius) of the moving object, observed the current information of the target, employed the Bernstein polynomial to represent the target trajectory, and forecasted the possible trajectory of the target in the future time by solving the unconstrained quadratic programming (QP) problem, and acquired the fast reachable set of the target. Chen et al. [66] assumed the target motion was smooth, employed Taylor expansion to represent the target trajectory, and formulated the prediction problem as an unconstrained QP problem to determine the target trajectory in the future short time. Ji et al. [67] employed EKF to process the current position of the target, represented the target trajectory as a Bezier regression polynomial, and employed the hybrid A* algorithm to determine the target trajectory in the next short time. Pan et al. [68,69] utilized polynomials to approximate the target motion, and employed the Bernstein-based polynomial (Bézier curve) to enhance the dynamic constraints, and combined with the historical information of the target to predict the target motion.

Other research explores the integration of environmental factors and dynamic behaviors into target prediction. Techniques like A* path planning, visibility measures, and regression-based models consider obstacles, interactions, and the movement context of the target to enhance the prediction accuracy in real-world scenarios. Vasishta et al. [70] employed sociological principles and the sociological concept of Natural Vision to model sidewalks, buildings, and vehicles, established a function of the built environment where pedestrian behavior is located in urban areas, and constructed a potential field cost map. Then utilized the A* algorithm [71] to plan the trajectory of the target in the potential field cost map, and took the planning results as the predicted trajectory of the target. Yi et al. [72] proposed a pedestrian prediction approach, which employs the stationary crowd group as a key component to simulate pedestrian behavior, studies pedestrian behavior by inferring the interaction between the stationary crowd and the pedestrian, models the impact of the target and obstacles on the target trajectory as energy, and plans the trajectory of the target via the fast marching method to fulfill the purpose of prediction (Four examples are presented in Fig. 7). The above prediction methods assume that the movement trajectory of pedestrians is optimal. But in the real world, the movement mode of the moving target is uncertain, and it cannot be guaranteed that the trajectory is optimal at all times. Thus, the above method is inaccurate and has deviations. Khan et al. [73] tackled the challenge of low-complexity target tracking using flying robots by employing a cover-set coverage method. This method involves clustering moving targets and estimating the camera locations and orientations for each cluster. To enhance the efficiency of their algorithm, they leveraged partial knowledge of target mobility. Consequently, they developed three computationally efficient approaches: predictive fuzzy, predictive incremental fuzzy, and local incremental fuzzy. The primary objective of these approaches is to balance coverage efficiency, the distance traveled, the number of UAVs used, and computational complexity. Jeon et al. [74,75] employed a visibility measure reflecting the Euclidean signed distance functions to obtain a series of security view points. Then, in the subsequent modules, the viewpoints are smoothly interpolated by using quadratic programming, but this scheme fails to guarantee the visibility of the target as it moves between viewpoints, and the computational burden is significant.

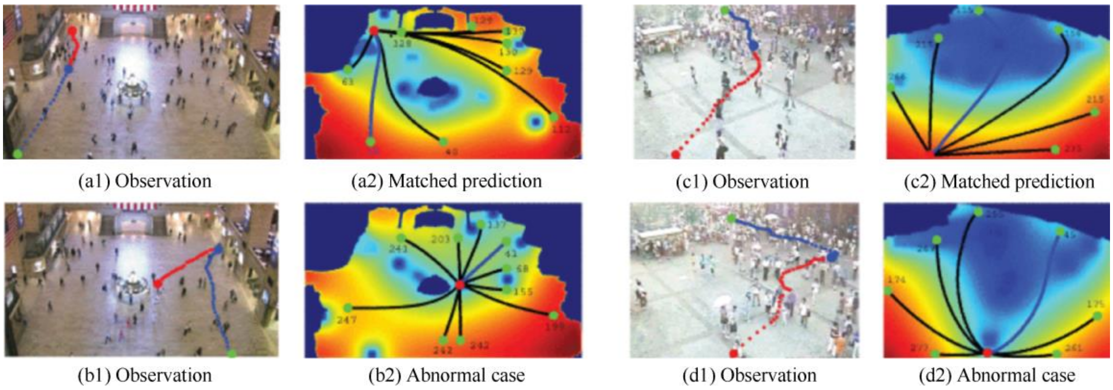


Fig. 7. Four examples of pedestrian destination prediction in Ref. [72].

The performance comparison of different target information prediction methods is summarized in Table 1. Here, Benchmark refers to the UAV tracking benchmarks used by each method, Precision indicates the accuracy of the target position prediction, area under the cure (AUC) measures the success rate of the tracking algorithm, and FPS represents the processing speed in terms of frames per second, NC stands for missing data for this method. When making the comparison, studies with unclear datasets or those using proprietary datasets were excluded.

Table 1

Performance comparison of different target information prediction methods.

Ref.	Benchmark	Precision	AUC	FPS
[39]	UAV123	65.9	48.8	NC
[40]	UAV123	68.6	47.9	14.69
[41]	UAVDT	71.6	45.7	50.2
[53]	UAV123	65.1	45.21	NC
[54]	UAVDark135	70.0	54.4	NC
[55]	UACDark135	71.6	50.1	NC
[59]	UAV123	83.5	64.0	25
[61]	UAV123	83.4	64.9	25

In summary, regression-based target prediction algorithms offer a straightforward and effective approach for predicting future positions by utilizing methods such as linear or polynomial regression to model the relationship between time and position. These algorithms are computationally efficient, making them ideal for scenarios with linear or simple motion patterns and applications requiring quick and lightweight calculations. They excel at capturing movement trends over time, particularly when integrated with features like velocity and acceleration, and are commonly used in UAV tracking and sports analysis. However, regression methods face limitations in handling complex or nonlinear motion patterns and may struggle in high-noise environments, lacking the robustness of deep learning models. Additionally, they often require trajectory correction methods, such as BFS or

A* algorithms, to avoid collisions or account for obstacles, which adds complexity. Consequently, while regression-based methods provide accurate and efficient predictions in simpler scenarios, their effectiveness diminishes in dynamic or unpredictable environments. The introduction of emerging technologies, such as more sophisticated sensor systems, edge computing for faster data processing, and advanced multi-modal tracking, could enhance the robustness and accuracy of regression-based algorithms, making them more adaptable to complex, real-time tracking challenges.

3. Status of target information tracking method

Tracking target information through UAVs is a pivotal technology for achieving autonomous flight and efficient monitoring, with research advancements primarily categorized into three approaches: control-based, planning-based, and deep learning-based strategies. The control-based strategy prioritizes real-time feedback and dynamic adjustments, enabling UAVs to flexibly respond to changes in the target. In contrast, the planning-based strategy focuses on designing optimal flight paths by utilizing environmental information and target characteristics to develop effective navigation strategies. Meanwhile, the reinforcement learning-based strategy leverages data-driven models, utilizing neural networks to learn optimal decision-making strategies through interaction with the environment and reward feedback, thereby significantly enhancing the accuracy and adaptability of tracking. As technology advances, the potential applications of these strategies in complex environments are continually expanding, providing innovative solutions to improve the target tracking capabilities of UAVs.

3.1. Control-based strategy

The control-based strategy effectively enables UAVs to track targets by utilizing real-time feedback and dynamic adjustments. This approach typically involves the use of closed-loop control systems, which rely on real-time sensor data to continuously update the UAVs' status, including parameters such as heading, speed, and altitude.

Several UAV control strategies utilize dynamic models and optimization techniques to enhance target tracking performance. These methods often incorporate predictive models that forecast the target's future trajectory, and optimization algorithms that adjust the UAV's path to minimize tracking errors and maximize efficiency. By considering the system dynamics and constraints, these methods aim to provide precise control over the UAV's movement in complex scenarios. According to the sliding mode control theory, Wang et al. [76] put forward a continuous time and discrete-time distributed formation tracking protocol based on adjacent relative information, and employed the Lyapunov stability method to provide sufficient conditions for multi-UAV systems to achieve expected formation tracking, and presented the quasi-sliding mode domain width of the discrete-time protocol. Panetsos et al. [56] employed the nonlinear model predictive control (NMPC) method to take into consideration the nonlinear dynamics of the UAV system, and incorporated the future trajectory of the target into the prediction range of the NMPC, and produced an appropriate reference for the autopilot's internal attitude control loop for minimizing the tracking error between the target and the target. Naxgeli et al. [77] put forward a method for real-time control of UAVs equipped with gimbals, which automatically solves out UAV trajectories and gimbal control with target prediction position as input. It employs a real-time retreat horizon planner to automatically record the scene with moving targets, while optimizing the visibility under occlusion and guaranteeing a collision-free trajectory, and sets up the cost minimization problem under constraints as a finite horizon MPC optimal problem and solves it in real-time.

Some control approaches focus on real-time sensor feedback without relying on explicit system models. These methods employ adaptive algorithms that adjust the UAV's behavior based on continuous sensor inputs, such as vision or position data, to track the target effectively. This model-free approach offers robustness, particularly in unpredictable environments where traditional model-based methods might struggle. Li et al. [78] devised a control law employing estimated variables for small UAVs fitted with gimbal cameras, which is capable of driving the range to the desired value by merely controlling the UAV turning rate without employing the range value as feedback for static and moving targets having constant velocity. Zhao et al. [79] put forward a yaw compensator module, which combined with the help of the image information of the target for adjusting the yaw of the UAV, and finally employed the model prediction controller (MPC) for obtaining the optimal speed of the UAV taking trajectory and yaw as inputs. Boudjit et al. [80] proposed a target tracking control law using a fuzzy logic controller that processes camera data. The algorithm is designed with minimal input parameters, reducing computational power requirements. Kendall et al. [81] relied solely on low-frequency target image information, and employed a Kalman filter to mitigate the excessive noise from the measurement range of the object's pixel area, and finally achieved the control of the target tracking by UAVs via a parallel proportional integral derivative (PID) controller (see Fig. 8). Then, Rabah et al. [82] developed a Fuzzy-PI controller that adjusts the parameters of a PI controller based on position and velocity data to improve target tracking in quadcopters.

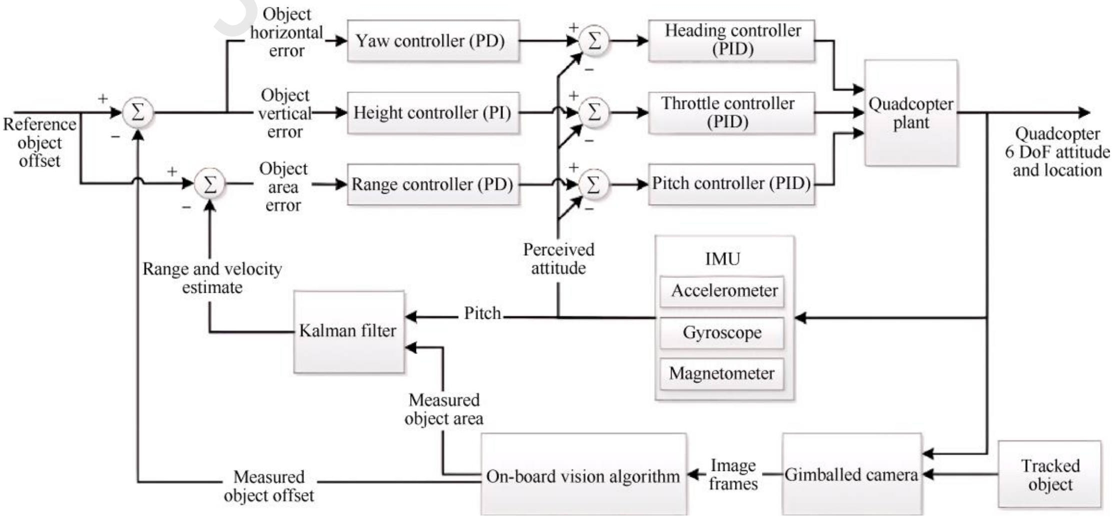


Fig. 8. Object tracking control system structure in Ref. [81].

In summary, control-based strategies for target tracking utilize real-time feedback and dynamic adjustments, enabling UAVs to effectively follow their targets. These algorithms rely on closed-loop control systems that continuously update the UAV's state based on sensor data, facilitating precise modifications in heading, speed, and altitude. Techniques such as sliding mode control, NMPC, and PID control are particularly effective in managing the UAV's trajectory and minimizing tracking errors. These methods can adapt to changing conditions and provide robust performance across various operational scenarios, making them well-suited for real-time applications. However, control-based strategies can be sensitive to model inaccuracies and disturbances, potentially leading to instability if the system dynamics are not accurately represented. Additionally, achieving optimal performance may require complex tuning and calibration, which can be time-consuming. In environments with high noise levels or unpredictable target behavior, the dependence on real-time feedback might introduce delays that compromise tracking accuracy. Therefore, while control algorithms are powerful tools for target tracking, their effectiveness is contingent upon the accuracy of the models employed and the quality of the sensor data.

