

Review

Advances in Trajectory Prediction for High-Speed UAVs: A Review

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Highlights

What are the main findings?

- Model-driven, data-driven, and hybrid-driven trajectory prediction paradigms for high-speed UAVs are systematically reviewed and categorized, revealing a clear evolution from single-model reliance to multi-paradigm fusion.
- Hybrid-driven methods that combine the advantages of physical mechanisms and data-driven approaches offer superior prediction accuracy and adaptability compared to single-paradigm methods. However, key bottlenecks remain in addressing multi-uncertainty coupling and data scarcity.

What are the implications of the main findings?

- The established classification system and performance benchmarking metrics provide a standardized reference framework, enabling researchers to select and compare appropriate prediction methods for specific application scenarios.
- For the development of trajectory prediction methods for high-speed UAVs, future advances require an interdisciplinary collaborative framework that combines high-precision intelligent prediction models, lightweight algorithm design, and multisource data fusion to bridge the gap between theoretical models and engineering deployment.

Abstract

High-speed Unmanned Aerial Vehicles (UAVs), characterized by high velocity and maneuverability, represent critical strategic threats within the aerospace security domain. Accurate trajectory prediction is a fundamental prerequisite for effective early warning and decision-making in defense. Despite increasing research in the domain, model-, data-, and hybrid-driven methods have not yet been comprehensively examined under a unified framework, limiting the understanding of their relative strengths and applicability. To address this gap, this paper systematically reviews the evolution and current technical status of these paradigms, categorized by the core logic underlying prediction methods. The principles and applicability limits of physical process modeling and state estimation algorithms are analyzed, along with emerging applications of machine learning and deep learning for trajectory feature extraction and pattern recognition. State-of-the-art architectures involving the integration of physical constraints and data-driven learning are discussed. Standard evaluation metrics are introduced to facilitate performance benchmarking of existing methods. Comparative analysis reveals that no single technical route can fully address the coupled challenges of uncertainty, accuracy, and real-time performance, underscoring that hybrid frameworks are essential for balancing these competing requirements. Lastly, key challenges are summarized, and future research directions are outlined to advance trajectory prediction methodologies. The provided insights can inform method selection and promote the development of high-accuracy prediction systems.



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Keywords: high-speed UAVs; trajectory prediction; model-driven methods; data-driven methods; hybrid-driven methods

1. Introduction

Amid the continuous evolution of aerospace defense systems, high-speed Unmanned Aerial Vehicles (UAVs) have emerged as a strategic threat in the domain of national aerospace security [1,2]. Owing to their high velocity, high maneuverability, and diverse flight profiles [3], they can effectively penetrate conventional defense architectures, posing substantial challenges to existing early warning, detection, and tracking capabilities [4,5]. Consequently, high-precision trajectory prediction has become crucial for providing effective [6,7] and timely defense responses and supporting guidance and control decision-making [8], thereby serving as an essential basis for advanced defense systems [9,10].

Notably, trajectory prediction for high-speed UAVs faces unique and formidable technical challenges [11]. The motion trajectories of high-speed UAVs feature pronounced nonlinearity, time-varying dynamics, and uncertainty [12]. In particular, the glide phase often involves complex maneuvers such as skipping and turning [13], which significantly diminish the effectiveness of traditional deterministic model-based prediction methods [14]. Moreover, these vehicles typically operate within noncooperative scenarios, hindering the acquisition of critical information such as aerodynamic and control parameters. The scarcity of high-quality real flight data further compounds the problem [15]. Collectively, these factors increase the difficulty of temporal modeling, thereby limiting the applicability of data-driven methods.

To address these challenges, research paradigms for trajectory prediction have evolved in recent decades. Early studies primarily relied on model-driven or data-driven approaches. Model-driven approaches leverage physical principles to construct motion models, offering high interpretability. However, their accuracy depends on model fidelity [16]. Data-driven approaches adopt artificial intelligence techniques to mine patterns from data, providing adaptability. However, their performance remains limited by data availability and interpretability [17]. Recently, hybrid-driven methods that integrate physical principles with data-driven strategies to combine the strengths of both paradigms, have garnered increasing interest [18]. Using multilevel deep fusion, these methods incorporate physical constraints, embed physical equations, and infer game-theoretic intents. However, despite these advancements, a systematic review specifically dedicated to high-speed UAV trajectory prediction remains absent. This knowledge gap limits the comprehensive understanding of the evolution and applicability of different paradigms within this specific domain.

This paper presents a systematic review of the research progress in trajectory prediction methods for high-speed UAVs. Existing techniques are categorized into three major paradigms, namely model-driven, data-driven, and hybrid-driven methods, based on the core driving logic of prediction. This work serves as a comprehensive reference for researchers and practitioners, facilitating the optimal selection of algorithms for practical deployment and promoting the standardization of performance evaluation. The remainder of the paper is organized as follows. Section 3 describes the motion characteristics of high-speed UAVs and formulates the trajectory prediction problem. Section 4 provides a comprehensive review of current high-speed UAV trajectory prediction methods. Section 5 introduces evaluation metrics and presents a comparative analysis of the reviewed approaches. Section 6 summarizes key challenges and outlines future research directions. Section 7 concludes the paper.

2. Literature Screening Methodology

To ensure methodological rigor and transparency in the review process, a systematic literature screening procedure was conducted following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [19], an internationally recognized framework for enhancing the transparency and reproducibility of systematic reviews. The authors identified a total of 598 publications through systematic searches across six authoritative databases: Web of Science, IEEE Xplore, ScienceDirect, Scopus, CNKI (China National Knowledge Infrastructure), and the National University of Defense Technology Library. To supplement the database search, the first 15 pages of results from Google Scholar and Baidu Scholar were also screened. This protocol-guided approach facilitated the elimination of duplicates and irrelevant studies through sequential title/abstract screening and full-text evaluation, ultimately yielding a refined corpus of high-quality publications for critical analysis. The screening process is detailed in the following subsections.

2.1. Databases and Search Strategy

To ensure a comprehensive and unbiased coverage of the literature on high-speed UAV trajectory prediction, systematic searches were conducted across six authoritative academic databases: Web of Science, IEEE Xplore, ScienceDirect, Scopus, CNKI (China National Knowledge Infrastructure), and the National University of Defense Technology Library. To capture a wider range of literature, including preprints and technical reports, the first 15 pages of results from Google Scholar and Baidu Scholar were also screened. Boolean search strategies, adapted to the specific syntax of each platform, were employed to combine the following conceptual keywords:

- Subject terms: “high-speed UAV,” “high-speed vehicle,” “hypersonic vehicle,” “hypersonic target,” “trajectory prediction,” “flight path prediction”;
- Methodological terms: “physics model,” “neural network,” “machine learning,” “deep learning”;
- Application constraints: “real-time prediction,” “maneuvering target,” “uncertainty quantification,” “aerodynamic model”.

To supplement the database search, forward and backward snowballing techniques were applied to the reference lists of key identified articles to identify seminal and emerging studies that might not have been captured by the initial search queries.

2.2. Inclusion and Exclusion Criteria

Although Boolean search methods and keywords were predefined during the initial search, not all retrieved literature proved relevant to this review. To refine the dataset, a multi-stage screening protocol was implemented based on predefined inclusion and exclusion criteria. First, duplicate records and non-downloadable documents were removed, followed by preliminary screening based on publication titles to exclude studies clearly unrelated to high-speed UAV trajectory prediction.

Next, secondary screening focused on abstracts and summaries, further eliminating literature unrelated to trajectory prediction methods, lacking clear methodological descriptions, or focusing solely on low-speed vehicles or non-aerodynamic targets. Given the substantial workload and involvement of multiple reviewers, detailed discussions were held beforehand to establish unified evaluation standards, ensuring consistency across personnel. Finally, full-text content was assessed to exclude studies with redundant methodologies, low credibility, limited research value, or those that did not present novel prediction methods or significant improvements to existing approaches.

Through this rigorous process, 598 publications retrieved from the above-mentioned databases and academic search engines were systematically filtered. After removing

duplicates and irrelevant literature, 104 high-quality publications were retained as the foundational dataset for this review. The screening workflow and attrition rates are illustrated in Figure 1.

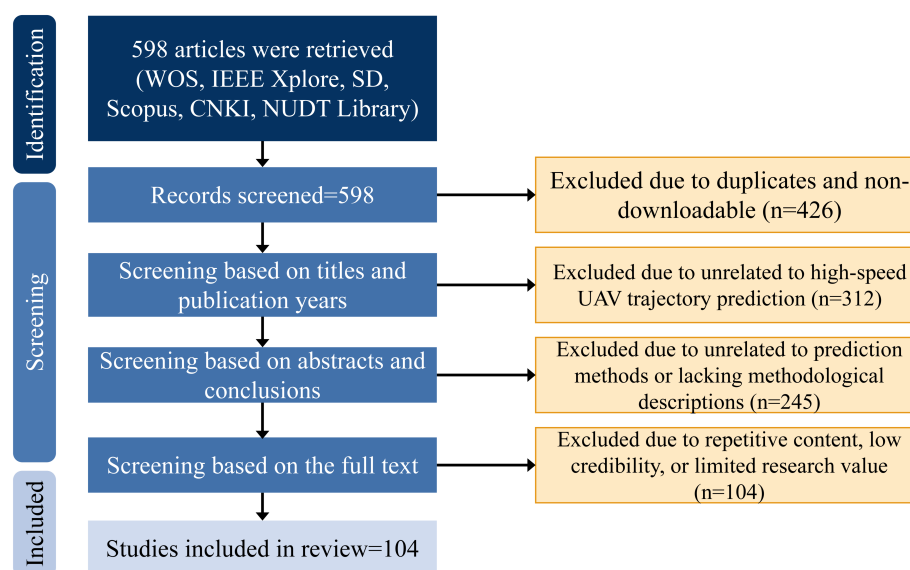


Figure 1. Screening process inspired by PRISMA.

2.3. Methods Classification Criteria

This review adopts a three-category taxonomy: model-driven, data-driven, and hybrid-driven methods. This classification is based on the core driving logic underlying each prediction method, rather than on superficial algorithmic differences.

Model-driven methods rely on prior physical knowledge encoded in differential equations of motion, offering transparent interpretability and low computational cost. Data-driven methods extract patterns directly from historical trajectory data without explicit physical principles, achieving superior accuracy in complex maneuvering scenarios at the expense of interpretability and data dependency. Hybrid-driven methods aim to integrate the advantages of both paradigms by combining physical constraints with data-driven network architectures, or by leveraging data to compensate for inherent model inaccuracies. This classification is not merely a formal arrangement but is justified by the following considerations.

Chronologically, this trichotomy reflects the evolution of the field: from early physics-based formulations, through the rise of deep learning, to the recent integration of both paradigms. Practically, different scenarios demand different tradeoffs between interpretability, accuracy, and computational efficiency—and the three categories naturally correspond to these distinct engineering requirements. The boundaries between them are not strictly rigid, yet this framework provides a coherent basis for organizing the reviewed literature and facilitates systematic comparison, as will be elaborated in Section 4.