3.2. Planning-based strategy

The planning-based strategy in UAV target tracking focuses on determining the optimal flight path to ensure efficient and precise monitoring [10,83,84]. By analyzing environmental characteristics, target behavior, and mission requirements, these methods generate adaptable flight plans. A critical aspect of this approach is the consideration of obstacles and flight constraints, which is essential for maintaining the safety and efficiency of the UAV during its mission. Furthermore, advancements in sensor technology and computing power have enhanced these methods, allowing for real-time path updates. This capability enables UAVs to respond flexibly to dynamically changing targets, thereby improving tracking accuracy and stability.

Trajectory optimization and path planning methods have been extensively explored to improve UAV target tracking. Several studies focus on optimization-based approaches, where the trajectory is represented using mathematical functions like Bézier curves or other approximations. These methods aim to minimize tracking errors, control costs, and ensure safety. Lin et al. [36] characterized the object tracking problem as an optimization-based trajectory generation, and suggested that the trajectory be represented as a Bézier curve using the Bernstein polynomial basis, and the weighting and cost functions jointly penalize the tracking error, the control cost of the trajectory, and the trajectory length, while imposing safety and feasibility constraints. Masnavi et al. [85] put forward for the first time a multi-convex approximation for trajectory optimization related to target tracking issues. It breaks down trajectory optimization into three smaller parts: a convex quadratic programming and two parallel univariate optimizations which can be solved in closed form. Zhou et al. [57] put forward a spatiotemporal motion planning method on the basis of safe corridors to generate safe and efficient spatiotemporal trajectories. This method can not only handle the uncertain motion of the obstacle, but also effectively respond to the change in the velocity of the dynamic obstacle by predicting the trajectory on the basis of the past motion and predicting its motion uncertainty accordingly.

Some methods integrate graph-based or sampling-based techniques for efficient path generation. Li et al. [64] employed a sampling-based search algorithm under target constraints to search for the path based on calculating the future trajectory of the target. The latter part utilizes flight corridors to constrain and optimize the trajectory. Jeon et al. [86] focused on enhancing target visibility by proposing an efficient trajectory generation method for chasing a dynamic target, emphasizing color detectability against the background. They defined a measure of color detectability and optimized a discrete path, which was then transformed into a dynamically feasible trajectory capable of real-time adaptation to the target's movement. Utilizing a directed acyclic graph (DAG) for efficient path generation, they ensured smooth trajectories through QP. Cai et al. [87] put forward a tracking algorithm that incorporates target state estimation into the UAV tracking path, which is a path planning strategy based on the improved A* algorithm, to address the issue that the traditional tracking algorithm cannot quickly track the target and the tracking efficiency is not high. To deal with the loss of the target, Zou et al. [88] put forward a proposal to determine the flight direction of the lost target by visual direction. First, the projection sphere of the obstacle in the center of the target position is created. Second, the sample method is employed to determine the point indicating the visual direction of the spherical surface of the object. Additionally, a trajectory generation strategy was devised to deal with the occlusion. Imitates an attractive force from the visual direction, thereby pushing the control point closer to the point by means of introducing a direction penalty term that penalizes the curve for deviating from the visual direction. Wang et al. [89] introduced a comprehensive metric for target visibility that incorporates factors such as observation distance, angle, and occlusion effects. This metric was formulated into a differentiable visibility cost function, facilitating the joint optimization of spatial trajectory and yaw while maintaining dynamic feasibility.

Visibility plays a crucial role in UAV target tracking, especially in environments where occlusions may affect the tracking process. Several studies have focused on optimizing UAV trajectories to enhance visibility and prevent occlusions. Lee et al. [65] focused on the target visible area to improve the visibility of both single and dual targets in both static and dynamic settings. By considering the set of reachable targets and obstacles, their proposed planner generates a target visible trajectory through the formulation and solution of a quadratic programming problem. Hui et al. [35] addressed the trade-off between target visibility and security in trajectory optimization. They utilized Model Predictive Path Integral (MPPI) to solve the nonlinear trajectory optimization problem, resulting in an efficient tracking trajectory that ensures full efficiency. Occlusion-aware trajectory generation is another critical area of research, where methods are developed to avoid scenarios where the target might be obstructed by obstacles in the environment. Penin et al. [90] explored online optimal trajectory generation for quadrotor target tracking, addressing image-based and actuation constraints. Their research concentrated on a camera-equipped quadrotor that must smoothly follow a moving target while avoiding obstacles and image occlusions. They proposed a multi-objective optimization strategy with occlusion constraints and an online replanning method based on MPC. This approach was formulated as a nonlinear program (NLP) using differential flatness and B-Splines, allowing for resolution via sequential quadratic programming (SQP) at 30 Hz. Fig. 9 depicts target visibility for different algorithms, shown as the distribution of target positions relative to the tracking quadrotor on the x-y plane. The red part represents the field of view of the drone.

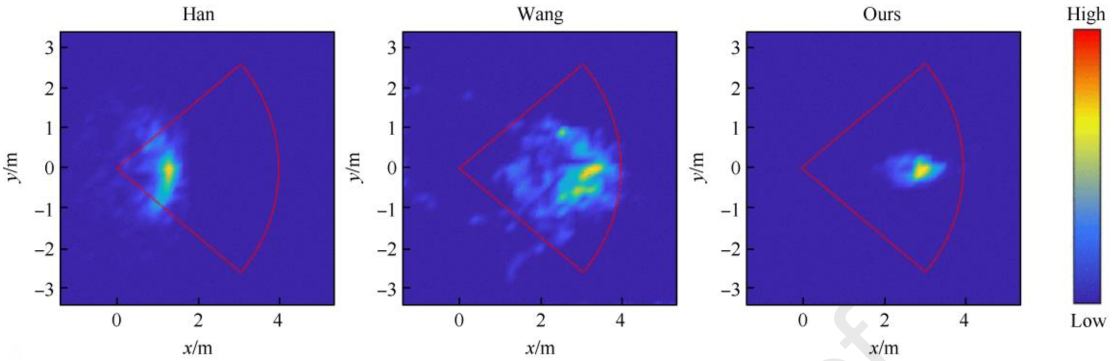


Fig. 9. Comparison with Ref. [69] and Ref. [89] on target visibility in Ref. [67].

Real-time control methods are essential for adapting to dynamic targets with changing velocities and unpredictable movements. Some approaches focus on adjusting the UAV's trajectory to synchronize with the dynamic perching surface of the target. Gao et al. [91] introduced a versatile terminal adjustment method designed to accommodate variations in flight time and to synchronize with the dynamic perching surface of the target at various angles. This method optimizes the tangential relative velocity and employs a relaxation strategy to address the dynamics and safety issues arising from rigid boundary conditions. In real world experiments, UAV successfully tracks and perches at 30 km/h (8.3 m/ s) on the top of the sports utility vehicle (SUV), and at 3.5 m/s with 60° inclined into the trunk of the SUV. Li et al. [92] proposed a dynamic window approach local path planning algorithm tailored for dynamic target tracking tasks. This algorithm adaptively adjusts the yaw angle of the UAV to keep the tracking target centered in the camera image, thereby achieving precise tracking and path planning. In addition to dynamic adjustment, path planning methods like the dynamic window approach allow for adaptive changes in the UAV's flight path based on the target's movement. Liu et al. [10] presented a novel path planning algorithm based on an elliptical tangent model. This approach enables feasible path planning without the requirement for map building, offering a flexible solution for various navigation scenarios.

Certain UAV trajectory optimization methods are tailored for specific applications, focusing on challenges unique to those domains. Bonatti et al. [93] developed a method for autonomous aerial cinematography that prioritizes the capture of aesthetically pleasing videos without human intervention. Their approach stands out by balancing shot smoothness, occlusion, and cinematography guidelines in real time, unlike existing methods that depend on offline trajectory generation or short-term planning with simplistic obstacle representations. They achieved this through an innovative algorithm for real-time covariant gradient descent, optimizing trajectories based on multiple cost functions. Han et al. [69] presented a perceptual trajectory optimization method for security visibility guidance in aerial tracking, which is capable of simultaneously handling occlusion and collision in complex environments (The detailed structure is shown in Fig. 10). It sets up a new view-based metric field to prevent targets from being occluded by obstacles. Based on this, the complexity of the environment is introduced so as to adjust the relative distance between the quadcopter and the target to further lower the occlusion probability. Next, a critical relative angle is put forward to strengthen the obstacle perception in the direction of quadrotor motion. Additionally, a time optimization method is presented to enhance the smoothness of quadrotor flight.

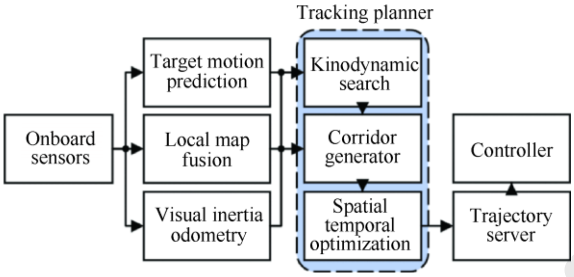


Fig. 10. Description of the fast-tracker system structure in Ref. [69].

In summary, planning-based algorithms for UAV target tracking focus on devising optimal flight paths to ensure efficient and precise monitoring of targets. These methods excel in generating adaptive flight plans by analyzing environmental features, target behavior, and mission requirements. By considering obstacles and flight restrictions, they ensure both safety and efficiency during mission execution. Advances in sensor technology and computational power have enabled these algorithms to provide real-time path updates, allowing UAVs to respond swiftly to dynamic changes in target positions, thereby enhancing tracking accuracy and stability. However, these planning methods can be computationally intensive, particularly in complex environments with numerous obstacles and dynamic elements. The necessity for detailed environmental modeling can also introduce delays in path planning, potentially affecting real-time performance. Additionally, these algorithms may struggle in highly unpredictable scenarios where target behavior is erratic or rapid adjustments are required. Consequently, while planning-based methods offer robust solutions for target tracking, their effectiveness may be limited by computational demands and environmental complexity.

3.3. Reinforcement learning-based strategy

Reinforcement learning (RL) strategies for target tracking by UAVs enhance decision-making capabilities in dynamic environments through an iterative process of trial and error. UAVs continuously interact with their surroundings, refining their tracking strategies by receiving rewards or penalties that provide performance feedback. By defining a reward function that includes key objectives-such as maintaining an optimal distance from the target, minimizing energy consumption, and maximizing tracking accuracy-UAVs can autonomously discover effective tracking policies. These RL approaches enable UAVs to adapt dynamically to fluctuations in target behavior and environmental conditions, making them highly suitable for complex and unpredictable scenarios. Consequently, these strategies have demonstrated significant potential in improving the adaptability and efficiency of UAVs in target tracking missions. Overall, existing research on RL-based strategies can be categorized into two main types.

Some scholars use RL to conduct research from the planning level. Li et al. [94] put forward an online path planning method for UAVs by employing deep RL to enhance maneuvering target tracking and obstacle avoidance. They constructed a deep deterministic policy gradient (DDPG) framework, which was enhanced by mixed noises in their MN-DDPG method. Additionally, they introduced a task-decomposition algorithm to improve the generalization capability of the UAV control model. Xia et al. [95] proposed a cooperative multi-agent reinforcement learning scheme. They introduced a propulsion power consumption model and an energy-saving strategy to prolong the lifespan of the UAV tracking system. Meanwhile, the use of spatial information entropy improved detection coverage. Wang et al. [96] proposed a two-stage deep RL method to improve data utilization and learning speed. They created a sample generator that combines artificial potential fields with a traditional control scheme for expert experience data. In the first stage, the policy and critic networks are pre-trained with expert data. In the second stage, the policy network is guided by the agent's best experiences based on average returns. Li et al. [97] proposed an enhanced DDPG algorithm. They designed a reward function based on line of sight and artificial potential fields to guide the UAV's behavior for target tracking, incorporating a penalty term to ensure smooth trajectory generation. Bhagat et al. [98] introduced a deep Q-network (DQN) approach for the persistent tracking of a dynamic target. They validated their proposed method through both qualitative and quantitative assessments, employing a set of three diverse metrics to evaluate its effectiveness. Wang et al. [99] presented an online distributed algorithm for tracking and searching with fleets of UAVs. They addressed the challenge of energy replenishment and incorporated a quantum probability model to characterize the partially observable positions of targets. Furthermore, they developed an upper confidence bound tree algorithm to identify the optimal path, utilizing a teammate learning model to tackle non-stationarity issues in distributed reinforcement learning. Seungyeon et al. [100] proposed a framework for target tracking using only a monocular camera. The framework comprises two components: a perception module and a planning module. The perception module employs a variational autoencoder architecture and a joint objective function across heterogeneous data to extract cross-modal representations from RGB input, capturing information from multiple data modalities. The planning module leverages latent vectors derived from the pre-trained perception module to generate appropriate next-time-step waypoints through imitation learning. Additionally, the planning module integrates temporal information of the target to enhance tracking performance through consecutive cross-modal representations.

Some scholars have explored RL for research from the control level. Ma et al. [101] proposed a RL control algorithm to address wind disturbances during tracking. They formulated the problem as a Markov decision process with specific system states and reward functions. Najmaddin et al. [102] improved the twin delayed DDPG algorithm for reinforcement learning by incorporating a proportional-differential controller, a new reward function, and multistage training. These enhancements led to a significant improvement in tracking performance, reducing errors by up to 86% for both fixed and moving targets. Zhao et al. [103] introduced a deep RL-based end-to-end control method specifically designed for dynamic target tracking using UAVs. This approach effectively addresses the challenges posed by uncertain motion and limited perception capabilities. The framework leverages onboard camera images and integrates a neural network with reward functions to enhance the UAV's ability to perceive speed commands. Li et al. [104] introduced the meta twin delayed DDPG, a novel approach that integrates deep RL with meta-learning for the control of UAVs. This method is particularly effective in addressing the challenges of uncertain target tracking in complex scenarios such as wildlife protection and emergency aid.

In summary, RL strategies for UAV target tracking provide a robust framework for optimizing decision-making in dynamic environments. A key strength of RL is its capacity to learn and adapt through trial and error, allowing UAVs to refine their tracking strategies based on real-time feedback from their surroundings. This adaptability makes RL particularly suitable for complex and unpredictable scenarios where traditional methods may struggle. By defining customized reward functions, UAVs can autonomously discover effective tracking policies that prioritize objectives such as maintaining an optimal distance from the target or minimizing energy consumption, thereby enhancing tracking accuracy and overall efficiency. However, RL approaches face significant challenges, particularly concerning convergence speed and computational demands. Achieving optimal performance may require extensive interactions with the environment, resulting in prolonged learning times. Furthermore, the effectiveness of RL strategies is heavily reliant on the design of the reward function, which can be complex to formulate and may not always yield desired behaviors unless meticulously tuned. Additionally, RL methods may struggle in highly dynamic environments where targets rapidly change behavior, necessitating continuous retraining or adaptation to sustain performance. As RL algorithms evolve, the incorporation of emerging technologies like edge computing further boosts their efficiency. By offloading computation to nearby edge servers, RL algorithms can operate with reduced latency and better handle real-time adjustments in target tracking. This reduces the computational burden on UAVs, enabling faster decision-making and more responsive control, particularly in complex or congested environments. Therefore, while RL offers promising advantages in target tracking, it also presents challenges related to training efficiency and environmental variability.

4. Status of swarm cooperation-based method

UAVs equipped with cameras provide a dynamic tracking capability that surpasses static cameras or ground sensors, but accurately tracking targets with a single UAV is still challenging due to appearance variations and occlusions. To overcome these obstacles, Swarm cooperation-based methods leverage swarms of UAVs working collaboratively to improve tracking efficiency and accuracy. In this setup, UAVs communicate in real time to share information about their positions and target states, creating a unified system capable of dynamic response [105–107]. Each UAV can focus on specialized tasks-some may track the target while others monitor the environment or plan paths. As shown in Fig. 11[3], this collaborative strategy not only broadens the surveillance range but also enhances the swarm's adaptability to complex and changing scenarios. As the potential for

[3] Fig. 11 is reproduced based on
https://www.sandboxx.us/news/why-cant-the-us-stop-drone-swarms-from-penetrating-restricted-airspace/

swarm-based approaches grows, they offer promising solutions for effective target tracking in various applications, from search and rescue operations to wildlife monitoring.

Fig. 11. Multiple UVAs collaborate to expand tracking range.

Effective communication within UAV swarms facilitates real-time data sharing and coordination, while efficient task allocation optimizes resource use and enhances mission success rates. Numerous researchers have studied this field. Deng et al. [108] investigated energy-efficient task distribution for UAVs by leveraging edge computing, which enables the offloading of computation tasks to ground edge nodes rather than relying on cloud resources. In their study, they developed a target tracking system that considered both the diverse capabilities of ENs and the specific requirements of the tasks. This comprehensive approach facilitated the creation of an energy-efficient UAV task distribution algorithm. Wang et al. [76] devised time-varying formation tracking control protocols for multi-UAV systems by employing sliding mode control and neighboring information. They established stability conditions for successful formation tracking and defined the quasi-sliding mode domain for discrete protocols. Upadhyay et al. [109] proposed a collaborative computer vision method for UAV target tracking to address performance decline due to GPS signal strength variations. A master UAV is designated based on GPS strength or proximity to target, calculating relative positions and adjusting formation flying. Stable tracking is achieved via a high-resolution FPV camera, with all UAVs communicating with ground station for data sharing. Zhou et al. [110] introduced a RL framework aimed at optimizing both communication and action policies for UAV swarms. This approach empowers UAVs to autonomously determine the content of messages based on their current status. To achieve this, the researchers employed neural networks for policy approximation, which facilitated the derivation of optimization procedures. Consequently, this method allows for the simultaneous learning of both communication and action policies, enhancing the autonomy and efficiency of UAV operations. Xiao et al. [111] proposed a data-efficient deep RL method specifically designed for collaborative target search using visual UAV swarms. This innovative approach effectively addresses the challenges associated with 3-D sparse rewards and UAV collaboration. By decomposing the primary task into manageable subtasks, the method employs multistage learning to enhance performance. Furthermore, it incorporates an adaptive curriculum that dynamically adjusts the difficulty level based on the success rates, thereby optimizing the learning process.

Additionally, as shown Fig. 12[4], compared to a single UAV, UAV swarms can more effectively address situations where the target is obscured during tracking, a topic that has garnered significant research interest. In order to address the critical challenges of identity association and target occlusion in multi-UAV multi-target tracking tasks, Liu et al. [112] put forward the multi-matching identity authentication network based on the designed dataset, by employing topological relationships and a local-global matching algorithm to resolve cross-UAV associations and enhance tracking of occluded targets. Zhu et al. [113] developed a specific dataset and introduced two evaluation metrics: the automatic fusion score and the ideal fusion score. On this basis, they proposed the agent sharing network, which improves tracking accuracy by integrating template sharing, target re-detection, and view-aware fusion. Li et al. [114] developed a multi-target tracking method for UAV swarms that employs self-attentive feature masks and graph convolutional networks to enhance trajectory aggregation and target differentiation. Their approach is combined with possibility-based clustering and incorporates a graph attention network for optimizing the tracking results in infrared UAVs. Chen et al. [115] introduced the RL network that utilizes self-attention for multi-UAV feature fusion and incorporates a cross-UAV mapping mechanism to assist UAVs in recalibrating when they lose track of targets. They then constructed a system perception index that combines temporal and spatial information to assess the tracking status of multiple UAVs.

Fig. 12. UAV swarms are better able to handle situations where the target is obscured.

Furthermore, as shown in Fig. 13, UAV swarms can also track multiple targets cooperatively. Some researchers are focusing on the study of multi-target tracking using UAV swarms. Zhou et al. [116] proposed a cooperative tracking architecture for UAV swarms that emphasizes efficient resource scheduling. Central to their approach is a Lyapunov-based optimization model, which, along with an energy allocation scheme, aims to enhance multi-target tracking capabilities while maximizing flight time. The proposed algorithm improves dynamic associations between UAVs and targets, allowing for rapid adaptation to changes in target trajectories.

[4] The source information for Fig. 12 is as follows:
https://www.theverge.com/2022/5/5/23058160/drone-swarm-autonomous-navigation-dense-forest-person-tracking

Nagrare et al. [117] introduced a traverse order generation scheme that plays a crucial role in determining the sequence in which targets are tracked and in assigning these targets to UAVs. This scheme enables UAVs to effectively utilize predicted information about the targets for both path planning and tracking purposes. As the targets transition from one region to another, the UAVs are responsible for seamlessly handing off the targets to neighboring UAVs, ensuring continuous and efficient tracking. Qamar et al. [118] developed a policy-based deep RL framework for UAV swarms, enabling autonomous navigation, multi-target tracking, and obstacle avoidance. This framework includes a memory mechanism for optimal path recollection, enhancing navigation and adapting to changes in swarm size.

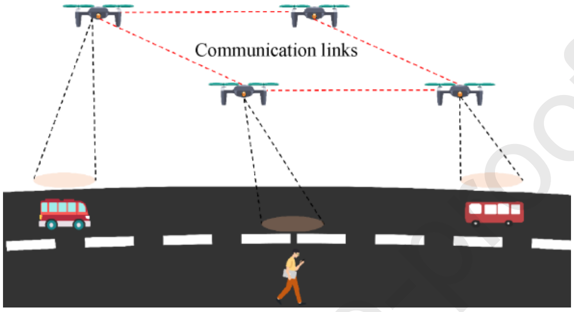


Fig. 13. A UAV swarm are tracking multiple targets.

In summary, the investigation of swarm cooperation-based methods in UAV swarm research highlights notable advancements in operational efficiency and coordination. By organizing UAVs into swarms, these methods enhance communication and resource allocation, thereby effectively addressing challenges such as target occlusion and identity association. Researchers have developed innovative algorithms that employ clustering techniques for energy-efficient task distribution, dynamic path planning, and collaborative operations. This approach allows UAVs to share information efficiently and respond swiftly to environmental changes. In addition, the integration of technologies such as 5G enhances communication speed and reliability, allowing for better coordination, faster data transfer, and improved swarm responsiveness in dynamic environments. This makes UAV swarms more adaptable and efficient in complex scenarios, contributing to the success of applications like search and rescue, wildlife monitoring, and surveillance. Consequently, swarm cooperation-based methods significantly improve the reliability and effectiveness of UAV swarm applications across diverse scenarios.

Table 2 provides a summary and analysis of the primary methods for tracking moving targets by using UAVs, highlighting their advantages and disadvantages and citing representative literature.

Table 2

Summary and analysis of UAV tracking of moving targets.

Category	Strategy	Advantages	Disadvantages	Refs.
Target prediction algorithms	Filtering	Real-time state estimation Noise suppression	Model dependency Occlusion handling	[30–34]

		Flexible integration	Reduced performance in complex environments	
	Deep learning-based	Adaptability to dynamic environments	High computational cost	[49–53]
		Strong adaptability	Real-time implementation challenges	
		Ability to learn complex motion patterns	Extensive data collection and training	
	Regression-based	Effectiveness in linear motion	Poor robustness in noisy environments	[64,70,71, 74,75,]
		High computational efficiency	Dependence on trajectory correction	
		Effective at tracking movement trends	Struggles with complex motion patterns	
Target tracking algorithms	Control-based	Real-time feedback and dynamic adjustments	Complex tuning and calibration	[76,–79,81]
		Adaptability to dynamic environments	Sensitivity to model errors	
		Optimization and predictive capabilities	Reduced tracking accuracy in noisy environments	
	Planning-based	Obstacle and flight constraint management	Path planning delays in complex environments	[10,35,57,64,65]
		Adaptive flight planning	Computationally intensive	
		Real-time path updates for dynamic tracking	Dependence on environmental modeling	
	RL-based	Self-optimization through interaction	Slow convergence and long training times	[87,98–100]
		Handling uncertainty in complex environments	Dependence on reward function design	
		Efficient decision-making	High computational demands	
Swarm cooperation-based		Improved tracking efficiency	Vulnerability to interference	[108–112,114]
		Cooperative multi-target tracking	Synchronization challenges	
		Better robustness	Communication issues	
		Increased adaptability	Complexity in large-scale operations	

5. Technical challenges and future research

5.1. Technical challenges

UAV-based moving target tracking has made significant advancements, yet several technical challenges are anticipated as the field evolves. As shown in Fig. 14, this section discusses four critical challenges: target visibility and occlusion, real-time prediction and tracking in dynamic environments, flight safety and coordination, resource management and energy efficiency.

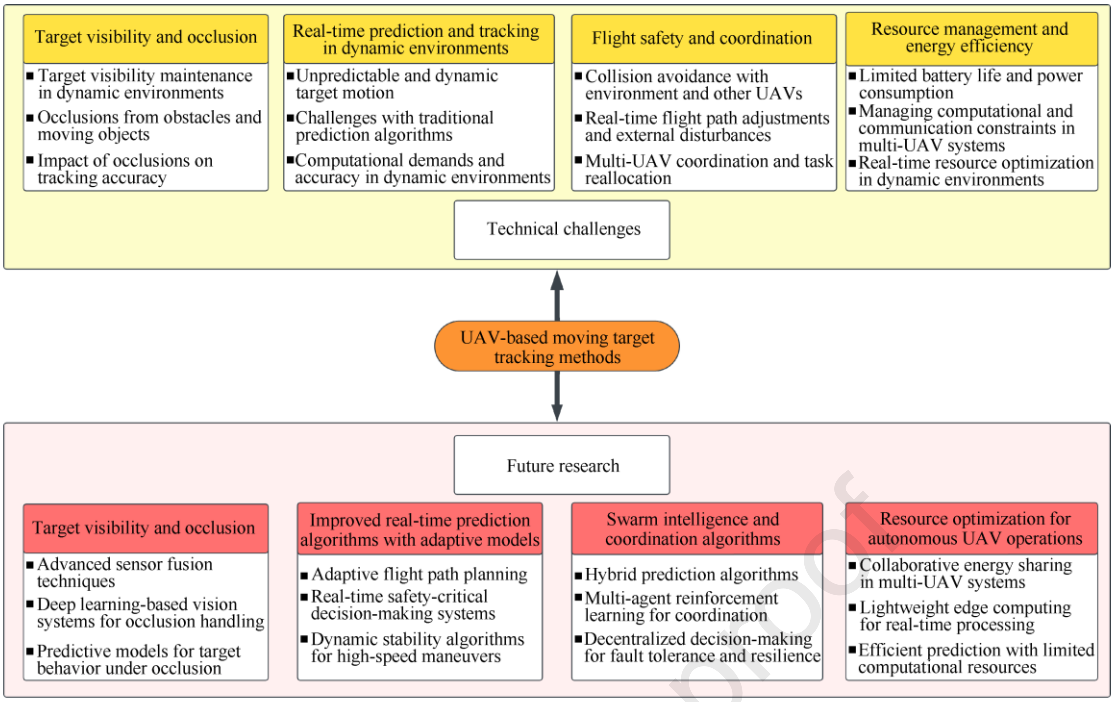


Fig. 14. Technical challenges and future research of UAV-based moving target tracking methods.