3. Motion Characteristics of High-Speed UAVs

Understanding the motion characteristics of high-speed, high-maneuverability UAVs is crucial for feature extraction and the construction of prediction models. The flight trajectory of a high-speed UAV is typically segmented into boost, mid-course, and terminal phases. During the boost phase, powered flight is predominant. This phase is characterized by a short duration and well-defined dynamics. In the terminal phase, frequent attitude adjustments and trajectory corrections are executed. Concurrently, the high velocity exacerbates aero-thermal coupling effects, increasing state uncertainty and narrowing the

effective prediction window [20]. The mid-course phase features a prolonged duration and serves as the core stage for range extension and large-scale maneuvers. Consequently, high-precision trajectory prediction during this phase is essential to provide critical warning time for defense systems [21]. High-speed UAVs are primarily categorized into gliding and cruising types. Their representative flight trajectories are illustrated in Figure 2. The motion characteristics during the mid-course phase are discussed in this section.

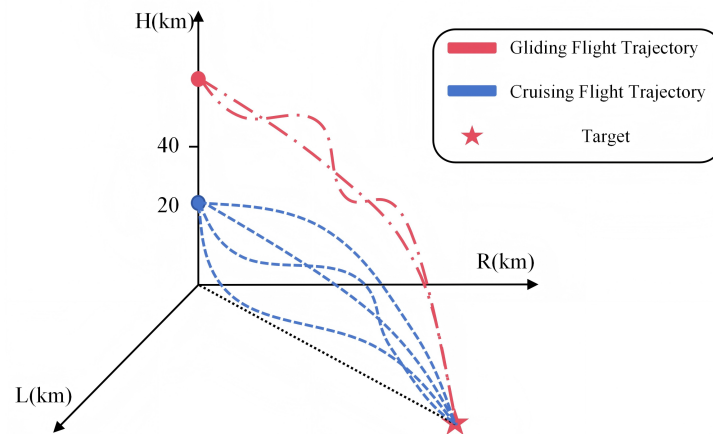


Figure 2. Trajectories of high-speed UAVs. The trajectories are plotted in a three-dimensional ground coordinate system, where R denotes the downrange distance, L represents the lateral displacement, and H indicates the altitude above ground. All axes are measured in kilometers (km).

Gliding high-speed UAVs execute unpowered glide missions within the near-space regime (20–100 km altitude), with their motion governed primarily by aerodynamic–gravitational coupling. The first phase centers on path constraints, including heat flux density, dynamic pressure, and normal load factor. These constraints must be satisfied within a narrow flight corridor through real-time modulation of the angle of attack and bank angle [22,23]. Heat flux constraints ensure the efficacy of the thermal protection system, dynamic pressure boundaries help maintain control surface efficiency, and load factor limits ensure the preservation of structural integrity [24]. Under these stringent constraints, their motion exhibits pronounced nonlinearity and time-varying characteristics. Aerodynamic coefficients vary considerably with Mach number and the angle of attack, while attitude maneuvers dynamically reconfigure lift and drag, exacerbating the complexity of state evolution [25]. Following this phase, typical trajectories exhibit a skip–glide pattern, in which gravitational potential energy and kinetic energy are efficiently exchanged through periodic oscillations to extend range [26]. Moreover, bank angle modulation endows these UAVs with large-scale lateral maneuverability, enabling trajectories to breach initial launch-plane constraints, with lateral deviations of hundreds of kilometers. In noncooperative defense scenarios, trajectory prediction is subject to multiple sources of uncertainty. These include deviations in aerodynamic model parameters arising from discrepancies between real flight environments and ground test conditions, time-varying mass characteristics due to center-of-mass shifts induced by fuel consumption, and the unobservability of guidance laws resulting from unknown angle-of-attack and bank-angle control strategies [27]. Modern gliding high-speed UAV guidance systems often employ methods such as sequential convex optimization to generate optimal trajectories that satisfy multiple constraints online. Consequently, motion-state evolution relies heavily on real-time optimization, which increases the complexity of prediction-model development.

Cruising high-speed UAVs employ scramjet engines to generate sustained thrust, and their kinematic behavior is governed by strong thrust–aerodynamics coupling mechanisms [28]. Although their flight altitudes partially overlap with those of gliding high-speed

UAVs, their trajectories must strictly adhere to the engine's operational limits. Specifically, the angle of attack and dynamic pressure must remain within safe inlet and combustion boundaries. This constraint differs from those for gliding high-speed UAVs, which focus solely on aerodynamic limits [29]. Sustained thrust helps maintain near-constant dynamic pressure during cruising. Slow variations in altitude suppress severe ballistic oscillations, thereby ensuring engine stability [30]. Consequently, the trajectories typically exhibit smooth, serpentine patterns or constant-altitude cruise phases. Although lateral maneuverability is restricted by engine capabilities, heading corrections can be achieved via bank-angle adjustments. Guidance usually relies on trajectory linearization control to optimize fuel consumption along the flight path while ensuring precise heading through lateral lead-angle management. Owing to this layered control scheme, trajectories exhibit nonlinear, coupled behavior [31]. These traits, together with uncertainties in propulsion dynamics, represent the key challenges for trajectory prediction.

The mid-course kinematic characteristics of gliding and cruising high-speed UAVs differ considerably. Gliding high-speed UAVs leverage aerodynamic–gravitational coupling to perform unpowered gliding in the near-space regime. They exhibit skip–glide trajectories marked by strong nonlinearity, pronounced time-varying dynamics, and extensive lateral maneuverability. In contrast, cruising high-speed UAVs rely on sustained thrust from scramjet engines, enabling smoother cruise trajectories that are constrained by the engine's operating envelope. These differences in motion characteristics stem from distinct mechanisms for energy acquisition and management, which directly define the theoretical boundaries of trajectory prediction. In noncooperative scenarios, the unobservability of guidance strategies, parameter uncertainties, and strongly coupled dynamic characteristics constitute the core challenges for trajectory prediction.

4. Trajectory Prediction Methods for High-Speed UAVs

Methods for high-speed UAV trajectory prediction have evolved alongside advances in the understanding of motion dynamics and computing power, transitioning from physics-based models to data-driven learning and, more recently, to hybrid approaches. This evolution reflects a shift from reliance on prior knowledge to effective data utilization, and ultimately, to leveraging the strengths of both paradigms. Based on the core logic underlying prediction methods, current approaches can be categorized into model-driven, data-driven, and hybrid-driven techniques. This section outlines the key theories, technical features, and application scenarios of each category.

4.1. Model-Driven Methods

Model-driven methods represent foundational techniques for high-speed UAV trajectory prediction. Dynamic or kinematic models are constructed based on Newtonian mechanics and aerodynamics, and are numerically solved to predict trajectories. Observational data are usually used to calibrate model parameters or update state estimates, rather than to directly identify trajectory patterns. These methods are physically interpretable, as their equations of motion follow basic physical laws. Even when observational data are limited, they maintain stable extrapolation prediction capability.

4.1.1. Physical Models

Physical models represent a fundamental approach for high-speed UAV trajectory prediction. By combining an in-depth understanding of high-speed UAV motion mechanisms with mathematical descriptions, predictive models that reflect physical characteristics can be established. Such models are typically based on fundamental theories, including Newto-

nian mechanics and aerodynamics, enabling accurate characterization of high-speed UAV motion both within and outside the atmosphere.

It should be noted that trajectory prediction modeling differs fundamentally from high-fidelity flight vehicle design modeling. The latter requires the comprehensive incorporation of aero-thermal coupling, structural deformation, and fuel consumption to support thermal protection system design and structural integrity assessment. In contrast, trajectory prediction aims primarily at the rapid estimation of future motion states. Constrained by the stringent inference speed requirements in defense scenarios, the dynamic model must be reasonably simplified. Therefore, trajectory prediction studies universally adopt reduced-order kinematic models, focusing on the macroscopic motion governed by mass, aerodynamic forces, and gravity, without resolving thermodynamic states or multi-physics coupling processes in detail. Consider, for example, the glide phase of a gliding high-speed UAV. The motion dynamics can be described using Equation (1) [32].

$$\left\{ \begin{array}{l} \frac{dV}{dt} = -\frac{D}{m} - g \sin \theta \\ \frac{d\theta}{dt} = \frac{L \cos \nu}{mV} + \left(\frac{V}{r} - \frac{g}{V} \right) \cos \theta \\ \quad + 2\omega_e \cos \phi \sin \sigma \\ \frac{d\sigma}{dt} = \frac{L \sin \nu}{mV \cos \theta} + \frac{V \cos \theta \sin \sigma \tan \phi}{r} \\ \quad - 2\omega_e (\cos \phi \tan \theta \cos \sigma - \sin \phi) \\ \frac{d\phi}{dt} = \frac{V \cos \theta \cos \sigma}{r} \\ \frac{d\lambda}{dt} = \frac{V \cos \theta \sin \sigma}{r \cos \phi} \\ \frac{dr}{dt} = V \sin \theta \end{array} \right. \quad (1)$$

where m denotes the vehicle mass, g represents gravitational acceleration, t indicates time, and ω_e is a coefficient related to Earth rotation. V , θ , σ , r , λ , and ϕ are state variables representing vehicle velocity, flight-path angle, velocity azimuth angle, geocentric radial distance, longitude, and latitude, respectively. ν denotes the bank angle, while L and D represent lift and drag forces, respectively. The above dynamic model is specifically formulated for the unpowered glide phase, during which the fuel of the vehicle has been largely depleted and the mass m can be treated as constant. It should be noted that, in trajectory prediction applications, for the boost phase of gliding high-speed UAVs, as well as for the entire flight envelope of cruising high-speed UAVs, the time-varying mass effect induced by fuel consumption is non-negligible. In such cases, the dynamic modeling must be augmented with an additional mass variation term.

Trajectory prediction tasks are typically formulated using six-degree-of-freedom (6-DOF) dynamic equations. For example, Bashir et al. [33] used DATCOM to calculate aerodynamic coefficients and established a 6-DOF ballistic model to analyze the dynamic stability characteristics of uncontrolled projectiles across various Mach numbers. To achieve high-precision prediction, high-fidelity models must be integrated with advanced numerical methods. Hamlan et al. [34] developed a ballistic prediction program for a solid rocket using the Runge–Kutta–Fehlberg method and experimentally validated its effectiveness in flight performance and trajectory prediction. Furthermore, Calvo et al. [35] achieved accurate prediction of the boost-phase trajectory of a high-speed UAV by coupling flight mechanics with aerodynamics, integrating semi-empirical programs, Euler/Navier–Stokes solvers, and trajectory optimization programs. Building on these advancements, Tacchi et al. [36] investigated thermomechanical coupling effects by combining an inverse estimation method with trajectory simulations to reconstruct spacecraft reentry trajectories.

Given the pronounced nonlinearity and strong coupling inherent in the dynamics of gliding high-speed UAVs, various simplified analytical frameworks have been developed. For trajectories involving large lateral maneuvers, Yu et al. [37] constructed a novel flight dynamics model based on generalized longitude and latitude coordinates. The authors used perturbation techniques to decompose the complex model into three analytically solvable subsystems, obtaining closed-form approximate solutions. Qi et al. [38] proposed analytical expressions for equilibrium glide trajectories. By introducing intermediate variables and applying scaling methods, they circumvented the singularity problems encountered near critical points when using traditional methods. Liu et al. [39] developed a real-time trajectory prediction method based on a three-dimensional flight corridor. By solving reduced-order differential equation systems within a redefined coordinate system, rapid trajectory prediction was achieved with enhanced computational efficiency.