5.1.1. Target visibility and occlusion

The ability to maintain continuous target visibility is a fundamental challenge in dynamic environments, where occlusions—such as buildings, trees, or other moving objects—can obstruct the view of the target. This often leads to the UAV losing track of the target, making it difficult to update the target's position and trajectory. Occlusions are particularly problematic in environments with dense obstacles or in scenarios where the target may be intermittently hidden. When the target becomes partially or fully obscured, tracking systems can experience significant delays, resulting in reduced tracking accuracy and, in some cases, total loss of the target.

As the number of UAVs involved increases, the coordination required to ensure uninterrupted tracking becomes more complex. When one UAV loses sight of the target due to occlusion, others must take over the task. This requires a seamless sharing of information and real-time communication among the UAVs to ensure smooth handover. Communication delays, limited bandwidth, and interference from environmental factors can hinder this process, causing misalignment between UAVs or gaps in the target data. The challenge intensifies when the target's behavior changes unexpectedly or when UAVs are not optimally positioned to maintain visibility.

Overall, ensuring reliable target visibility in environments with occlusions is a critical challenge. Occlusions can severely disrupt tracking accuracy, and the need for real-time communication and dynamic adjustment becomes even more demanding in collaborative systems. Both in individual and multi-vehicle tracking, maintaining a continuous, accurate track of the target in such complex environments remains a key challenge.

5.1.2. Real-time prediction and tracking in dynamic environments

Predicting the future position of a moving target in real-time is a significant challenge due to the often unpredictable and dynamic nature of target motion. Targets may exhibit erratic behaviors such as sudden changes in speed or direction, nonlinear movements, or abrupt stops, which can be difficult for traditional prediction algorithms to handle. For example, in complex environments, the motion may not follow easily identifiable patterns, making it hard to use simple models like Kalman filters or regression-based methods effectively. While deep learning models hold promise for improving prediction accuracy, they require large datasets for training and substantial computational resources, making them difficult to deploy in real-time scenarios, particularly in fast-moving or highly dynamic environments.

When there are multiple UAVs involved, the challenge becomes even more complex. Each UAV needs to predict the target's future position not only based on its own observations but also in coordination with the actions of other UAVs. This requires sophisticated algorithms that can account for the interaction between multiple agents while making real-time adjustments to tracking paths. Furthermore, when UAVs need to collaborate to track a single target, there is the added complexity of ensuring all UAVs are in sync with the target's predicted trajectory, which requires precise communication and coordination.

The task of predicting and tracking a target's position in dynamic environments presents substantial challenges, both in terms of accurately forecasting the target's motion and ensuring that the UAV can adapt their flight paths in real-time. Whether using individual UAVs or a collaborative system, real-time prediction is a computationally demanding task, and achieving optimal tracking accuracy remains difficult when dealing with unpredictable behaviors and high-speed movements.

5.1.3. Flight safety and coordination

Ensuring the safety of UAVs in dynamic environments, particularly in complex tracking scenarios, involves maintaining stable flight paths and avoiding collisions with both the environment and other UAVs. This is especially challenging when the target's movement is unpredictable, as the UAV must continuously adjust its flight trajectory to avoid obstacles while staying on track with the target. External disturbances like wind or sudden changes in weather conditions can further complicate this task, potentially destabilizing the UAV's flight path. Accurate and real-time control is essential for maintaining the safety and stability of the UAV while tracking the target.

In scenarios where multiple UAVs are used for collaborative tracking, the complexity of maintaining flight safety increases significantly. Coordinating multiple UAVs requires advanced algorithms to prevent collisions not only with the target but also with other UAVs. As the number of UAVs grows, the challenge of synchronizing their actions and ensuring safe trajectories becomes more difficult. Communication delays and bandwidth limitations can hinder the real-time coordination needed for effective collision avoidance. Additionally, UAVs need to dynamically reassign tasks and adjust their positions, which introduces additional layers of complexity in ensuring safety across all involved UAVs.

In summary, flight safety and coordination in dynamic environments present significant technical challenges, particularly when dealing with real-time adjustments, environmental disturbances, and coordination among multiple agents. Whether tracking with a single UAV or coordinating a swarm of UAVs, ensuring both safe flight and precise target tracking requires complex algorithms and robust systems that can adapt to unpredictable conditions.

5.1.4. Resource management and energy efficiency

In UAV-based target tracking, efficient resource management is a critical challenge, particularly when multiple UAVs are involved in tracking tasks. UAVs rely on onboard resources such as battery power, processing capacity, and communication bandwidth, all of which are limited. These resources must be managed effectively to ensure that UAVs can maintain continuous operation while tracking a target, especially in scenarios that demand long-duration missions or involve multiple UAVs. In particular, energy consumption becomes a major concern during extended flights or when UAVs are required to maintain high levels of performance in unpredictable environments.

When multiple UAVs are operating in coordination, the challenge extends to the allocation of tasks and resources across the swarm. Not only must each UAV handle its tracking and communication duties, but the system must also dynamically allocate resources such as power and computational capacity in real-time to optimize overall performance. For example, UAVs may need to switch between different modes of operation—such as active tracking or low-power idle states—to conserve energy while still ensuring efficient tracking. Additionally, communication between UAVs must be optimized to prevent network congestion or data loss, which could affect tracking accuracy.

Managing resources efficiently, particularly in terms of energy, computation, and communication, is a key challenge in ensuring that UAVs can track targets over extended periods while maintaining performance. This challenge becomes even more pronounced as the number of UAVs increases, requiring advanced algorithms for task distribution, energy conservation, and real-time adjustments to optimize system-wide resource usage.

The challenges in UAV-based target tracking—whether involving a single UAV or a coordinated group—are centered around maintaining accurate and continuous target visibility, predicting the target's movement in dynamic environments, ensuring flight safety, and managing resources effectively. These challenges are exacerbated by factors such as environmental interference, unpredictable target behaviors, and the complexity of coordinating multiple UAVs in real-time. Additionally, the need for efficient resource allocation, particularly with respect to energy and communication bandwidth, further complicates the task of sustained and reliable tracking. Despite advances in prediction algorithms and multi-agent coordination techniques, achieving efficient, accurate, and safe tracking while managing limited resources remains a critical difficulty in UAV systems.

5.2. Future research

To address these challenges, future research in UAV-based target tracking should focus on developing innovative solutions that can enhance system performance in complex and dynamic environments. Efforts should be directed toward improving target visibility and overcoming occlusions through advanced sensor fusion techniques and novel tracking algorithms. Additionally, real-time prediction models that can handle unpredictable target behaviors and adapt to dynamic changes will be crucial for improving tracking accuracy. In parallel, research into optimizing flight safety and resource management, especially in multi-UAV systems, will be essential to ensure efficient operation and coordination. By advancing these areas, UAV systems can achieve more robust, accurate, and efficient tracking capabilities, paving the way for their broader application in real-world scenarios.

5.2.1. Advanced occlusion handling and vision systems

Future research could focus on developing more robust algorithms for handling occlusions and maintaining target visibility, especially in environments with high-density obstacles. This could include innovations in sensor fusion, where data from various sensors (e.g., LiDAR, thermal cameras, and radar) are integrated to provide a more comprehensive view of the environment. Additionally, exploring advanced computer vision techniques, such as deep learning-based object recognition and tracking in partially occluded conditions, can help UAVs predict target behavior even when the line-of-sight is temporarily lost.

5.2.2. Improved real-time prediction algorithms with adaptive models

To enhance prediction accuracy in dynamic environments, future research should focus on the development of more adaptive and efficient real-time prediction algorithms. This could involve combining deep learning with traditional methods like Kalman filters, creating hybrid models that can better capture both linear and nonlinear behaviors of moving targets. Researchers may also explore reinforcement learning-based approaches that allow UAVs to adapt their prediction models continuously as they gather new data, improving accuracy without requiring large datasets upfront.

5.2.3. Swarm intelligence and coordination algorithms

As UAV swarms become more prevalent, developing scalable and fault-tolerant coordination algorithms is critical. Future research should focus on decentralized decision-making frameworks that enable UAVs to collaborate without relying heavily on a central controller. This would improve the system's robustness to communication delays, environmental interference, and other disruptions. Additionally, improving multi-agent reinforcement learning techniques for coordinated flight paths and task allocation could lead to more efficient and reliable swarm-based tracking systems.

5.2.4. Resource optimization for autonomous UAV operations

Efficient resource management, particularly energy and communication bandwidth, is an ongoing challenge in UAV-based tracking. Future research should explore energy-efficient flight strategies, such as dynamic task switching and collaborative energy sharing between UAVs in a swarm. Additionally, optimizing communication protocols to minimize latency and prevent data congestion in real-time environments is crucial for maintaining accurate tracking and coordination among UAVs. Investigating lightweight edge computing techniques to reduce computational overhead while maintaining high-performance tracking could also be a key area of focus.

6. Conclusions

In this paper, we provide a comprehensive review of UAV-based moving target tracking methods, focusing on three key aspects: the status of target information prediction methods, the status of target information tracking methods, and the status of swarm cooperation-based methods. While significant advancements have been made in these areas, challenges remain in terms of real-time prediction accuracy, maintaining continuous target visibility in dynamic environments, ensuring flight safety, and efficiently coordinating multiple UAVs. Additionally, issues such as resource limitations, including energy consumption and computational capacity, continue to impact the performance of UAV systems. Despite the progress, there are still notable gaps in existing methods, and the future research directions in UAV-based target tracking hold substantial promise for overcoming these challenges and enhancing overall system performance.

In conclusion, the field of UAV-based moving target tracking is both highly interdisciplinary and challenging, yet it holds significant potential across various applications. Continuous research and development efforts are crucial in driving the enhancement of tracking techniques and systems, thereby enabling UAVs to assume an increasingly vital role in modern society. As technological advancements persist, we can anticipate the emergence of more sophisticated and reliable UAV-based moving target tracking solutions, which are poised to have a profound impact on our lives.

Acknowledgements

The authors appreciate the financial support provided by the Natural Science Foundation of Hunan Province of China (Grant No. 2021JJ10045), the Open Research Subject of State Key Laboratory of Intelligent Game (Grant No. ZBKF-24-01), the Postdoctoral Fellowship Program of CPSF (Grant No. GZB20240989) and the China Postdoctoral Science Foundation (Grant No. 2024M754304).

Data Availability Statement

Data availability is not applicable to this article as no new data were created or analyzed in this study.

References

[1] G. Yuan, H. Duan, Extremum seeking control for UAV close formation flight via improved pigeon-inspired optimization, Science China Technological Sciences 67 (2) (2024) 435–448. doi:10.1007/ s11431-023-2463-0.

[2] L. Yang, S. Li, C. Li, A. Zhang, X. Zhang, A survey of unmanned aerial vehicle flight data anomaly detection: Technologies, applications, and future directions, Science China Technological Sciences 66 (4) (2023) 901–919. doi:10.1007/s11431-023-2463-0.

[3] S. Lee, H. Kang, J. Lee, Y. Kim, Optimal policy of pitch-hold phase for mine detection of UAV based on mixed-integer linear programming, International Journal of Aeronautical and Space Sciences 23 (4) (2022) 746–754. doi:10.1007/s42405-022-00454-7.

[4] M. Hakim, S. Choukri, Froude similarity and flying qualities assessment in the design of a low-speed BWB UAV, International Journal of Aeronautical and Space Sciences 25 (1) (2024) 46–60. doi:10.1007/ s42405-023-00670-9.

[5] W. Ma, Y. Fang, W. Fu, S. Liu, E. Guo, Cooperative localisation of uav swarm based on adaptive sa-pso algorithm, The Aeronautical Journal 127 (1307) (2023) 57–75. doi:10.1017/aer.2022.54.

[6] S. A. H. Mohsan, M. A. Khan, F. Noor, I. Ullah, M. H. Alsharif, Towards the unmanned aerial vehicles (UAVs): A comprehensive review, Drones 6 (6) (2022) 147. doi:10.3390/drones6060147.