Kinematic fitting methods provide an effective alternative when physical models are constrained or rapid prediction is required. Han et al. [40] analyzed the kinematic characteristics of unpowered gliding high-speed UAVs during the glide phase and verified the feasibility of using a polynomial model to predict target trajectories. The influence of state estimation errors on prediction accuracy was mitigated using segmentation and midpoint smoothing techniques. Building on this concept, Ma et al. [41] proposed a high-speed UAV trajectory prediction method based on acceleration fitting, in which observed data were used to fit the variation law of UAV acceleration, and subsequent flight trajectories were estimated via integral iteration. Similarly, Yu et al. [42] adopted fitting methods to predict target trajectories and determine the expected impact point, providing insights for cooperative defense strategies. Zheng et al. [43] proposed a prediction method based on trajectory simulation, in which expressions for the UAV's position coordinates as a function of time were derived by simulating ideal trajectories under different typical flight paths and guidance laws, thereby providing decision-making support. From a geometric perspective, Kim et al. [44] predicted the future path of cruising high-speed UAVs by considering the current flight-path angle and load factor and designed tracking trajectories based on known terrain data.

Certain modeling methods also exhibit advantages for specific flight modes. Xu et al. [45] analyzed the general characteristics of high-speed UAV trajectories and proposed a trajectory prediction algorithm based on the damped oscillation model. The prediction accuracy was noted to be higher than that of conventional kinematic models. Li et al. [46] reported that the aerodynamic acceleration of skip-glide high-speed UAVs follows a relatively stable pattern. The trend of aerodynamic acceleration was extracted via empirical mode decomposition, and the future states of the UAVs were predicted through basis function fitting. Liu et al. [47] established a trajectory database under various maneuvering modes based on 6-DOF motion equations, providing a data foundation for subsequent intelligent prediction methods.

Overall, physical models adhere to explicit physical laws, and their modeling parameters generally correspond to actual physical quantities. These features result in strong physical interpretability, facilitating the understanding and validation of model behaviors from a mechanistic perspective. For UAVs with known flight patterns operating under standard conditions, such models can achieve satisfactory prediction accuracy. Nevertheless, physical models suffer from several limitations. In situations involving unknown or unmodeled maneuvers, the fixed model structure results in insufficient adaptability, leading to significant degradation in prediction performance. Additionally, the introduction of complex physical effects to improve accuracy substantially increases model complexity and computational overhead, making it difficult to meet the real-time control requirements of high-speed UAVs. With continuous improvements in the maneuverability of modern

high-speed UAVs, the flight envelope has expanded steadily. Consequently, flight states exhibit stronger nonlinearity, rapid time variation, and tight coupling. Single physical models that rely on accurate prior knowledge are thus often incapable of fully adapting to such complex, variable flight environments.

4.1.2. State Estimation Algorithms

State estimation methods represent a key technique for high-speed UAV trajectory prediction. These methods recursively update the target state and predict future trajectories by fusing measurement data with a dynamic model of a high-speed UAV. One of the most widely used recursive optimal estimation algorithms in this context is the Kalman filter (KF) [48,49]. Its core framework involves two steps, namely prediction and update, as defined in Equations (2) and (3), respectively.

$$\begin{cases} \hat{x}_{k|k-1} = F_k \hat{x}_{k-1|k-1} + B_k u_k \\ P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \end{cases} \quad (2)$$

$$\begin{cases} K_k = P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R_k)^{-1} \\ \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k (z_k - H_k \hat{x}_{k|k-1}) \\ P_{k|k} = (I - K_k H_k) P_{k|k-1} \end{cases} \quad (3)$$

where $\hat{x}$ denotes the state estimation vector, F_k is the state transition matrix, B_k represents the control input matrix, u_k is the control vector, P denotes the error covariance matrix, Q_k is the process noise covariance matrix, K_k is the Kalman gain, H_k represents the observation matrix, R_k is the measurement noise covariance matrix, z_k denotes the measurement vector, and I is the identity matrix.

For linear Gaussian systems, the standard KF yields optimal estimation results. Using this approach, Qin et al. [50] effectively estimated three-axis position states for near-space high-speed UAVs. To realize trajectory prediction during blackout phases, Zhang et al. [51] adopted the unscented transformation combined with environmental force models and radar error propagation to predict vehicle positions after the blackout phase. To enable accurate tracking and prediction under short-term occlusion or tracking loss, Xu et al. [52] fused the KF with an improved mean-shift algorithm to provide visual tracking compensation during signal loss.

To cope with strong nonlinearity and unmodeled dynamics, various strategies have been developed beyond standard nonlinear extensions of the KF. A representative approach is the adaptive Kalman filter (AKF) proposed by Liu et al. [53], which integrates a recursive input estimator with the EKF to online estimate unmodeled accelerations, thereby directly compensating for model errors without requiring explicit knowledge of the maneuver dynamics. For scenarios involving frequent bank angle reversals and discontinuous trajectories, Sun et al. [54] developed an intention inference-based square-root cubature Kalman filter (Int-SRCKF). To handle the strong nonlinearity, the SRCKF employs the spherical-radial cubature rule to numerically compute Gaussian-weighted integrals, avoiding the linearization errors inherent in the EKF. To address the unmodeled dynamics caused by abrupt changes in the bank angle, a multi-intention model is constructed and Bayesian theory is applied to infer the sign of the bank angle, which is then used to constrain the state estimation, leading to improved tracking performance under high-maneuverability conditions. In a different application context, Lai et al. [55] implemented a UKF for projectile trajectory estimation, which handles the nonlinear measurement model through deterministic sigma-point sampling. The UKF propagates the mean and covariance through the nonlinear measurement equation without requiring analytical linearization, and the ex-

perimental results demonstrate its superior accuracy over the conventional KF in projectile trajectory estimation.

Notably, a single model is often incapable of adapting to the complex maneuvering characteristics of highly maneuverable targets. In this regard, the interacting multiple model (IMM) method presents remarkable advantages. Zhou et al. [56] fused IMM with the constant velocity, constant acceleration, and Singer models for trajectory estimation; designed a cooperative coverage algorithm based on probability density functions; and optimized the coverage of high-probability regions by the seeker. Other prediction methods have also been developed based on state estimation. Akcal et al. [57] combined recursive least squares with fixed-time-domain nonlinear programming to develop a predictive guidance scheme with online learning capability. This approach improved mission time and miss distance by iteratively learning the adjustment behavior of the target model. Yang et al. [58] proposed a prediction method based on feature extraction and the vector autoregressive moving average model. Nonstationarity was addressed using the discrete Fourier transform and differencing, and coefficient estimation was transformed into a convex optimization problem. This approach effectively addresses the challenges of nonstationarity and unknown noise in parameter prediction for gliding high-speed UAVs.

In summary, different state estimation methods present distinct advantages and limitations for high-speed UAV trajectory prediction. The KF offers high computational efficiency but suffers from considerable approximation errors under strong nonlinearity. The IMM method exhibits strong adaptability to complex maneuvers; however, its parallel architecture results in high computational complexity. Although Bayesian inference and Monte Carlo sampling methods enable flexible modeling and can handle non-Gaussian noise and uncertainties, they impose a heavy computational burden. Therefore, in practical applications, it remains crucial to comprehensively consider target maneuvering characteristics, computational resources, and prediction duration; to rationally select or integrate the strengths of different methods; and to construct a hybrid prediction architecture that offers strong adaptability and a favorable balance between efficiency and accuracy.

4.2. Data-Driven Methods

Data-driven methods offer an alternative paradigm for predicting high-speed UAV trajectories. The core concept is to automatically learn motion laws from historical data rather than relying on predefined physical equations. These methods treat trajectory prediction as a time-series modeling task and employ machine-learning or deep-learning algorithms to explore the complex mapping among state variables and infer future trajectories. Unlike model-driven methods, which mainly use observational data for parameter calibration, data-driven approaches use trajectory data as the knowledge source. By constructing end-to-end networks, these methods can effectively capture nonlinear dynamic characteristics that are difficult to explicitly describe under complex environments. Although data-driven methods typically require high data quality and quantity and exhibit weaker interpretability than physical models, they can achieve superior adaptability and prediction accuracy in scenarios involving sufficient data and complex motion patterns.

4.2.1. Machine-Learning-Based Methods

Machine-learning-based methods [59,60] represent key techniques for high-speed UAV trajectory prediction, displaying distinct advantages in handling complex motion characteristics and uncertain environments. Compared with conventional model-driven methods, machine learning methods can more accurately capture nonlinear laws and adapt more effectively to abrupt maneuvers and external disturbances.

Gaussian process regression (GPR) [61] has been widely applied to high-speed UAV trajectory prediction as it can provide probabilistic interpretations of prediction results and effectively quantify uncertainties. GPR is a non-parametric modeling method based on Bayesian theory, and its core formulation is presented in Equation (4).

$$\begin{cases} f(x) \sim \mathcal{GP}(m(x), k(x, x')), \\ y = f(x) + \varepsilon, \quad \varepsilon \sim \mathcal{N}(0, \sigma_n^2), \\ \hat{f}_* = \mathbf{K}_*^T (\mathbf{K} + \sigma_n^2 \mathbf{I})^{-1} \mathbf{y}, \\ \text{Var}(\hat{f}_*) = k_{**} - \mathbf{K}_*^T (\mathbf{K} + \sigma_n^2 \mathbf{I})^{-1} \mathbf{K}_*. \end{cases} \quad (4)$$

where $f(x)$ denotes the unknown function governed by a Gaussian process, $m(x)$ is the mean function, and $k(x, x')$ represents the covariance kernel function. The term y denotes the observation, ε denotes Gaussian white noise, and σ_n^2 is the noise variance. $\hat{f}_*$ represents the predictive mean, and $\text{Var}(\hat{f}_*)$ is the predictive variance. $\mathbf{K}$, $\mathbf{K}_*$, and k_{**} represent the training-sample covariance matrix, cross-sample covariance vector, and self-covariance at the test point, respectively. $\mathbf{I}$ is the identity matrix.

Wang et al. [62] developed an online GPR-based trajectory prediction method that combines fast and slow UAV motion models with an EKF. This method uses sequential iteration to predict future acceleration, effectively balancing accuracy and real-time requirements. Hou et al. [63] incorporated motion intention within the GPR framework, introduced a conditional kernel, and developed an online time-to-target learning mechanism, which considerably improved trajectory prediction accuracy.

However, the standard Gaussian process assumes that noise follows a normal distribution, reducing its effectiveness in handling the heavy-tailed noise often observed in high-speed UAV trajectories. To address this, non-Gaussian probabilistic models have been proposed. For example, Xue et al. [64] developed the adaptive multivariate Student's t -process regression method, as shown in Figure 3. This method adopts Student's t -distribution to represent heavy-tailed noise and tunes parameters using an accelerated expectation-maximization algorithm with Pearson correlation analysis. It achieves greater prediction accuracy than multivariate Gaussian process regression in heavy-tailed environments. Liang et al. [65] proposed a Student- t mixture filtering algorithm with an adaptive online model, which updates parameters without prior noise data and effectively estimates states under nonstationary measurement noise.

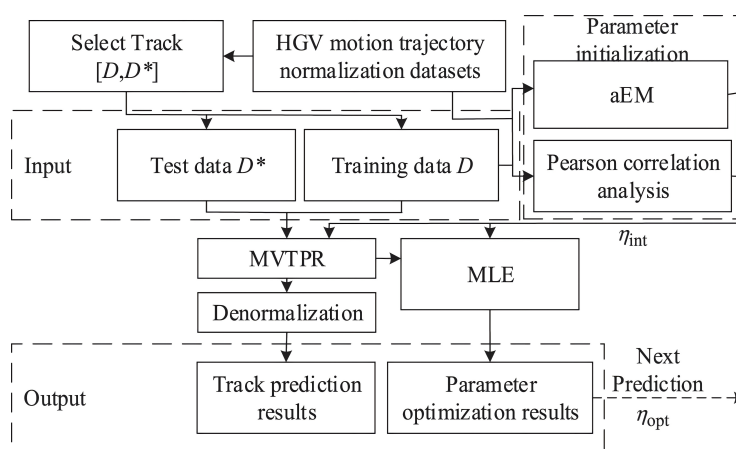


Figure 3. Trajectory prediction using the adaptive multivariate Student's t -process regression method (aEM-MVTPR) [64]. D and D^* denote the training and test datasets corresponding to time periods $t_1 \sim t_n$ and $t_{n+1} \sim t_{n+m}$, respectively. η_{int} represents the initial parameter set obtained using aEM and Pearson correlation analysis, while η_{opt} denotes the optimized parameter set obtained using MLE for the next prediction cycle.

To develop more advanced machine learning methods, Bartusiak et al. [66] applied stochastic grammars to the behavior prediction of gliding high-speed UAVs. This method describes the transition patterns of trajectory sequences and infers future kinematic characteristics such as altitude, velocity, and acceleration from partial trajectories. Experimental results demonstrate that this approach can successfully predict the UAV state several minutes ahead, even in noisy environments. Furthermore, Bartusiak et al. [67] implemented automatic identification of gliding high-speed UAVs and ballistic reentry vehicles using machine learning classification. The method, based on aerodynamic state estimation, achieved high-precision classification by analyzing key maneuver features, and the classification accuracy improved significantly with increasing flight time and data volume.

Overall, machine learning-based methods can mine trajectory patterns of high-speed UAVs and offer advantages in nonlinear modeling without relying on complex dynamic equations. However, their practical application is limited by various factors. Feature selection and parameter tuning directly affect model performance, and long-term, multistep prediction often leads to cumulative errors that impair stability. Moreover, training models require large amounts of data, leading to high computational costs and sensitivity to noise and missing data. Thus, practical use requires balancing data scale, computational resources, and task requirements when selecting or integrating suitable prediction methods.

4.2.2. Deep-Learning-Based Methods

Deep-learning-based methods [68] provide a powerful approach for feature representation and pattern mining in trajectory prediction for high-speed UAVs, owing to their hierarchical abstraction and end-to-end learning capabilities. Unlike traditional machine learning methods that rely on manually engineered features, deep learning can automatically extract multilevel spatiotemporal features from raw data, thereby mitigating the subjectivity and information loss inherent in manual feature engineering. Models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can handle strong nonlinearity, long-range dependence, and complex trajectory dynamics. These architectures capture the deep coupling among state variables and achieve high-precision long-term prediction when sufficient data are available. Therefore, deep learning has emerged as an effective technical approach to improve the accuracy and adaptability of trajectory prediction in highly dynamic and uncertain environments.

For temporal trajectory modeling, RNNs [69,70] and their variants typically constitute the fundamental architecture of deep-learning-based prediction methods. Long short-term memory (LSTM) networks [71,72] effectively overcome the vanishing gradient problem of conventional RNNs through gating mechanisms, enabling them to capture long-term dependencies. This makes LSTMs suitable for highly dynamic, strongly nonlinear trajectory time-series prediction tasks. The core update formulas are presented in Equation (5).

$$\begin{cases} f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f), \\ i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \\ \tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C), \\ C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t, \\ o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o), \\ h_t = o_t \odot \tanh(C_t). \end{cases} \quad (5)$$

where f_t , i_t , and o_t denote the forget gate, input gate, and output gate, respectively; C_t is the cell state and $\tilde{C}_t$ represents the candidate cell state; h_t is the hidden state and x_t is the input at time t ; W_f , W_i , W_C , and W_o are weight matrices, while b_f , b_i , b_C , and b_o are bias terms;

$\sigma(\cdot)$ denotes the sigmoid activation function; $\tanh(\cdot)$ is the hyperbolic tangent activation function; and $\odot$ represents the element-wise product.

Meng et al. [73] developed an LSTM model for predicting the skip trajectories of near-space high-speed UAVs. The model uses a six-dimensional state input, including three-dimensional position, velocity, trajectory inclination angle, and angle of attack, enabling effective prediction of future trajectories. Sun et al. [74] modeled skip trajectories as time-varying approximate expressions using linear attenuation terms and amplitude-attenuated sinusoidal terms. LSTM was applied to predict the dynamic range of parameters and calculate the reachable region of the trajectory, thereby improving prediction accuracy. Zhang et al. [75] applied LSTM to beam tracking of high-speed UAVs. By integrating trajectory prediction, this method reduced beam-switching frequency and improved communication stability. Notably, various modifications to the conventional LSTM architecture have been proposed to optimize predictive performance. Gao et al. [76] proposed a corrected prediction model based on bidirectional LSTM (BiLSTM), as shown in Figure 4. This model integrates dual subnetworks to separately predict the future trajectory and reverse launch point, reducing prediction error.

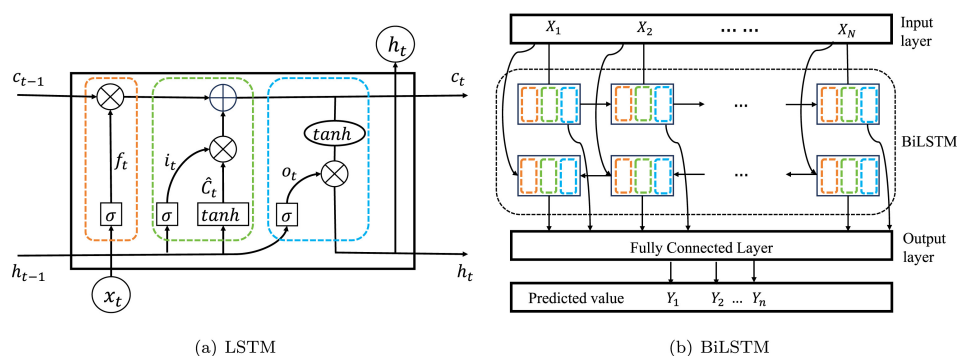


Figure 4. Structure of LSTM and BiLSTM [76]. (a) Internal structure of a single LSTM cell, illustrating the forget gate, input gate, output gate, and cell state transitions. (b) Overall architecture of BiLSTM network consisting of an input layer, bidirectional LSTM layers, a fully connected layer, and an output layer for sequence prediction.

Luo et al. [77] compared the performance of temporal convolutional networks (TCNs) and LSTM models in predicting gliding high-speed UAV trajectories. The TCN yielded better long-term predictions owing to the use of causal convolutions and residual connections. Consequently, TCNs are well-suited for tasks involving complex nonlinear trajectories. Wang et al. [78] used a deep neural network with double hidden layers for high-speed UAV trajectory prediction. This approach increased prediction speed by four times while reducing errors compared with numerical integration methods.

The attention mechanism has demonstrated remarkable performance in trajectory prediction. This framework enhances the ability of a model to focus on critical spatiotemporal features. At its core, it allows the model to automatically concentrate on informational segments crucial for future prediction rather than processing all historical trajectory data equally. Xu et al. [79] integrated the multihead attention mechanism with LSTM for prediction tasks. The network structure is illustrated in Figure 5. To address low input dimensions, this method uses fully connected layers to improve feature representation. An LSTM network is combined with an attention mechanism to capture the target dynamics, enabling high-precision trajectory estimation for near-space high-speed UAVs in complex maneuvering environments.

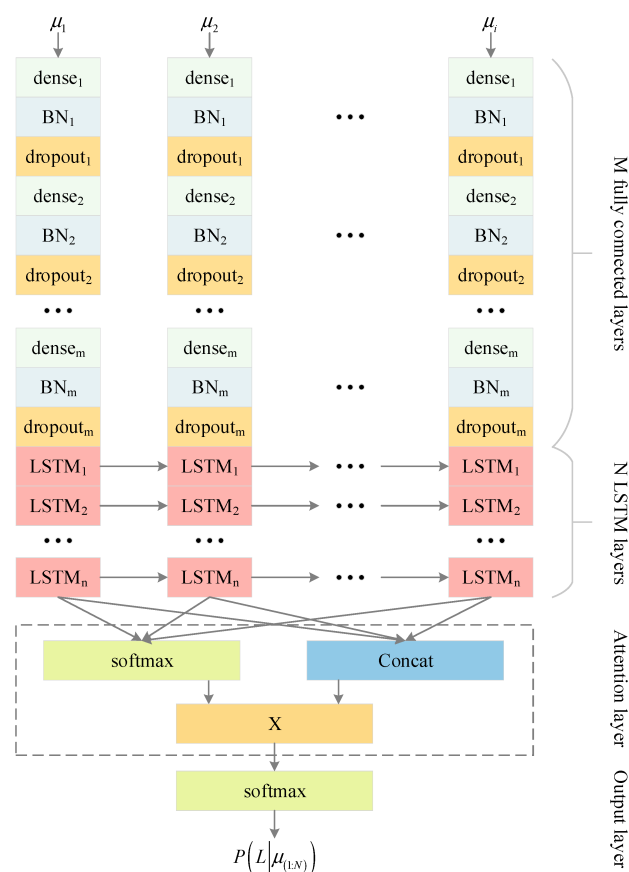


Figure 5. LSTM network incorporating an attention mechanism [79]. $\mu_1, \mu_2, \dots, \mu_i$ denote input trajectory data sequences. dense_j , BN_j , and dropout_j ($j = 1, \dots, m$) represent m fully connected layers for dimensionality enhancement, batch normalization layers, and dropout layers with a dropping probability of 0.2, respectively. LSTM_i ($i = 1, \dots, n$) denotes n LSTM layers for capturing temporal dependencies. Concat represents the concatenation operation for multihead attention outputs. X is the attention weight matrix. $P(L|\mu_{1:N})$ denotes the output probability distribution of trajectory labels given input sequences μ_1 to μ_N .

Ding et al. [80] proposed an algorithm that integrates a multiattention mechanism with an encoder–decoder structure. This approach mines the semantic and spatial relationships among features, significantly improving prediction accuracy. Xu et al. [81] proposed the MSCNN-BiLSTM-AM framework, which employs an improved squeeze-and-excitation network and dual-channel pooling design to capture key features. The model combines the spatial feature extraction capability of CNNs with the temporal modeling ability of BiLSTMs. It not only outperforms baseline methods in conventional performance metrics but also maintains high accuracy and strong robustness under challenging conditions such as outliers and missing data.