[7] Z. Zuo, C. Liu, Q.-L. Han, J. Song, Unmanned aerial vehicles: Control methods and future challenges, IEEE/CAA Journal of Automatica Sinica 9 (4) (2022) 601–614. doi:10.1109/JAS.2022.105410.

[8] M. Ghamari, P. Rangel, M. Mehrubeoglu, G. S. Tewolde, R. S. Sherratt, Unmanned aerial vehicle communications for civil applications: A review, IEEE Access 10 (2022) 102492–102531. doi:10.1109/ACCESS. 2022.3208571.

[9] V. Shaferman, T. Shima, Unmanned aerial vehicles cooperative tracking of moving ground target in urban environments, Journal of guidance, control, and dynamics 31 (5) (2008) 1360–1371. doi:10.2514/1.33721.

[10] Y. Liu, Q. Wang, H. Hu, Y. He, A novel real-time moving target tracking and path planning system for a quadrotor UAV in unknown unstructured outdoor scenes, IEEE Transactions on Systems, Man, and Cybernetics: Systems 49 (11) (2019) 2362–2372. doi:10.1109/TSMC.2018.2808471.

[11] T. Oliveira, A. P. Aguiar, P. Encarnac¸a˜o, Moving path following for unmanned aerial vehicles with applications to single and multiple target tracking problems, IEEE Transactions on Robotics 32 (5) (2016) 1062–1078. doi:10.1109/TRO.2016.2593044.

[12] J. Wang, Y. X. Wu, Y.-Q. Chen, S. Ju, Multi-uavs collaborative tracking of moving target with maximized visibility in urban environment, Journal of the Franklin Institute 359 (11) (2022) 5512–5532. doi:10.1016/ j.jfranklin.2022.05.004.

[13] S. Liao, R. Zhu, N. Wu, T. A. Shaikh, M. Sharaf, A. M. Mostafa, Path planning for moving target tracking by fixed-wing uav, Defence Technology 16 (4) (2020) 811–824. doi:10.1016/j.dt.2019.10.010.

[14] M. Doostmohammadian, A. Taghieh, H. Zarrabi, Distributed estimation approach for tracking a mobile target via formation of uavs, IEEE Transactions on Automation Science and Engineering 19 (4) (2022) 3765–3776. doi:10.1109/TASE.2021.3135834.

[15] R. I. H. Abushahma, M. A. M. Ali, N. A. A. Rahman, O. I. Al-Sanjary, Comparative features of unmanned aerial vehicle (UAV) for border protection of libya: A review, in: 2019 IEEE 15th International Colloquium on Signal Processing & Its Applications (CSPA), 2019, pp. 114–119. doi:10.1109/CSPA.2019.8695991.

[16] P. K. Chittoor, B. Chokkalingam, L. Mihet-Popa, A review on UAV wireless charging: Fundamentals, applications, charging techniques and standards, IEEE Access 9 (2021) 69235–69266. doi:10.1109/ACCESS. 2021.3077041.

[17] H. Shakhatreh, A. H. Sawalmeh, A. Al-Fuqaha, Z. Dou, E. Almaita, I. Khalil, N. S. Othman, A. Khreishah, M. Guizani, Unmanned aerial vehicles (UAVs): A survey on civil applications and key research challenges, IEEE Access 7 (2019) 48572–48634. doi:10.1109/ACCESS.2019.2909530.

[18] J. Scherer, B. Rinner, Multi-UAV surveillance with minimum information idleness and latency

constraints, IEEE Robotics and Automation Letters 5 (3) (2020) 4812–4819. doi:10.1109/LRA.2020.3003884.

[19] Y. Khosiawan, I. Nielsen, A system of UAV application in indoor environment, Production & Manufacturing Research 4 (1) (2016) 2–22. doi:10.1080/21693277.2016.1195304.

[20] M. H. M. Saad, N. M. Hamdan, M. R. Sarker, State of the art of urban smart vertical farming automation system: Advanced topologies, issues and recommendations, Electronics 10 (12) (2021) 1422. doi:10.3390/ electronics10121422.

[21] J. Sandino, F. Vanegas, F. Maire, P. Caccetta, C. Sanderson, F. Gonzalez, UAV framework for autonomous onboard navigation and people/object detection in cluttered indoor environments, Remote Sensing 12 (20) (2020) 3386. doi:10.3390/rs12203386.

[22] M. Atif, R. Ahmad, W. Ahmad, L. Zhao, J. J. P. C. Rodrigues, Uav-assisted wireless localization for search and rescue, IEEE Systems Journal 15 (3) (2021) 3261–3272. doi:10.1109/JSYST.2020.3041573.

[23] Y. Cui, Y. He, T. Tang, Y. Liu, A new target tracking filter based on deep learning, Chinese Journal of Aeronautics 35 (5) (2022) 11–24. doi:10.1016/j.cja.2021.10.023.

[24] Z. Yao, J. Kong, Algorithm for target tracking using modified image filtering based on statistical features and GMM image modeling, in: 2021 China Automation Congress (CAC), 2021, pp. 7155–7159. doi:10.1109/ CAC53003.2021.9727974.

[25] L. Zhao, N. Gao, B. Huang, Q. Wang, J. Zhou, A novel terrain-aided navigation algorithm combined with the TERCOM algorithm and particle filter, IEEE Sensors Journal 15 (2) (2015) 1124–1131. doi:10.1109/JSEN.2014.2360916.

[26] W. Liu, Y. Liu, R. Bucknall, Filtering based multi-sensor data fusion algorithm for a reliable unmanned surface vehicle navigation, Journal of Marine Engineering & Technology 22 (2) (2023) 67–83. doi: 10.1080/20464177.2022.2031558.

[27] W. Wang, K. Dogˇanc¸ay, Widely linear adaptive filtering based on clifford geometric algebra: A unified framework [Hypercomplex signal and image processing], IEEE Signal Processing Magazine 41 (2) (2024) 86–101. doi:10.1109/MSP.2024.3379732.

[28] Z. Zhang, Q. Yu, Q. Zhang, N. Ning, J. Li, A kalman filtering based adaptive threshold algorithm for QRS complex detection, Biomedical Signal Processing and Control 58 (2020) 101827. doi:10.1016/j.bspc. 2019.101827.

[29] X. Zhao, F. Pu, Z. Wang, H. Chen, Z. Xu, Detection, tracking, and geolocation of moving vehicle from UAV using monocular camera, IEEE Access 7 (2019) 101160–101170. doi:10.1109/ACCESS.2019.2929760.

[30] H. Cheng, L. Lin, Z. Zheng, Y. Guan, Z. Liu, An autonomous vision-based target tracking system for rotorcraft unmanned aerial vehicles, in: 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2017, pp. 1732–1738. doi:10.1109/IROS.2017.8205986.

[31] R. Bonatti, W. Wang, C. Ho, A. Ahuja, M. Gschwindt, E. Camci, E. Kayacan, S. Choudhury, S. Scherer, Autonomous aerial cinematography in unstructured environments with learned artistic decision-making, Journal of Field Robotics 37 (4) (2020) 606–641. doi:10.1002/rob.21931.

[32] A. G. Howard, Mobilenets: Efficient convolutional neural networks for mobile vision applications, arXiv preprint arXiv:1704.04861 (2017).

[33] S. Ren, K. He, R. Girshick, J. Sun, Faster R-CNN: Towards real-time object detection with region proposal networks, IEEE Transactions on Pattern Analysis and Machine Intelligence 39 (6) (2017) 1137–1149. doi: 10.1109/TPAMI.2016.2577031.

[34] F. Farahi, H. S. Yazdi, Probabilistic kalman filter for moving object tracking, Signal Processing: Image Communication 82 (2020) 115751. doi:10.1016/j.image.2019.115751.

[35] Y. Hui, B. Tian, X. Zhang, H. Lu, H. Shen, Safe tracker: A robust aerial system for safe tracking in cluttered environments, in: 2023 42nd Chinese Control Conference (CCC), 2023, pp. 3792–3797. doi:10.23919/ CCC58697.2023.10240431.

[36] Z. Lin, W. Xu, W. Wang, A moving target tracking system of quadrotors with visual-inertial localization, in: 2023 IEEE International Conference on Robotics and Automation (ICRA), 2023, pp. 3296–3302. doi: 10.1109/ICRA48891.2023.10161323.

[37] C. Liu, Y. Song, Y. Guo, B. Xu, Y. Zhang, L. Li, Z. Li, Vision information and laser module based UAV target tracking, in: IECON 2019 45th Annual Conference of the IEEE Industrial Electronics Society, Vol. 1, 2019, pp. 186–191. doi:10.1109/IECON.2019.8927443.

[38] G. Unal, Visual target detection and tracking based on Kalman filter, Journal of Aeronautics and Space Technologies 14 (2) (2021) 251–259.

[39] C. Deng, S. He, Y. Han, B. Zhao, Learning dynamic spatial-temporal regularization for uav object tracking, IEEE Signal Processing Letters 28 (2021) 1230–1234. doi:10.1109/LSP.2021.3086675.

[40] Y. Li, C. Fu, Z. Huang, Y. Zhang, J. Pan, Keyfilter-aware real-time UAV object tracking, in: 2020 IEEE International Conference on Robotics and Automation (ICRA), 2020, pp. 193–199. doi:10.1109/ICRA40945. 2020.9196943.

[41] F. Lin, C. Fu, Y. He, F. Guo, Q. Tang, BiCF: Learning bidirectional incongruity-aware correlation filter for efficient UAV object tracking, in: 2020 IEEE International Conference on Robotics and Automation (ICRA), 2020, pp. 2365–2371. doi:10.1109/ICRA40945.2020.9196530.

[42] S. Yeom, Moving people tracking and false track removing with infrared thermal imaging by a multirotor, Drones 5 (3) (2021) 65. doi:10.3390/drones5030065.

[43] M. Wen, Z. Zhang, S. Niu, H. Sha, R. Yang, Y. Yun, H. Lu, Deep-learning-based drug–target interaction prediction, Journal of proteome research 16 (4) (2017) 1401–1409. doi:10.1021/acs.jproteome.6b00618.

[44] Y. Wang, Z. You, S. Yang, H. Yi, Z. Chen, K. Zheng, A deep learning-based method for drug-target interaction prediction based on long short-term memory neural network, BMC medical informatics and decision making 20 (2020) 1–9. doi:10.1186/s12911-020-1052-0.

[45] D. Neupane, J. Seok, A review on deep learning-based approaches for automatic sonar target recognition, Electronics 9 (11) (2020) 1972. doi:10.3390/electronics9111972.

[46] D. G. Lui, G. Tartaglione, F. Conti, G. De Tommasi, S. Santini, Long short-term memory-based neural networks for missile maneuvers trajectories prediction, IEEE Access 11 (2023) 30819–30831. doi:10.1109/ACCESS. 2023.3262023.

[47] N. M. Nasrabadi, Deeptarget: An automatic target recognition using deep convolutional neural networks, IEEE Transactions on Aerospace and Electronic Systems 55 (6) (2019) 2687–2697. doi:10.1109/TAES.2019.2894050.

[48] Y. Li, W. Liang, L. Peng, D. Zhang, C. Yang, K.-C. Li, Predicting drug-target interactions via dual-stream graph neural network, IEEE/ACM Transactions on Computational Biology and Bioinformatics 21 (4) (2024) 948–958. doi:10.1109/TCBB.2022.3204188.

[49] S. Veeraraghavan, A. Rathi, M. Sagayaraj, C. Nagar, Turn rate estimation techniques in imm estimators for esa radar tracking, in: 2008 IEEE Aerospace Conference, 2008, pp. 1–8. doi:10.1109/AERO.2008.4526441.

[50] B. R. Dalsnes, S. Hexeberg, A. L. Flåten, B.-O. H. Eriksen, E. F. Brekke, The neighbor course

distribution method with Gaussian mixture models for AIS-based vessel trajectory prediction, in: 2018 21st International Conference on Information Fusion (FUSION), 2018, pp. 580–587. doi:10.23919/ICIF.2018.8455607.

[51] S. Qiao, D. Shen, X. Wang, N. Han, W. Zhu, A self-adaptive parameter selection trajectory prediction approach via hidden Markov models, IEEE Transactions on Intelligent Transportation Systems 16 (1) (2015) 284–296. doi:10.1109/TITS.2014.2331758.

[52] A. Alahi, K. Goel, V. Ramanathan, A. Robicquet, L. Fei-Fei, S. Savarese, Social lstm: Human trajectory prediction in crowded spaces, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 961–971.

[53] W. Zhang, K. Song, X. Rong, Y. Li, Coarse-to-fine UAV target tracking with deep reinforcement learning, IEEE Transactions on Automation Science and Engineering 16 (4) (2019) 1522–1530. doi:10.1109/TASE.2018.2877499.

[54] J. Ye, C. Fu, G. Zheng, Z. Cao, B. Li, Darklighter: Light up the darkness for UAV tracking, in: 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2021, pp. 3079–3085. doi:10.1109/ IROS51168.2021.9636680.