To fully exploit the spatiotemporal coupling in trajectory data, various spatiotemporal fusion architectures have been proposed. These architectures achieve high-precision prediction of high-speed UAV trajectories by integrating spatial feature extraction with temporal dependency modeling. Gong et al. [82] proposed an intelligent prediction method for reentry impact points based on dynamic data processing. Key state variables were screened through correlation analysis, while a temporal attenuation factor and a feature change rate mechanism were introduced to adaptively select important time steps. A CNN–LSTM network was constructed to control the prediction error at the kilometer level. Baradaran et al. [83] developed a hybrid deep learning architecture to integrate the strengths of CNNs, LSTMs, and gated recurrent units (GRUs). In this approach, a CNN is

used for spatial feature extraction, LSTM is applied for modeling long-term dependencies, and GRU is employed for improving efficiency. The proposed hybrid method achieves high-precision prediction of complex high-speed UAV trajectories. For intention recognition, He et al. [84] designed an LSTM–CNN network combined with an autoencoder to distinguish target categories, improving trajectory prediction accuracy in complex flight scenarios. Considering the strong maneuvering characteristics of gliding high-speed UAVs, Xie et al. [85] proposed a dual-channel bidirectional neural network that captures complex temporal dependencies and explicit patterns through nonlinear and linear components. Notably, this model effectively learns mixed dependencies between long- and short-term patterns, demonstrating significant advantages in predicting nondetectable regions. To address cumulative errors in long-term prediction, Hu et al. [86] combined a TCN with an LSTM. Spatiotemporal features were extracted using convolution, while prediction errors were corrected through the LSTM. Zeng et al. [87] combined CNN with LSTM for trajectory classification. This approach maintained strong performance under observation noise, providing a basis for future targeted trajectory prediction. To simultaneously enhance computational efficiency and accuracy, Cai et al. [88] integrated frequency-enhanced channel attention (to facilitate feature fusion) and a lightweight sampling multilayer perceptron with reversible instance normalization (to enable high-precision prediction). Lastly, Wu et al. [89] proposed a CNN-BiLSTM-Attention model that combined trajectory clustering with a spatiotemporal feature network, as shown in Figure 6. Dedicated prediction models were established using K-medoids clustering. Moreover, hidden motion patterns were mined by integrating the advantages of multiple networks, effectively mitigating the degradation in prediction accuracy caused by high maneuverability.

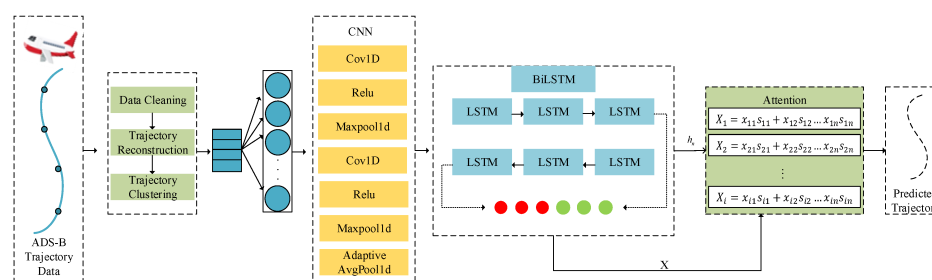


Figure 6. Architecture of a hybrid trajectory prediction model [89]. h_n denotes the final hidden state of BiLSTM. X represents the sequence of hidden states output from BiLSTM. x_{ij} and s_{ij} denote the input feature and attention weight at time step j , respectively. X_i is the weighted sum output, calculated using x_{ij} and s_{ij} .

Zhang et al. [90] integrated motion-state recognition with trajectory prediction and adaptively selected linear or nonlinear schemes based on the recognition results. This method can effectively capture the trajectory characteristics of gliding high-speed UAVs while maintaining satisfactory stability during maneuver-state transitions. Gontumukkala et al. [91] compared the performance of LSTM and RNN in path clustering and trajectory prediction of aerial targets. LSTM demonstrated superior performance, validating the potential of deep learning for trajectory analysis.

In summary, deep-learning-based methods excel in trajectory prediction. Their strong nonlinear fitting and automatic feature extraction capabilities enable them to learn complex spatiotemporal dynamics from large volumes of data. Additionally, they can capture interactions between targets and environments. Among commonly used networks, RNNs model temporal dependencies, while CNNs extract local spatial features. Attention mechanisms highlight long-range dependencies and key information. However, a single network cannot comprehensively handle complex spatiotemporal coupling. Consequently, research is shifting toward hybrid architectures that combine the strengths of multiple methods.

Despite their excellent performance, data-driven methods face several challenges. First, they lack physical constraints and exhibit weak interpretability, rendering them unsuitable for high-reliability scenarios. Second, these methods require large-scale labeled data and generalize poorly when data are scarce or their distribution varies considerably from that of the training set. Notably, research on high-speed UAV trajectory prediction under data-scarce scenarios remains limited.

4.3. Hybrid-Driven Methods

Hybrid-driven methods combine the advantages of physical mechanisms and data-driven approaches. By integrating dynamic equations and motion constraints with data-driven strategies, these methods can address the challenges of strong nonlinearity and high maneuverability in high-speed UAV trajectory prediction. Such methods employ prior physical knowledge to guide model learning, while leveraging data-driven techniques to capture complex dynamics that are difficult to model. Consequently, hybrid-driven methods can achieve remarkable improvements in prediction accuracy and robustness.

Within this framework, deep learning methods based on physics-informed embedding have attracted considerable attention. Lu et al. [92] proposed a physics-embedded neural ordinary differential equation (ODE) model named PhysNODE. As shown in Figure 7, this model adopts the following dual-path parallel mechanism: one path encodes observed states via a neural network to predict implicit aerodynamic parameters, while the other path computes state derivatives based on physical equations. The outputs of the two paths are fused through a mapping matrix, and the trajectory is predicted using an ODE solver. This method directly embeds motion equations into the neural ODE and yields high-precision prediction by estimating implicit parameters, especially when training data are limited.

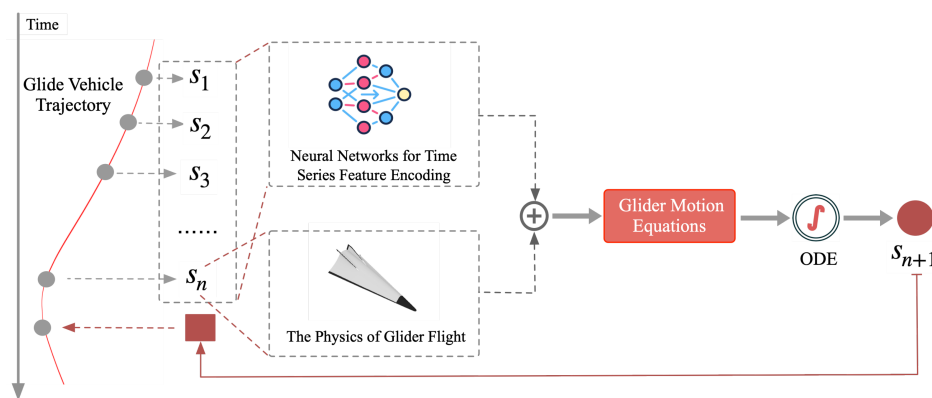


Figure 7. Architecture of PhysNODE [92]. $s_1, s_2, \dots, s_n$ denote the observed state sequences input to the neural network for feature encoding. s_n represents the last observed state used by the physics module to compute time derivatives, while s_{n+1} denotes the predicted next state generated by the ODE solver.

Ren et al. [93] proposed the physics-informed transformer (PIT) model, which incorporates physical knowledge at both the input and output ends. It employs a top- τ -mean attention mechanism and a generative decoder, enabling effective extraction of long-range dependencies and reduction of cumulative errors. The model maintains high prediction accuracy even when radar data are partially missing. Lian et al. [94] constructed a deformable cross-attention residual LSTM architecture, integrating energy management pattern recognition with adaptive spatiotemporal feature extraction. This framework offers an innovative solution for predicting reentry trajectories under sparse telemetry conditions. Moreover, the deep fusion of physical constraints and neural networks also provides sig-

nificant advantages. Zhou et al. [95] proposed an interpretable model based on physical modeling and an attention mechanism. During training, nonlinear dynamic constraints were incorporated, along with binary encoding and inertial modules. This method improves prediction accuracy and interpretability by using interpretable evaluation metrics to quantify the consistency between the model and theoretical formulas, which helps reduce dependence on complete training data.

Another important direction in hybrid-driven methods is the joint optimization of maneuver pattern recognition and trajectory prediction. Liang et al. [96] proposed a trajectory prediction algorithm based on maneuver analysis. This method classifies trajectories by extracting new maneuver parameters, predicts equilibrium gliding trajectories using autoregressive methods, and employs an error compensation mechanism to handle large maneuvering behaviors. These improvements significantly enhance long-term prediction performance. Li et al. [97] developed an intelligent prediction algorithm based on maneuver pattern recognition. By analyzing typical maneuver patterns, the authors proposed a set of parameters to describe maneuver characteristics. Pattern recognition and parameter estimation were achieved using an LSTM, resulting in enhanced prediction accuracy.

Xu et al. [98] fused model-driven and data-driven approaches. Target states and lateral maneuver parameters were extracted using the IMM, and prediction and discrimination were performed via an attention-augmented LSTM network, achieving accurate identification of lateral maneuvers for gliding high-speed UAVs. Sun et al. [99] addressed trajectory discontinuities in gliding high-speed UAVs by proposing a prediction method combining LSTM and intent inference. An intent cost function was introduced to integrate the attack intent model with Bayesian inference, enabling effective prediction of the sign of the bank angle and improving trajectory prediction accuracy.

To meet the requirements of computational efficiency and real-time performance for trajectory prediction, various innovative hybrid architectures have been developed. For example, Xu et al. [100] combined an equivariant graph neural network with the Transformer architecture. Geometric motion characteristics were modeled through dynamic graph structures, SE(3) covariance spatial features were extracted using equivariant message passing, and the improved whale optimization algorithm was introduced to dynamically adjust the learning rate, thereby balancing accuracy and efficiency. Sun et al. [101] proposed an LSTM-based trajectory pipeline prediction model. Altitude, velocity, and direction were formulated as analytical functions containing linear attenuation terms and amplitude-attenuated sinusoidal terms, and model parameters were dynamically estimated using an improved LSTM, providing accurate velocity vector information for midcourse guidance. Zhang et al. [102] proposed a prediction method based on empirical wavelet transform and an attention-based convolutional LSTM (AConvLSTM) network. This method selects aerodynamic acceleration components as parameters, estimates them in real time using a dynamic tracking model, and employs empirical wavelet transform and grey relational analysis for data decomposition and reconstruction to refine the data. Finally, AConvLSTM is used to learn spatiotemporal patterns from the denoised data, achieving high-precision prediction while reducing noise interference.

To address conditions with limited information support, Yuan et al. [103] proposed a trajectory prediction method based on a backpropagation neural network and the least squares method. This method constructs a trajectory library to learn nonlinear relationships and estimate the optimal initial state, addressing the limitations of traditional methods under constrained data-link transmission rates. Similarly, Wang et al. [104] integrated a GRU with a cubature KF. This method uses an intention recognition model to determine the attack target, followed by state estimation and trajectory prediction using the high-

order cubature rule. Compared with the traditional KF, this approach exhibits more rapid convergence and higher accuracy.

Overall, hybrid-driven methods integrate the advantages of model- and data-driven approaches, overcoming challenges in high-speed UAV trajectory prediction such as poor model adaptability and strong data dependence. These methods exhibit stronger generalization capability and higher prediction accuracy. Physical constraints are introduced to prevent trajectories from violating dynamic principles, thus improving the rationality and interpretability of results. Moreover, these methods employ data-driven learning to capture unmodeled dynamics and disturbance characteristics, thereby enhancing adaptability to unknown maneuvers and uncertain environments. Future research can be aimed at strengthening model interpretability and generalization ability under extreme maneuvers to improve reliability in complex scenarios such as those involving limited data. Additionally, system intelligence can be enhanced via the deep fusion of physical mechanisms and deep learning, multisource heterogeneous information fusion, and online adaptive learning.

5. Evaluation Metrics and Performance Comparison of Existing Methods

5.1. Evaluation Metrics

The effectiveness of prediction models is typically evaluated by comparing predicted trajectories with ground-truth trajectory data, thereby objectively verifying model accuracy and reliability. Commonly used evaluation metrics are listed below.

(1) Mean squared error (MSE) measures the average of the squared differences between predicted and ground-truth trajectories. It is sensitive to large errors and can effectively reflect the overall prediction accuracy. The MSE can be calculated using Equation (6).

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N \sum_{t=1}^T \|\hat{y}_{i,t} - y_{i,t}\|_2^2 \quad (6)$$

where N denotes the number of samples, T represents the prediction time step, $\hat{y}_{i,t}$ is the predicted position of the i -th sample at time step t , $y_{i,t}$ is the corresponding ground-truth position, and $\|\cdot\|_2$ denotes the Euclidean norm.

(2) Root mean squared error (RMSE) represents the square root of MSE and shares the same dimensions as the original data. It intuitively reflects the absolute magnitude of prediction errors, facilitating the understanding of the physical meaning of errors. The RMSE can be calculated using Equation (7).

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N \sum_{t=1}^T \|\hat{y}_{i,t} - y_{i,t}\|_2^2} \quad (7)$$

where the variables have the same meanings as in the definition of MSE. The units of RMSE are the same as those of the original trajectory coordinates.

(3) Mean absolute error (MAE) calculates the average of the absolute errors between predicted and ground-truth trajectories. It is insensitive to outliers and can robustly reflect the average deviation degree of predictions. The MAE can be calculated using Equation (8).

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N \frac{1}{T} \sum_{t=1}^T \|\hat{y}_{i,t} - y_{i,t}\|_1 \quad (8)$$

where $\|\cdot\|_1$ denotes the Manhattan distance, i.e., the L1 norm.

(4) Mean relative error (MRE) measures the ratio of the prediction error to the ground-truth value, eliminating the influence of dimensions. This makes it suitable for performance

comparison across different speed ranges or flight phases. The MRE can be calculated using Equation (9).

$$\text{MRE} = \frac{1}{N} \sum_{i=1}^N \frac{1}{T} \sum_{t=1}^T \frac{\|\hat{y}_{i,t} - y_{i,t}\|_2}{\|y_{i,t}\|_2 + \epsilon} \quad (9)$$

where ϵ is an extremely small constant used to avoid division by zero. This metric reflects the relative error magnitude in percentage form.

(5) Average displacement error (ADE) calculates the average Euclidean distance over all time steps between the predicted and ground-truth trajectories, comprehensively reflecting the trajectory accuracy over the entire prediction time window. The ADE can be calculated using Equation (10).

$$\text{ADE} = \frac{1}{N} \sum_{i=1}^N \frac{1}{T} \sum_{t=1}^T \|\hat{y}_{i,t} - y_{i,t}\|_2 \quad (10)$$

This metric focuses on the average deviation degree throughout the trajectory.

(6) Final displacement error (FDE) evaluates the Euclidean distance between the end points of the predicted and ground-truth trajectories, which is crucial for assessing the final impact point or target arrival accuracy of high-speed UAVs. The FDE can be calculated using Equation (11).

$$\text{FDE} = \frac{1}{N} \sum_{i=1}^N \|\hat{y}_{i,T} - y_{i,T}\|_2 \quad (11)$$

where T refers to the last time step of the predicted trajectory; $\hat{y}_{i,T}$ and $y_{i,T}$ represent the end positions of the predicted and ground-truth trajectories, respectively.

The formulas, physical meanings, and computation methods of the commonly used metrics have been introduced above. Based on this introduction, these metrics can be further characterized from different dimensions, including the degree of error penalization, dimensional interpretation, robustness to outliers, and temporal scope of interest. To facilitate appropriate metric selection in practical tasks and to clearly present the applicable boundaries of each metric, Table 1 systematically summarizes their advantages, limitations, and typical application scenarios. In general, MSE and RMSE are suitable for safety-critical tasks requiring severe penalty for large deviations; MAE is preferred for robust evaluation in the presence of sporadic anomalies; MRE provides a dimensionless means for comparisons across speed ranges and flight phases; and ADE and FDE reflect trajectory prediction quality from two complementary perspectives—the overall fit of the entire path and the terminal accuracy, respectively. In practice, these metrics are often combined according to task requirements, such as pairing ADE with FDE to obtain a complete assessment of both process and endpoint, or combining MAE with RMSE to balance typical error representation and the suppression of large deviations.

Importantly, the core concern of the geometry-based metrics discussed above lies in the possible future positions of the target. However, for terminal prediction and defense tasks, relying solely on geometric position deviation is insufficient to comprehensively assess the usability of prediction results. On the defense side, successful mission execution depends not only on position matching accuracy, but also heavily on factors such as terminal impact angle, velocity vector matching, and time-to-go accuracy. These metrics collectively determine whether the defensive vehicle can reach the target at the right time and with the correct engagement attitude. Although these metrics have significant reference value in engineering applications, they are rarely reported systematically in the open literature on trajectory prediction. The main reasons include the following: simulation verification usually lacks the support of relevant closed-loop models, making it difficult to establish a quantitative mapping from prediction errors to mission effectiveness; the priorities of these

metrics vary significantly across different defense schemes and mission scenarios, hindering the formation of a unified evaluation standard; and high-fidelity mission simulation data involve sensitive information and are not easily presented in open literature. In light of this, this review still adopts geometry-based distance metrics as the primary basis for method comparison, while recommending that readers conduct targeted assessments of the above extended metrics according to specific mission conditions when applying prediction methods to terminal prediction and similar specific scenarios.

Table 1. Characteristics and application scenarios of common trajectory prediction metrics.

Metric	Advantage	Limitation	Typical Application Scenario
MSE	Squared penalty amplifies significant deviations; highly sensitive to large errors, effectively highlighting severely inaccurate predictions.	The unit is the square of the coordinate unit, weakening physical interpretability; a few outliers can dominate the overall score and mask the prediction quality of most samples.	Safety-critical tasks where large deviations are unacceptable (e.g., terminal defense trajectory prediction, collision risk assessment).
RMSE	Same unit as trajectory coordinates, offering intuitive physical meaning; retains sensitivity to large errors and directly expresses the absolute magnitude of errors.	Similar to MSE, it is notably affected by outliers; its value may not reflect typical prediction error but rather a “penalized” average error.	Engineering evaluations requiring errors with clear physical units (e.g., miss distance estimation in defense missions, standardized trajectory accuracy reports).
MAE	Equally weighted average absolute error; robust to outliers and stably reflects the typical prediction deviation without being dominated by a few anomalous points.	Penalty for large errors is much weaker than that of squared metrics, potentially tolerating occasional dangerous deviations and making it difficult to highlight high-risk events.	Robust evaluation when data frequently contain sporadic anomalies or noise (e.g., transient sensor jumps, trajectory prediction under aerodynamic disturbances during cruise).
MRE	Dimensionless ratio that naturally eliminates differences in speed and scale; well-suited for performance comparisons across speed regimes and flight phases.	Numerically unstable when the true value norm approaches zero, prone to singularities; the relative error distribution is often skewed, and the mean can be inflated by samples with small denominators.	Algorithm accuracy comparison across different Mach numbers or flight phases (e.g., comparison of prediction models for subsonic, supersonic, and high-speed UAVs).
ADE	Equal-weight averaging over all time steps; comprehensively evaluates the overall fit between predicted and true trajectories and reflects the average deviation along the entire path.	Does not emphasize terminal accuracy; even with a large endpoint deviation, ADE may still give an optimistic evaluation as long as the intermediate process is close to the truth.	Tasks requiring continuous monitoring of overall trajectory accuracy (e.g., persistent target tracking and situation assessment in early warning).
FDE	Directly measures terminal spatial error and accurately reflects the prediction accuracy of the final impact point or arrival position.	Completely ignores intermediate process errors; a trajectory with a severely distorted shape may still yield a small FDE if its endpoint happens to be close to the true endpoint.	Tasks with rigid endpoint-accuracy requirements (e.g., terminal defense endpoint prediction, impact point forecasting for high-speed UAVs).

5.2. Method Comparison

This section systematically compares the core characteristics and applicable scenarios of three mainstream trajectory prediction approaches: model-driven, data-driven, and hybrid-driven methods. It should be noted that unified validation standards and benchmarking frameworks have not yet been established in this field. The vast majority of studies conduct experimental validation in self-developed simulation environments, typically re-

lying on customized aerodynamic models or maneuver libraries to generate trajectory data. This isolated and heterogeneous validation paradigm makes it difficult to perform meaningful cross-comparisons of the absolute accuracy metrics reported in different works.

To transcend the aforementioned limitations and effectively address the core engineering concerns regarding prediction accuracy, computational overhead, and application scenarios, this paper selects twelve representative works that report complete experimental data from the reviewed literature and summarizes their key performance indicators in Table 2, aiming to provide readers with quantifiable performance boundaries. Regarding the source of trajectory data, the data generation approaches adopted by the selected literature can be categorized into the following three types: (1) Only Ref. [100] explicitly specifies the employed dataset—the Northwestern Polytechnical University (NPU) trajectory dataset. (2) Refs. [37,38,56,58,79,82,88,92,96] all adopt the publicly available CAV-H aerodynamic model from Lockheed Martin and generate simulated trajectories by integrating three-degree-of-freedom or six-degree-of-freedom dynamic equations with numerical methods. (3) Refs. [64,93] employ other vehicle models or customized aerodynamic parameters for trajectory generation. Although the above data sources are not entirely consistent, the performance metrics summarized in Table 2 can still identify consistent systematic disparities across different algorithms in computational complexity, inference speed, and prediction accuracy from a quantitative evaluation perspective, thus offering guidance for algorithm screening and practical engineering deployment. The computational complexity and processing time in the table are evaluated solely for the inference/prediction phase, while the prediction accuracy is reported directly from the original literature.

Model-driven methods are characterized by high computational efficiency and low data requirements, relying on well-defined physical or statistical models for state propagation and parameter estimation. Their strengths lie in strong physical interpretability and fast inference speed, making them suitable for engineering scenarios where the physical model is clear, prior information is sufficient, real-time performance is critical, and training data are scarce. However, the prediction accuracy of such methods is inherently constrained by the fidelity of the underlying model and the validity of its assumptions. Once the actual flight mode deviates from the preset maneuver library or assumptions such as equilibrium glide, performance degrades significantly, rendering these methods inadequate for handling unknown maneuvering patterns.