[55] Y. Wang, L. Ding, R. Laganiere, Real-time UAV tracking based on PSR stability, in: Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops, 2019, pp. 1–9.

[56] F. Panetsos, G. C. Karras, K. J. Kyriakopoulos, An NMPC framework for tracking and releasing a cablesuspended load to a ground target using a multirotor UAV, in: 2024 IEEE International Conference on Robotics and Automation (ICRA), 2024, pp. 10057–10063. doi:10.1109/ICRA57147.2024.10610034.

[57] M. Zhou, H. Lee, Dynamic obstacle avoidance for an MAV using optimization-based trajectory prediction with a monocular camera, IEEE Access 12 (2024) 140948–140957. doi:10.1109/ACCESS.2024.3459963.

[58] D. Guo, J. Wang, Y. Cui, Z. Wang, S. Chen, Siamcar: Siamese fully convolutional classification and regression for visual tracking, in: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2020, pp. 6269–6277. doi:10.1109/cvpr42600.2020.00630.

[59] X. Jin, D. Zhang, Q. Wu, X. Xiao, P. Zhao, Z. Zheng, Improved SiamCAR with ranking-based pruning and optimization for efficient UAV tracking, Image and Vision Computing 141 (2024) 104886. doi:10.1016/j. imavis.2023.104886.

[60] A. Giusti, J. Guzzi, D. C. Cires¸an, F.-L. He, J. P. Rodr´ıguez, F. Fontana, M. Faessler, C. Forster, J. Schmidhuber, G. D. Caro, D. Scaramuzza, L. M. Gambardella, A machine learning approach to visual perception of forest trails for mobile robots, IEEE Robotics and Automation Letters 1 (2) (2016) 661–667. doi:10.1109/LRA. 2015.2509024.

[61] P. Voigtlaender, J. Luiten, P. H. Torr, B. Leibe, Siam R-CNN: Visual tracking by re-detection, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2020, pp. 6578–6588.

[62] S. Cui, Y. Chen, X. Li, A robust and efficient UAV path planning approach for tracking agile targets in complex environments, Machines 10 (10) (2022) 931. doi:10.3390/machines10100931.

[63] H. Wang, X. Zhang, Y. Liu, X. Zhang, Y. Zhuang, SVPTO: Safe visibility-guided perception-aware trajectory optimization for aerial tracking, IEEE Transactions on Industrial Electronics 71 (3) (2024) 2716–2725. doi: 10.1109/TIE.2023.3270541.

[64] H. Li, H. Zhong, Y. Lv, J. Sha, Y. Long, Y. Wang, Steady tracker: Tracking a target stably using a quadrotor, in: 2022 IEEE International Conference on Robotics and Biomimetics (ROBIO), 2022, pp.

1–6. doi:10.1109/ ROBIO55434.2022.10011871.

[65] Y. Lee, J. Park, S. Jung, B. Jeon, D. Oh, H. J. Kim, QP chaser: Polynomial trajectory generation for autonomous aerial tracking, arXiv preprint arXiv:2302.14273 (2023) 1–15doi:10.48550/arXiv.2302.14273.

[66] J. Chen, T. Liu, S. Shen, Tracking a moving target in cluttered environments using a quadrotor, in: 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2016, pp. 446–453. doi: 10.1109/IROS.2016.7759092.

[67] J. Ji, N. Pan, C. Xu, F. Gao, Elastic tracker: A spatio-temporal trajectory planner for flexible aerial tracking, in: 2022 International Conference on Robotics and Automation (ICRA), 2022, pp. 47–53. doi:10.1109/ ICRA46639.2022.9811688.

[68] N. Pan, R. Zhang, T. Yang, C. Cui, C. Xu, F. Gao, Fast-Tracker 2.0: Improving autonomy of aerial tracking with active vision and human location regression, IET Cyber-Systems and Robotics 3 (4) (2021) 292–301. doi:10.1049/csy2.12033.

[69] Z. Han, R. Zhang, N. Pan, C. Xu, F. Gao, Fast-Tracker: A robust aerial system for tracking agile target in cluttered environments, in: 2021 IEEE International Conference on Robotics and Automation (ICRA), 2021, pp. 328–334. doi:10.1109/ICRA48506.2021.9561948.

[70] P. Vasishta, D. Vaufreydaz, A. Spalanzani, Natural vision based method for predicting pedestrian behaviour in urban environments, in: 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), 2017, pp. 1–6. doi:10.1109/ITSC.2017.8317848.

[71] P. E. Hart, N. J. Nilsson, B. Raphael, A formal basis for the heuristic determination of minimum cost paths, IEEE Transactions on Systems Science and Cybernetics 4 (2) (1968) 100–107. doi:10.1109/TSSC.1968.300136.

[72] S. Yi, H. Li, X. Wang, Pedestrian behavior modeling from stationary crowds with applications to intelligent surveillance, IEEE Transactions on Image Processing 25 (9) (2016) 4354–4368. doi:10.1109/TIP.2016.2590322.

[73] M. Khan, K. Heurtefeux, A. Mohamed, K. A. Harras, M. M. Hassan, Mobile target coverage and tracking on drone-be-gone UAV cyber-physical testbed, IEEE Systems Journal 12 (4) (2018) 3485–3496. doi:10.1109/ JSYST.2017.2777866.

[74] B. Jeon, Y. Lee, H. J. Kim, Integrated motion planner for real-time aerial videography with a drone in a dense environment, in: 2020 IEEE International Conference on Robotics and Automation (ICRA), 2020, pp. 1243– 1249. doi:10.1109/ICRA40945.2020.9196703.

[75] B. F. Jeon, H. J. Kim, Online trajectory generation of a mav for chasing a moving target in 3D dense environments, in: 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2019, pp. 1115–1121. doi:10.1109/IROS40897.2019.8967840.

[76] J. Wang, L. Han, X. Dong, Q. Li, Z. Ren, Distributed sliding mode control for time-varying formation tracking of multi-UAV system with a dynamic leader, Aerospace Science and Technology 111 (2021) 106549. doi: 10.1016/j.ast.2021.106549.

[77] T. Na¨geli, J. Alonso-Mora, A. Domahidi, D. Rus, O. Hilliges, Real-time motion planning for aerial videography with dynamic obstacle avoidance and viewpoint optimization, IEEE Robotics and Automation Letters 2 (3) (2017) 1696–1703. doi:10.1109/LRA.2017.2665693.

[78] Z. Li, N. Hovakimyan, V. Dobrokhodov, I. Kaminer, Vision-based target tracking and motion estimation using a small UAV, in: 49th IEEE Conference on Decision and Control (CDC), 2010, pp. 2505–2510. doi:10. 1109/CDC.2010.5718149.

[79] Y. Zhao, L. Yan, Y. Chen, J. Dai, Y. Liu, Robust and efficient trajectory replanning based on

guiding path for quadrotor fast autonomous flight, Remote Sensing 13 (5) (2021) 972. doi:10.3390/rs13050972.
[80] K. Boudjit, C. Larbes, Detection and target tracking with a quadrotor using fuzzy logic, in: 2016 8th International Conference on Modelling, Identification and Control (ICMIC), 2016, pp. 127–132. doi: 10.1109/ICMIC.2016.7804285.
[81] A. G. Kendall, N. N. Salvapantula, K. A. Stol, On-board object tracking control of a quadcopter with monocular vision, in: 2014 International Conference on Unmanned Aircraft Systems (ICUAS), 2014, pp. 404–411. doi: 10.1109/ICUAS.2014.6842280.
[82] M. Rabah, A. Rohan, S. A. S. Mohamed, S.-H. Kim, Autonomous moving target-tracking for a UAV quadcopter based on Fuzzy-PI, IEEE Access 7 (2019) 38407–38419. doi:10.1109/ACCESS.2019.2906345.
[83] P. Yao, H. Wang, Z. Su, Cooperative path planning with applications to target tracking and obstacle avoidance for multi-uavs, Aerospace Science and Technology 54 (2016) 10–22. doi:10.1016/j.ast.2016.04.002.
[84] Y. Yang, L. Liao, H. Yang, S. Li, An optimal control strategy for multi-uavs target tracking and cooperative competition, IEEE/CAA Journal of Automatica Sinica 8 (12) (2021) 1931–1947. doi:10.1109/JAS.2020.1003012.
[85] H. Masnavi, V. K. Adajania, K. Kruusama¨e, A. K. Singh, Real-time multi-convex model predictive control for occlusion-free target tracking with quadrotors, IEEE Access 10 (2022) 29009–29031. doi:10.1109/ACCESS. 2022.3157977.
[86] B. F. Jeon, D. Shim, H. Jin Kim, Detection-aware trajectory generation for a drone cinematographer, in: 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2020, pp. 1450–1457. doi: 10.1109/IROS45743.2020.9341368.
[87] Y. Cai, Q. Xi, X. Xing, H. Gui, Q. Liu, Path planning for uav tracking target based on improved a-star algorithm, in: 2019 1st International Conference on Industrial Artificial Intelligence (IAI), 2019, pp. 1–6. doi:10.1109/ ICIAI.2019.8850744.
[88] L. Zou, Z. Wang, An agile quadrotor motion planning method for dynamic target following flight, in: 2023 IEEE 6th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), Vol. 6, 2023, pp. 1495–1499. doi:10.1109/ITNEC56291.2023.10082365.
[89] Q. Wang, Y. Gao, J. Ji, C. Xu, F. Gao, Visibility-aware trajectory optimization with application to aerial tracking, in: 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2021, pp. 5249– 5256. doi:10.1109/IROS51168.2021.9636753.
[90] B. Penin, P. R. Giordano, F. Chaumette, Vision-based reactive planning for aggressive target tracking while avoiding collisions and occlusions, IEEE Robotics and Automation Letters 3 (4) (2018) 3725–3732. doi: 10.1109/LRA.2018.2856526.
[91] Y. Gao, J. Ji, Q. Wang, R. Jin, Y. Lin, Z. Shang, Y. Cao, S. Shen, C. Xu, F. Gao, Adaptive tracking and perching for quadrotor in dynamic scenarios, IEEE Transactions on Robotics 40 (2024) 499–519. doi:10.1109/TRO. 2023.3335670.
[92] H. Li, M. Yang, Y. Li, L. Dai, C. Zhao, Dynamic target tracking of small uavs in unstructured environment, Electronics 12 (5) (2023) 1078. doi:10.3390/electronics12051078.
[93] R. Bonatti, Y. Zhang, S. Choudhury, W. Wang, S. Scherer, Autonomous drone cinematographer: Using artistic principles to create smooth, safe, occlusion-free trajectories for aerial filming, in: Proceedings of the 2018 international symposium on experimental robotics, Springer, 2020, pp. 119–129. doi:10.1007/ 978-3-030-33950-0_11.

[94] B. Li, Z. Yang, D. Chen, S. Liang, H. Ma, Maneuvering target tracking of UAV based on MN-DDPG and transfer learning, Defence Technology 17 (2) (2021) 457–466. doi:10.1016/j.dt.2020.11.014.

[95] Z. Xia, J. Du, J. Wang, C. Jiang, Y. Ren, G. Li, Z. Han, Multi-agent reinforcement learning aided intelligent UAV swarm for target tracking, IEEE Transactions on Vehicular Technology 71 (1) (2022) 931–945. doi: 10.1109/TVT.2021.3129504.

[96] J. Wang, P. Zhang, Y. Wang, Autonomous target tracking of multi-UAV: A two-stage deep reinforcement learning approach with expert experience, Applied Soft Computing 145 (2023) 110604. doi:10.1016/j. asoc.2023.110604.

[97] B. Li, Y. Wu, Path planning for uav ground target tracking via deep reinforcement learning, IEEE Access 8 (2020) 29064–29074. doi:10.1109/ACCESS.2020.2971780.

[98] S. Bhagat, P. Sujit, Uav target tracking in urban environments using deep reinforcement learning, in: 2020 International Conference on Unmanned Aircraft Systems (ICUAS), 2020, pp. 694–701. doi:10.1109/ ICUAS48674.2020.9213856.

[99] T. Wang, R. Qin, Y. Chen, H. Snoussi, C. Choi, A reinforcement learning approach for uav target searching and tracking, Multimedia Tools and Applications 78 (2019) 4347–4364. doi:10.1007/s11042-018-5739-5.

[100] S. Yoo, S. Jung, Y. Lee, D. Shim, H. J. Kim, Mono-camera-only target chasing for a drone in a dense environment by cross-modal learning, IEEE Robotics and Automation Letters 9 (8) (2024) 7254–7261. doi:10.1109/LRA.2024.3407412.

[101] B. Ma, Z. Liu, W. Zhao, J. Yuan, H. Long, X. Wang, Z. Yuan, Target tracking control of UAV through deep reinforcement learning, IEEE Transactions on Intelligent Transportation Systems 24 (6) (2023) 5983–6000. doi:10.1109/TITS.2023.3249900.

[102] N. Abo Mosali, S. S. Shamsudin, O. Alfandi, R. Omar, N. Al-Fadhali, Twin delayed deep deterministic policy gradient-based target tracking for unmanned aerial vehicle with achievement rewarding and multistage training, IEEE Access 10 (2022) 23545–23559. doi:10.1109/ACCESS.2022.3154388.