Data-driven methods, in contrast, do not require explicit modeling of the vehicle's physical motion equations; instead, they directly learn the mapping from historical trajectory data. These methods rely minimally on prior physical knowledge and are capable of adapting to scenarios with unknown aerodynamic parameters and complex, time-varying maneuvering modes. With sufficient observational data, they can achieve high prediction accuracy. Nevertheless, their performance is highly dependent on the scale and quality of training data. They suffer from limited interpretability, and their extrapolation capability is confined to the distribution of training samples. Moreover, compared to model-driven methods, data-driven methods typically incur substantially longer inference time. When introduced into a control loop, this computational latency can act as an additional phase lag that degrades system stability. This concern is particularly relevant for hybrid-driven methods, which combine neural networks with physical models yet still inherit the inference overhead of the data-driven components.

Hybrid-driven methods aim to embed physical prior knowledge into deep learning architectures in various forms, striking a balance between the fitting capacity of data-driven approaches and the physical consistency of model-driven ones. In terms of physical integration strategies, some schemes impose soft constraints via physics-informed loss terms, while others adopt hard embedding by directly encoding the complete motion equations into the

network architecture. These methods demonstrate significant advantages in scenarios that demand high prediction accuracy, physical reliability, and model interpretability, effectively mitigating the physically inconsistent predictions that pure data-driven methods may produce. Furthermore, certain hybrid-driven approaches maintain robust generalization performance even under data-scarce or incomplete observation conditions, representing a promising direction for methodological advancement in this field.

Based on the quantitative analysis of the above representative works, this paper preliminarily presents the performance boundaries of different methods in terms of computational complexity, inference speed, data consumption, and prediction accuracy. However, these 12 references cannot yet cover all the methods discussed in this review, and quantitative metrics alone cannot fully reflect the differences among methods in aspects such as interpretability, data dependency, and hyperparameter tuning complexity. To address this limitation, Table 3 provides a qualitative summary of all reviewed methods from the paradigm level, systematically summarizing the advantages, disadvantages, and applicable preconditions of each category of methods. Model-driven methods offer transparent physical interpretability and low computational overhead, making them well-suited for scenarios where the aerodynamic model is sufficiently accurate and onboard computing resources are strictly limited. In contrast, data-driven and hybrid-driven methods are capable of learning complex maneuvering patterns directly from trajectory data, achieving superior prediction accuracy in scenarios where the underlying model cannot be precisely formulated. These methods therefore exhibit prominent application value in decision-support tasks such as early warning and situational assessment, where prediction accuracy takes priority over model interpretability.

However, data-driven and hybrid-driven methods suffer from poor interpretability and a lack of theoretical performance guarantees. If such black-box deep learning models are directly embedded into aerospace closed-loop control systems, these deficiencies escalate into severe safety concerns. Unlike physics-based models, black-box deep neural networks generally lack rigorous theoretical guarantees of error boundedness, and their behavior under out-of-distribution inputs remains difficult to predict. Such unpredictability may lead to unconstrained propagation of prediction errors, thereby compromising the reliability of downstream guidance and decision-making modules.

Table 2. Quantitative comparison of representative trajectory prediction methods for High-Speed UAVs.

Method	Category	Computational Complexity	Inference Speed	Data Requirement	Prediction Accuracy
Closed-Form Analytical Solution [37]	Model-driven	$O(1)$, closed-form expression evaluation; constant number of arithmetic and trigonometric operations	Fast (fastest among model-driven methods; ~ 3 orders of magnitude faster than numerical integration)	Low (only initial states required)	MRE < 2%; improves accuracy by ~ 80 – 98% over BS, YCS-1, and YCS-2
EGS Equilibrium Glide Solution [38]	Model-driven	$O(1)$, elementary function evaluation; no iteration required	Fast (fastest among model-driven methods; analytical inference without iteration)	Low (only reentry initial conditions required)	MEAE: geocentric radius < 3.20 km, velocity < 181.39 m/s; improves by ~ 60 – 88% over baseline methods
IMM [56]	Model-driven	$O(r \cdot n^3)$, $r = 3$ models, $n = 9$ state dimension per model; r parallel KFs each with $n \times n$ matrix inversion	Moderate (relative to model-driven methods; parallel KF with multiple matrix inversions per step)	Moderate (requires real-time radar measurements + preset transition probabilities)	Tracking RMSE < 100 m; 100 s prediction spread ~ 18 – 21 km
VARMA [58]	Model-driven	$O((p + q) \cdot d^2)$, p, q are AR/MA orders (typically 1–2), $d = 3$ variables	Fast (relative to model-driven methods; only constant-order matrix-vector multiplications)	Moderate (requires ~ 1800 time samples for offline modeling)	RMSE improves by $\sim 41\%$ over AR and VAR methods
Student's t -Process [64]	Data-driven	$O(n^3 + n \cdot m)$, $n = 120$ training samples, $m =$ prediction horizon; kernel matrix inversion is cubic complexity	Slow (slowest among compared methods; kernel matrix inversion grows cubically with sample size, limiting real-time application)	High	Altitude RMSE: 50.59 m; improves by 77% over MVGPR
Attention-LSTM+BN [79]	Data-driven	LSTM: $O(H^2)$ (H : hidden state dimension, 128 or 256) + Multi-Head Attention: $O(h \cdot L^2)$ (h : number of heads, L : input sequence length, 50–300 in experiments)	Moderate (relative to model-driven methods; LSTM recurrent + attention matrix operations; complexity grows quadratically with sequence length)	High	MSE: 0.03 (normalized results); achieves the lowest MSE among all compared methods (LSTM, LSTM + BN, Att-LSTM)
FECA-LSMN [88]	Data-driven	$O(L \log L + L \cdot d)$, $L =$ sequence length, $d =$ feature dimension; DCT: $O(L \log L)$, MLP: $O(L \cdot d)$	Moderate (relative to model-driven methods; fully MLP-based, significantly faster than Transformers)	High	128s prediction: RMSE 1.72 km, MAE 0.70 km; improves by $\sim 14.4\%$ over iTransformer
CNN-LSTM [82]	Data-driven	CNN: $O(k^2 \cdot C \cdot L)$ (k : kernel size, C : channels, L : sequence length) + LSTM: $O(H^2)$ ($H = 36$ hidden states)	Moderate (relative to model-driven methods; CNN parallel + LSTM recurrent, meets real-time requirements)	High	FDE: 6.64 km; improves by $\sim 83.6\%$ over direct coordinate mapping and $\sim 90.8\%$ over sliding window method

Table 2. Cont.

Method	Category	Computational Complexity	Inference Speed	Data Requirement	Prediction Accuracy
Maneuver-based Transformer [96]	Hybrid-driven	$O(L \log L)$, L = sequence length; ProbSparse attention reduces standard Transformer's $O(L^2)$ to $O(L \log L)$	Moderate (relative to model-driven methods; sparse attention reduces computation; $\sim 22.4\%$ faster than standard Transformer)	High	ARMSE: equilibrium glide 1.32 km, skip glide 2.79 km, turning 5.25 km; improves by $\sim 48\text{--}52\%$ over PE-Transformer
PIT [93]	Hybrid-driven	$O(L \log L)$, L = sequence length; Top- τ mean sparse attention retains only top- u queries	Moderate (relative to model-driven methods; sparse attention is $\sim 19.6\%$ faster with 32.9% less memory than standard Transformer)	High	MSE: 0.0422, MAE: 0.0726 (512-step prediction, normalized); improves by $\sim 39\%$ over LSTM-4D
PhysNODE [92]	Hybrid-driven	CNN: $O(N_c \cdot M \cdot L)$ (N_c : kernels, M : kernel size, L : seq. len.) + ODE solver: $O(S \cdot N_c)$ (S : adaptive solver steps)	Moderate (relative to model-driven methods; ODE solver depends on adaptive steps, but avoids point-by-point numerical integration)	Moderate (strong small-sample performance)	MAE: 1.85 km (1200 samples), 5.55 km (100 samples); small-sample improves by $\sim 87\%$ over LSTM
EGNN-Transformer [100]	Hybrid-driven	Graph message passing: $O(L^2)$ (L : nodes/sequence length, pairwise message passing) + Self-attention: $O(L^2)$	Moderate (relative to model-driven methods; double quadratic complexity, but only 2.75 M parameters, the lowest among compared methods)	High	Altitude RMSE: 532.1 m, velocity RMSE: 268.3 m/s; improves by $\sim 23.8\%$ and $\sim 38.8\%$ over suboptimal ST-GCN, respectively

Table 3. Comparison of Prediction Methods for High-Speed UAVs.

Method	Category	Advantages	Disadvantages
6-DOF Model [33–35]	Model-driven	Strong physical interpretability; fully captures complex dynamic characteristics of high-speed UAVs; suitable for long-duration and wide-range trajectory prediction	High computational complexity; highly dependent on aerodynamic parameter accuracy; difficult to adapt to non-standard maneuver modes
Analytical Methods [37–39]	Model-driven	Obtains closed-form approximate solutions based on perturbation techniques or equilibrium glide conditions; high computational efficiency; suitable for real-time prediction	Excessive model simplification; limited applicable conditions; potential singularity issues after critical points
Kinematic Fit [40–44]	Model-driven	Independent of complex dynamic equations; fast prediction via polynomial or acceleration fitting; suitable for scenarios with constrained physical models	Accuracy depends on fitting order and data quality; weak extrapolation capability; difficult to handle strong maneuvers
Damped Oscillation Model [45]	Model-driven	Tailored modeling for special flight modes; higher accuracy than traditional kinematic models	Limited applicable scope; poor adaptability to general maneuver modes

Table 3. Cont.

Method	Category	Advantages	Disadvantages
EMD-Based Fit [46]	Model-driven	Extracts aerodynamic acceleration trends via Empirical Mode Decomposition (EMD); suitable for skip-glide high-speed UAVs	Relies on decomposition effectiveness; sensitive to noise
KF [50]	Model-driven	High computational efficiency; provides optimal estimation in linear Gaussian systems; suitable for conventional trajectory tracking	Poor adaptability to strongly nonlinear systems; large approximation errors; difficult to handle highly maneuverable targets
EKF [53]	Model-driven	Fuses physical models with real-time observation data; handles nonlinear problems via linearization; corrects model errors	Linearization introduces approximation errors; significant performance degradation in highly nonlinear regions; relies on Jacobian matrix calculation
UKF [51,54,55]	Model-driven	No need to calculate Jacobian matrix; effectively handles nonlinear problems; higher accuracy than traditional Kalman filtering	Large computational burden; sensitive to initial parameters; difficult to meet high real-time requirements
IMM [56]	Model-driven	Strong adaptability to complex maneuvers; optimizes via multi-model interaction probability; covers multiple motion modes	High computational complexity due to parallel mechanism; relies on prior model library; difficult model set design
VARMA [57,58]	Model-driven	Handles non-stationarity via feature extraction; converts coefficient estimation into convex optimization; addresses unknown noise challenges	Sensitive to model order selection; requires certain data stationarity; error accumulation in long-sequence prediction
GPR [62,63]	Data-driven	Provides probabilistic interpretation; effectively quantifies uncertainty; balances prediction accuracy and real-time performance; suitable for small-sample scenarios	Standard model assumes Gaussian noise distribution; difficult to handle heavy-tailed noise; high computational cost
Student's <i>t</i> -process [64,65]	Data-driven	Effectively handles heavy-tailed noise distributions; strong robustness to outliers and non-Gaussian noise; suitable for complex flight environments	Increased model complexity; difficult adaptive parameter adjustment; relatively low computational efficiency
LSTM [73–75]	Data-driven	Effectively captures temporal dependencies of vehicle motion; avoids reliance on explicit physical models; strong adaptability	Highly dependent on training data quality; insufficient interpretability; error accumulation in long-sequence prediction
BiLSTM [76]	Data-driven	Captures bidirectional temporal information via dual-directional structure; significantly reduces prediction errors; adapts to complex maneuver characteristics	Complex structure; difficult training; high computational resource demand; generalization depends on data diversity
TCN [77]	Data-driven	Effectively captures long-range temporal dependencies; avoids gradient vanishing; suitable for long-term trajectory prediction	Large number of model parameters; long training time; relatively slow response to sudden maneuvers
DNN [78]	Data-driven	Simple structure; fast prediction speed; suitable for high real-time scenarios	Limited capability to capture temporal features; difficult training for deep networks
Attention [79–81]	Data-driven	Adaptively focuses on key information in historical trajectories; effectively handles complex dynamic environments; improves model robustness	Complex model structure; difficult training; high computational resource demand; limited interpretability
CNN-LSTM [82–84,86,87]	Data-driven	Combines CNN spatial feature extraction and LSTM temporal modeling; better handles spatiotemporal trajectory characteristics	Requires massive high-quality training data; high computational complexity; poor adaptability to small-sample scenarios
DCBNN [85]	Data-driven	Dual-channel design captures both nonlinear and linear features; bidirectional structure enhances temporal dependency modeling	Complex structure; difficult training; generalization depends on data diversity

Table 3. Cont.

Method	Category	Advantages	Disadvantages
FECA-LSMN [88]	Data-driven	Adopts frequency-enhanced channel attention to promote feature fusion; achieves high-precision prediction via lightweight sampling	Relies on specific frequency feature extraction; model design requires task-specific tuning
CNN-BiLSTM-Attention [89]	Data-driven	Integrates multiple network advantages to mine hidden motion laws; solves accuracy degradation caused by high maneuvers	Extremely complex model; high computational resource consumption; long training time
Motion State Recognition [90,91]	Data-driven	Adaptively selects linear/nonlinear schemes based on recognition results; maintains good stability during maneuver state changes	Relies on state recognition accuracy; complex switching logic design
PhysNODE [92]	Hybrid-driven	Integrates physical motion equations into neural networks; improves prediction accuracy and generalization; especially suitable for data-limited scenarios	Complex model construction; requires both physical modeling and deep learning knowledge; large computational overhead
PIT [93]	Hybrid-driven	Improves generalization via physical knowledge constraints; reduces cumulative error; strong robustness in data-missing scenarios	Complex physical constraint design; requires domain expertise; potentially unstable training process
DCAR [94]	Hybrid-driven	Integrates energy management pattern recognition and adaptive spatiotemporal feature extraction; addresses sparse observation and strong nonlinear dynamics challenges	Complex architecture design; difficult training; requires fine hyperparameter tuning
Physics-constrained ML [95]	Hybrid-driven	Imposes nonlinear dynamic constraints during training; improves prediction accuracy and interpretability; reduces reliance on complete training data	Constraint design requires domain knowledge; potentially unstable model training
Maneuver-based [96–99]	Hybrid-driven	Maps trajectory prediction to maneuver parameter time-series prediction from a dynamic perspective; effectively handles high-speed UAV trajectories	Relies on accurate maneuver mode recognition; limited adaptability to new sudden maneuver modes
EGNN-Transformer [100]	Hybrid-driven	Effectively models geometric motion characteristics and long-term spatiotemporal dependencies; high prediction accuracy; good physical consistency	Complex model; large training and inference overhead; high hardware requirements; difficult implementation
LSTM-Pipeline [101]	Hybrid-driven	Models trajectories as analytical functions combined with LSTM for dynamic parameter estimation; provides accurate velocity vector information for mid-course guidance	Analytical function assumptions may limit model flexibility; sensitive to parameter initialization
EWT-AConvLSTM [102]	Hybrid-driven	Reduces noise interference via signal decomposition; extracts key features with attention mechanism; significantly improves prediction accuracy in noisy environments	Preprocessing increases computational complexity; multi-stage structure prolongs training and inference time
BPNN-LSM [103]	Hybrid-driven	Learns nonlinear relationships via trajectory library construction and estimates optimal initial states; solves data link transmission rate constraints	Relies on trajectory library completeness; limited generalization to unknown trajectory modes
GRU-CKF [104]	Hybrid-driven	Fuses GRU and Cubature Kalman Filter (CKF); judges attack targets via intent recognition; faster convergence and higher accuracy	Higher computational complexity than standard Kalman filtering; certain reliance on noise statistical characteristics

6. Key Challenges and Future Research Directions

6.1. Key Challenges

A gap remains between the theory and engineering application of high-speed UAV trajectory prediction, stemming from the irreconcilable relationship among model complexity, real-time constraints, and insufficient prior information. Current research mainly faces the following three key challenges:

- (1) Coupling effects of multiple uncertainties. In noncooperative scenarios, the UAV trajectory is jointly determined by maneuvering intent, aerodynamic parameter errors, and environmental disturbances. As key prior information, such as target mass, aerodynamic characteristics, and control logic, are often inaccessible to the defensive entity, prediction models based on deterministic assumptions exhibit reduced reliability in practical scenarios.
- (2) Trade-off between accuracy and real-time performance. The early warning window for high-speed UAVs is extremely short, and thus, prediction algorithms must achieve rapid computation. However, numerical integration of high-fidelity physical models and inference with complex deep learning models incurs substantial computational overhead, while simplified models fail to accurately capture strong nonlinear dynamics, making it difficult to balance accuracy and real-time performance.
- (3) Insufficient generalization capability caused by data scarcity. Experimental data of real high-speed UAVs are scarce and sensitive. Consequently, data-driven methods face a severe small-sample dilemma. Models trained on limited data exhibit weak generalization when confronted with new configurations or unknown maneuver modes, failing to adapt to practical, complex scenarios. This limits the robustness and adaptability of prediction systems.

6.2. Future Research Directions

With the increasing complexity of high-speed UAV maneuver modes and continuous advances in intelligent algorithms, trajectory prediction technology is evolving toward higher accuracy, stronger adaptability, and improved real-time performance. To address current challenges, future technology development can be focused on the following three directions: intelligent modeling, lightweight computation, and multisource data fusion.

- (1) High-precision intelligent prediction models are essential for improving long-term prediction accuracy in complex, dynamic environments. To this end, a promising direction is to develop a hybrid modeling paradigm that integrates physical models with data-driven approaches. Such methods not only introduce physical prior constraints but also leverage the advantages of data-driven nonlinear fitting. By combining these complementary strengths, the accuracy and reliability of prediction results can be enhanced.
- (2) Lightweight algorithm design. To resolve the trade-off between accuracy and real-time performance, lightweight optimization should be promoted at the algorithmic level. For physical models, model order reduction techniques can be used to extract key features and construct efficient surrogate models. For deep learning, techniques such as neural architecture search and knowledge distillation can be applied to compress and optimize network structures. These measures can help improve computational efficiency.
- (3) Multisource data fusion mechanisms. To address data scarcity and improve generalization, a data system integrating physical simulation, data augmentation, and transfer learning should be established. Multiphysics simulations can generate high-confidence synthetic data, which can be augmented by small-sample generation

techniques such as generative adversarial networks and diffusion models. However, purely data-driven generative models without explicit physical constraints may produce trajectories that violate the vehicle's flight envelope. To prevent this, hard constraints such as maximum dynamic pressure, structural load factor, and heat flux limits must be embedded in the generation or enforced through post-generation screening. Only samples meeting aerodynamic feasibility and flight envelope limits should be used for training, avoiding unphysical motion characteristics that would compromise reliability in defense scenarios. This yields diverse, physically plausible trajectories, improving model adaptability and generalization in unseen scenarios.

7. Conclusions

This paper provides a systematic review of research progress in trajectory prediction for high-speed UAVs and establishes a classification system based on the core driving logic of prediction methods. The fundamental characteristics and evolutionary relationships of three major paradigms (model-, data-, and hybrid-driven approaches) are comprehensively evaluated. The findings indicate a shift from single physical models to a multifusion paradigm. The different types of methods exhibit complementarity in physical interpretability, adaptability to complex maneuvers, and real-time computational efficiency. Consequently, integrated development appears to be a key pathway toward addressing the bottlenecks of existing technologies.

High-speed UAV trajectory prediction faces several challenges, including the coupling of multiple uncertainties, the inherent trade-off between accuracy and real-time performance, and the difficulty of achieving sufficient generalization with limited data. These challenges reflect a notable gap between theoretical models and engineering practice. Given that no single technical route can fully resolve these issues, future research should move toward a collaborative framework that integrates physical laws, data-driven learning, and computational efficiency. In this context, uncertainty quantification modeling offers a promising direction for enhancing prediction reliability. At the same time, the safe deployment of data-driven and hybrid-driven models in closed-loop guidance systems necessitates rigorous stability analyses to guarantee dependable performance under real-world conditions. For practical implementation, real-time capability can be further improved through lightweight algorithmic designs and heterogeneous computing architectures, while the reliance on large-scale labeled data can be mitigated by integrating few-shot learning with high-fidelity simulations and embedded physical knowledge.

Breakthroughs in high-speed UAV trajectory prediction technology require not only algorithmic innovation but also interdisciplinary integration. In particular, collaboration among computational fluid dynamics, control theory, game theory, and artificial intelligence can promote advances in trajectory prediction in complex environments. Furthermore, establishing an open, standardized benchmarking environment and evaluation systems is crucial for facilitating fair comparisons and continuous optimization. By strengthening the integration of theoretical methods with practical scenarios and enhancing the performance of algorithms under real-world conditions, the current challenges can be addressed, providing a solid methodological foundation and technical support for the intelligent prediction of high-complexity dynamic systems. Nevertheless, given the rapid advancement of this field, this review may not encompass the most recently published works at the time of writing.

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DURC Statement: Current research is limited to the review and discussion of high-speed UAV trajectory prediction algorithms based on public literature, without any experimental data or specific equipment parameters. This research delivers potential benefits in civilian scenarios including aerospace safety, emergency response and space situational awareness, and does not pose a threat to public health or national security. Authors acknowledge the dual-use potential of the research involving high-speed UAV trajectory prediction and confirm that all necessary precautions have been taken to prevent potential misuse. As an ethical responsibility, authors strictly adhere to relevant national and international laws about DURC. Authors advocate for responsible deployment, ethical considerations, regulatory compliance, and transparent reporting to mitigate misuse risks and foster beneficial outcomes.

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