[103] J. Zhao, H. Liu, J. Sun, K. Wu, Z. Cai, Y. Ma, Y. Wang, Deep reinforcement learning-based end-to-end control for UAV dynamic target tracking, Biomimetics 7 (4) (2022) 197. doi:10.3390/biomimetics7040197.

[104] B. Li, Z. Gan, D. Chen, D. Sergey Aleksandrovich, UAV maneuvering target tracking in uncertain environments based on deep reinforcement learning and meta-learning, Remote Sensing 12 (22) (2020) 3789. doi:10.3390/ rs12223789.

[105] S. Javaid, N. Saeed, Z. Qadir, H. Fahim, B. He, H. Song, M. Bilal, Communication and control in collaborative UAVs: Recent advances and future trends, IEEE Transactions on Intelligent Transportation Systems 24 (6) (2023) 5719–5739. doi:10.1109/TITS.2023.3248841.

[106] X. Chen, Z. Feng, Z. Wei, F. Gao, X. Yuan, Performance of joint sensing-communication cooperative sensing UAV network, IEEE Transactions on Vehicular Technology 69 (12) (2020) 15545–15556. doi:10.1109/ TVT.2020.3042466.

[107] A. I. Hentati, L. C. Fourati, Comprehensive survey of UAVs communication networks, Computer Standards & Interfaces 72 (2020) 103451. doi:10.1016/j.csi.2020.103451.

[108] X. Deng, J. Li, P. Guan, L. Zhang, Energy-efficient UAV-aided target tracking systems based on edge computing, IEEE Internet of Things Journal 9 (3) (2022) 2207–2214. doi:10.1109/JIOT.2021.3091216.

[109] J. Upadhyay, A. Rawat, D. Deb, Multiple drone navigation and formation using selective target tracking-based computer vision, Electronics 10 (17) (2021) 2125. doi:10.3390/electronics10172125.

[110] W. Zhou, J. Li, Q. Zhang, Joint communication and action learning in multi-target tracking of UAV swarms with deep reinforcement learning, Drones 6 (11) (2022) 339. doi:10.3390/drones6110339.

[111]J. Xiao, P. Pisutsin, M. Feroskhan, Collaborative target search with a visual drone swarm: An adaptive curriculum embedded multistage reinforcement learning approach, IEEE Transactions on Neural Networks and Learning Systems (2023) 1–15doi:10.1109/TNNLS.2023.3331370.

[112] Z. Liu, Y. Shang, T. Li, G. Chen, Y. Wang, Q. Hu, P. Zhu, Robust multi-drone multi-target tracking to resolve target occlusion: A benchmark, IEEE Transactions on Multimedia 25 (2023) 1462–1476. doi:10.1109/TMM. 2023.3234822.

[113] P. Zhu, J. Zheng, D. Du, L. Wen, Y. Sun, Q. Hu, Multi-drone-based single object tracking with agent sharing network, IEEE Transactions on Circuits and Systems for Video Technology 31 (10) (2021) 4058–4070. doi: 10.1109/TCSVT.2020.3045747.

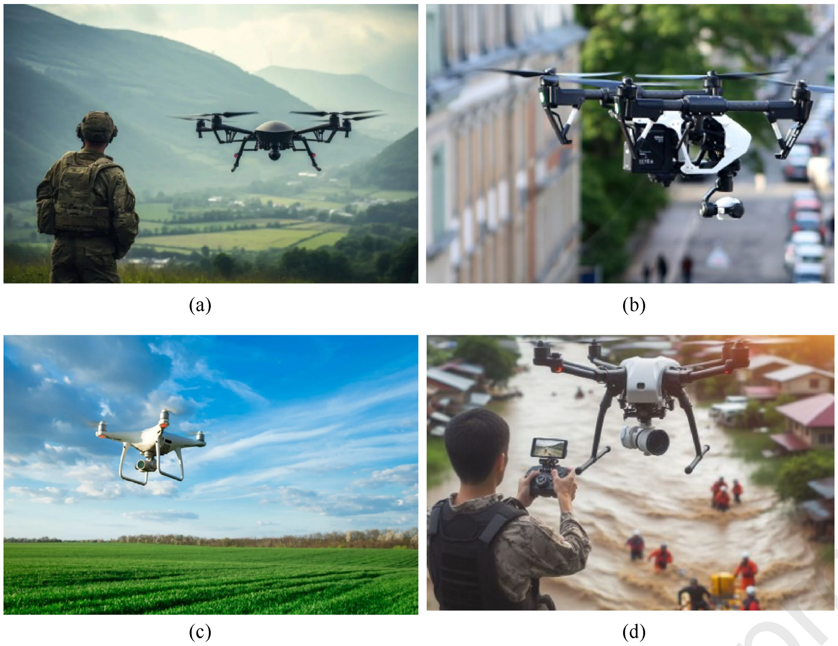
[114] Q. Li, J. Xi, X. Yang, R. Lu, Multi-target tracking method for drone swarm based on interaction feature extraction, in: 2024 3rd International Conference on Robotics, Artificial Intelligence and Intelligent Control (RAIIC), 2024, pp. 235–240. doi:10.1109/RAIIC61787.2024.10671345.

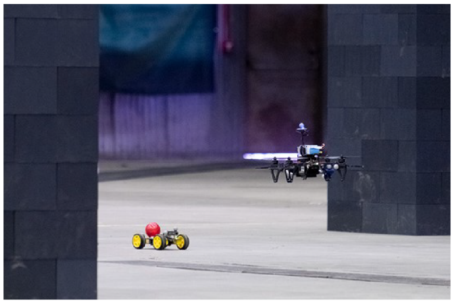
[115] G. Chen, P. Zhu, B. Cao, X. Wang, Q. Hu, Cross-drone transformer network for robust single object tracking, IEEE Transactions on Circuits and Systems for Video Technology 33 (9) (2023) 4552–4563. doi:10.1109/ TCSVT.2023.3281557.

[116] L. Zhou, S. Leng, Q. Liu, Q. Wang, Intelligent UAV swarm cooperation for multiple targets tracking, IEEE Internet of Things Journal 9 (1) (2022) 743–754. doi:10.1109/JIOT.2021.3085673.

[117] S. R. Nagrare, O. Chopra, S. Jana, D. Ghose, Decentralized path planning approach for crowd surveillance using drones, in: 2021 International Conference on Unmanned Aircraft Systems (ICUAS), 2021, pp. 1020– 1028. doi:10.1109/ICUAS51884.2021.9476774.

[118] S. Qamar, S. H. Khan, M. A. Arshad, M. Qamar, J. Gwak, A. Khan, Autonomous drone swarm navigation and multitarget tracking with island policy-based optimization framework, IEEE Access 10 (2022) 91073–91091. doi:10.1109/ACCESS.2022.3202208.

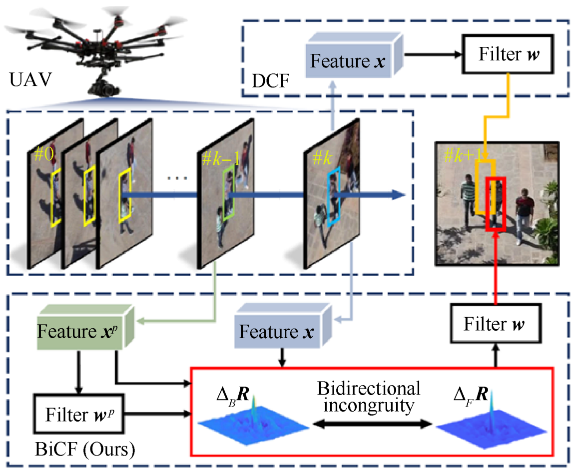

(a)
(b)
(c)
(d)

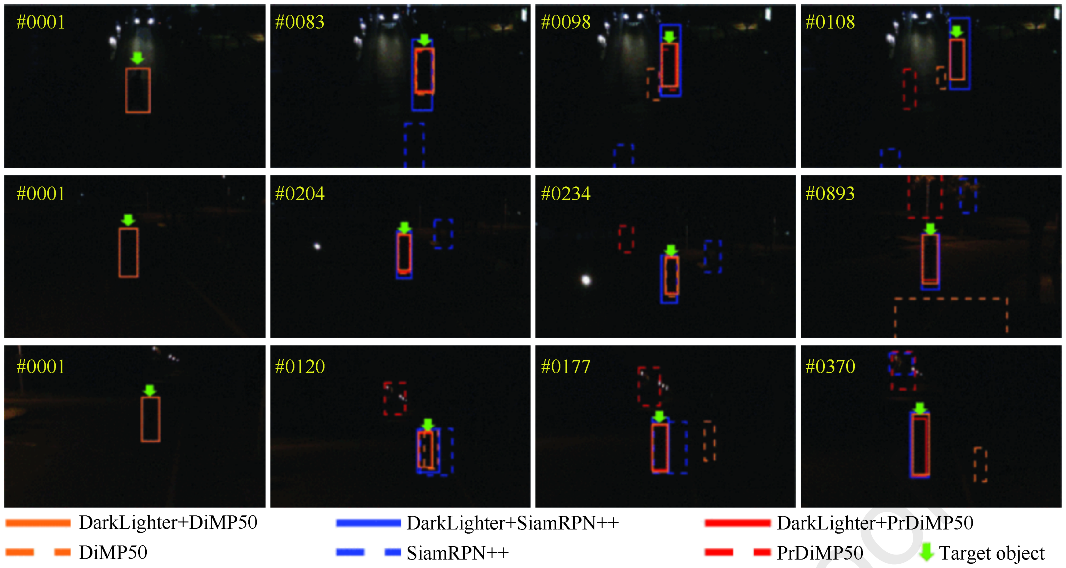


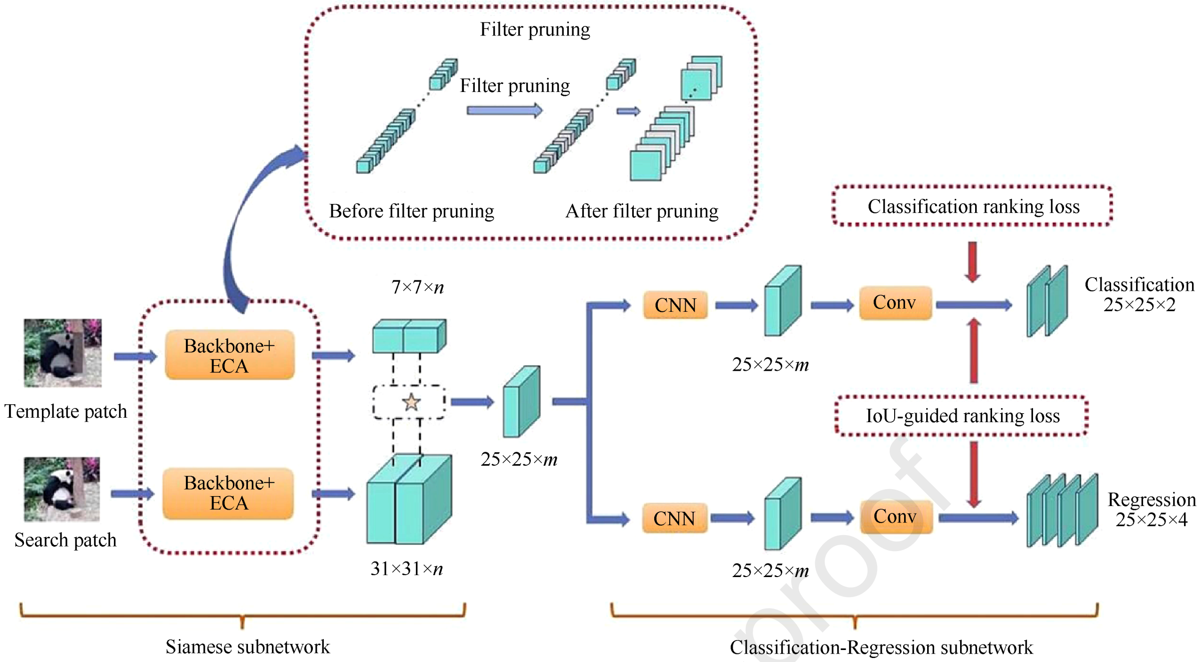
(a)

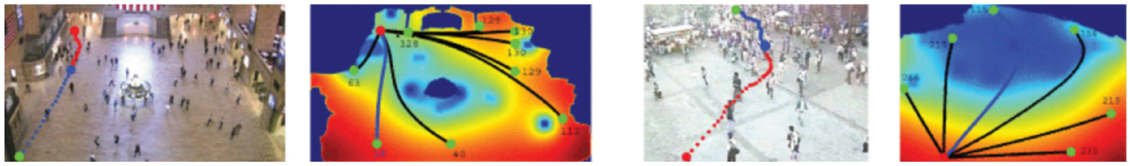
(b)


#000001
#000155
#000212
#000001
#000016
#000135
#000001
#000065
#000115
#000001
#000065
#000116
#000001
#000135
#000204
KAOT
ECO
ECO-HC
ARCF
UDT+

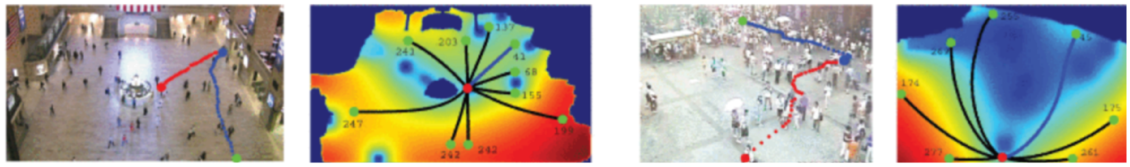

UAV
DCF
Feature $\boldsymbol{x}$
Filter $\boldsymbol{w}$
#0
#k−1
#k
#k+1
Feature $\boldsymbol{x}^p$
Feature $\boldsymbol{x}$
Filter $\boldsymbol{w}$
Filter $\boldsymbol{w}^p$
$\Delta_B\boldsymbol{R}$
Bidirectional incongruity
$\Delta_F\boldsymbol{R}$
BiCF (Ours)


#0001
#0083
#0098
#0108
#0001
#0204
#0234
#0893
#0001
#0120
#0177
#0370
DarkLighter+DiMP50
DarkLighter+SiamRPN++
DarkLighter+PrDiMP50
DiMP50
SiamRPN++
PrDiMP50
Target object

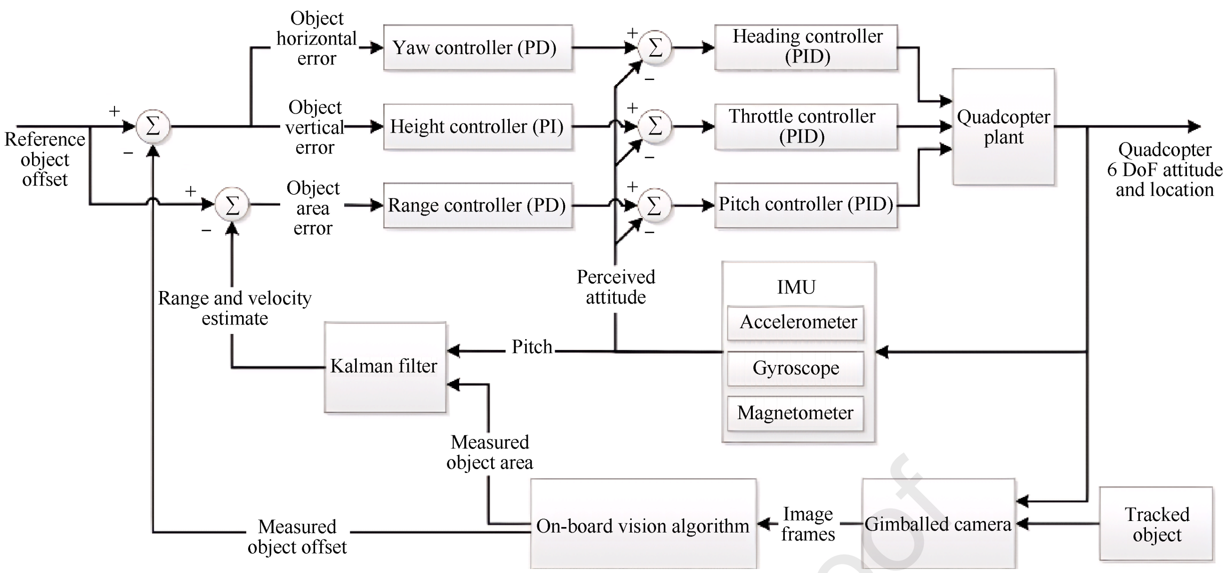

Filter pruning
Filter pruning
Before filter pruning
After filter pruning
Classification ranking loss
7×7×n
Backbone+ ECA
Template patch
Backbone+ ECA
Search patch
31×31×n
25×25×m
CNN
25×25×m
Conv
Classification 25×25×2
IoU-guided ranking loss
CNN
25×25×m
Conv
Regression 25×25×4
Siamese subnetwork
Classification-Regression subnetwork

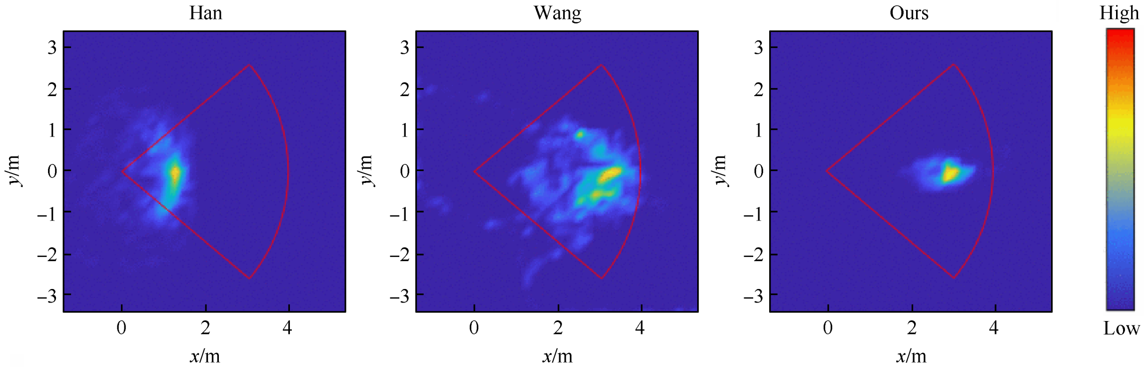


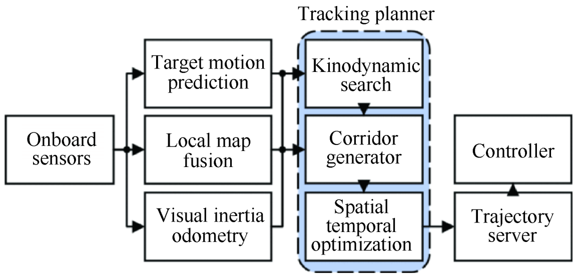
(a1) Observation (a2) Matched prediction (c1) Observation (c2) Matched prediction

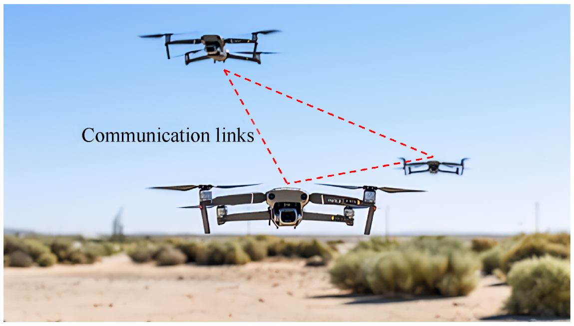


(b1) Observation (b2) Abnormal case (d1) Observation (d2) Abnormal case

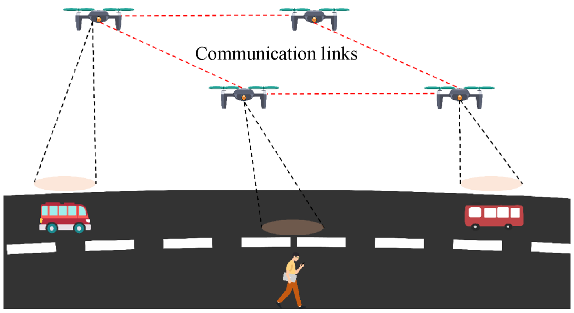

Object
horizontal
error
Yaw controller (PD)
Heading controller
(PID)
Object
vertical
error
Height controller (PI)
Throttle controller
(PID)
Quadcopter
plant
Reference
object
offset
Object
area
error
Range controller (PD)
Pitch controller (PID)
Quadcopter
6 DoF attitude
and location
Perceived
attitude
IMU
Accelerometer
Gyroscope
Magnetometer
Range and velocity
estimate
Kalman filter
Pitch
Measured
object area
Measured
object offset
On-board vision algorithm
Image
frames
Gimballed camera
Tracked
object

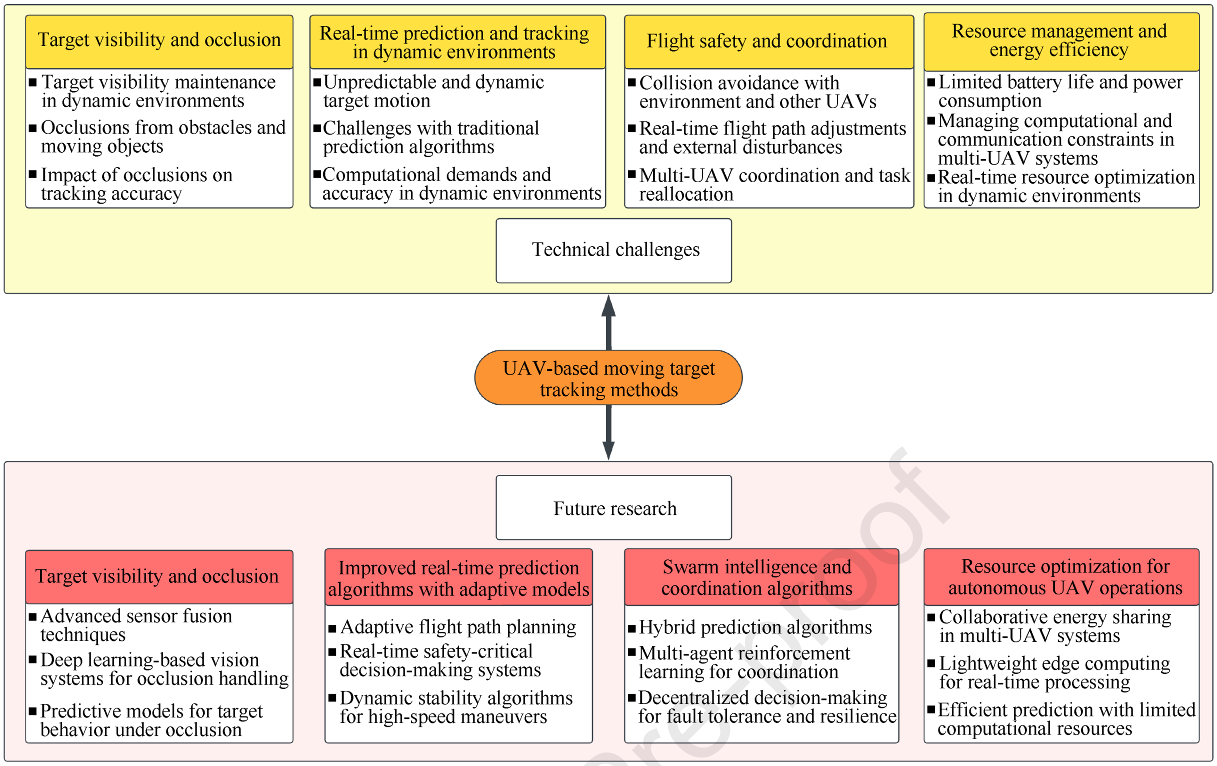

Han
Wang
Ours
High
Low
y/m
x/m
3
2
1
0
−1
−2
−3
0
2
4


Tracking planner
Target motion prediction
Kinodynamic search
Onboard sensors
Local map fusion
Corridor generator
Controller
Visual inertia odometry
Spatial temporal optimization
Trajectory server


Communication links


Speed X5
Robust to target lost
Video lost
Left view
Front view
Video lost
Back view
Right view


Communication links


Target visibility and occlusion
Target visibility maintenance in dynamic environments
Occlusions from obstacles and moving objects
Impact of occlusions on tracking accuracy
Real-time prediction and tracking in dynamic environments
Unpredictable and dynamic target motion
Challenges with traditional prediction algorithms
Computational demands and accuracy in dynamic environments
Flight safety and coordination
Collision avoidance with environment and other UAVs
Real-time flight path adjustments and external disturbances
Multi-UAV coordination and task reallocation
Resource management and energy efficiency
Limited battery life and power consumption
Managing computational and communication constraints in multi-UAV systems
Real-time resource optimization in dynamic environments
Technical challenges
UAV-based moving target tracking methods
Future research
Target visibility and occlusion
Advanced sensor fusion techniques
Deep learning-based vision systems for occlusion handling
Predictive models for target behavior under occlusion
Improved real-time prediction algorithms with adaptive models
Adaptive flight path planning
Real-time safety-critical decision-making systems
Dynamic stability algorithms for high-speed maneuvers
Swarm intelligence and coordination algorithms
Hybrid prediction algorithms
Multi-agent reinforcement learning for coordination
Decentralized decision-making for fault tolerance and resilience
Resource optimization for autonomous UAV operations
Collaborative energy sharing in multi-UAV systems
Lightweight edge computing for real-time processing
Efficient prediction with limited computational resources

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The author is an Editorial Board Member/Editor-in-Chief/Associate Editor/Guest Editor for [Journal name] and was not involved in the editorial review or the decision to publish this article.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: