

Article

A Dual-LSTM Collaborative Network for Maneuvering UAV Tracking with Incomplete Measurements in Maritime Environments

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Highlights

What are the main findings?

- A dual-LSTM cooperative network is proposed to jointly address two fundamental challenges in shipborne UAV tracking under complex maritime conditions: incomplete radar measurements and delayed model recognition in traditional IMM algorithms.
- Two LSTM-based methods are developed: one restores missing radar data using historical information, and the other directly identifies UAV maneuvering models from sequential measurements using GPS-derived optimal model probabilities as training labels to replace the probabilistic weighting mechanism of IMM.

What are the implications of the main findings?

- By integrating data compensation and model recognition in a unified framework, the proposed approach significantly improves three-dimensional velocity estimation accuracy and response speed during aggressive UAV maneuvers in maritime environments.
- The method reduces reliance on predefined model sets and enhances tracking robustness under both incomplete and complete measurement conditions, offering a practical deep learning solution for real-time, shipborne maneuvering target tracking with intelligent perception potential.

Abstract

Tracking highly maneuverable UAVs in complex maritime environments faces multiple challenges: dynamic sea surface interference and low-altitude occlusion make UAV motion trajectories difficult to predict; the strong maneuvering behavior of UAVs imposes high demands on tracking real-time performance and accuracy; and marine environmental noise and unstable shipborne sensor data lead to measurement incompleteness. These factors collectively limit the adaptability and robustness of existing maneuvering UAV tracking methods in complex maritime scenarios. In this context, accurate model recognition for UAVs becomes a key factor in improving tracking performance. Traditional interactive multiple model (IMM) methods rely on probabilistic weighting for model selection, suffering from response delays during UAV maneuvers, and fixed model sets cannot adapt to diverse maneuvering scenarios, resulting in degraded UAV velocity estimation accuracy. To address the above issues, this study proposes a dual long short-term memory (LSTM) cooperative network architecture, targeting the two key problems of incomplete measurements in shipborne radar measurements and inaccurate model probability estimation,



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and presents corresponding solutions. First, an online-trained LSTM-based incomplete-measurement compensation method is proposed, which achieves real-time fitting and restoration of historical measurement data, providing continuous and stable measurement inputs for shipborne platform UAV tracking in maritime environments. Second, building on this, an LSTM-based UAV model recognition method is developed to directly identify the UAV's current motion model from multi-frame historical measurement information, effectively reducing maneuvering delays. Furthermore, GPS data is used to generate optimal model probabilities as training labels, thereby improving model reliability. Simulation results show that, under incomplete-measurement conditions, the proposed method can effectively reconstruct missing measurements and ensure measurement continuity. Under complete-measurement conditions, the proposed LSTM-based model recognition method significantly improves UAV model recognition accuracy and three-dimensional velocity estimation performance, demonstrating the effectiveness of deep learning for maneuvering UAV tracking from shipborne platforms in maritime environments.

Keywords: maritime environment; incomplete measurements; deep learning; model recognition; maneuvering target tracking

1. Introduction

Target tracking is a core capability of shipborne platforms for the persistent surveillance of airborne UAVs. By processing sensor measurement data, it estimates UAV states and provides critical information support for situational awareness and firepower engagement. With the increasing complexity of maritime environments and the growing sophistication of electronic interference, measurements acquired by shipborne fire-control radar sensors are often incomplete, exhibiting issues such as missing dimensions and measurement inaccuracies [1]. As illustrated in Figure 1, incomplete measurements increase the uncertainty of UAV states and cause significant deviations in tracking trajectories, leading to a marked decline in the performance of traditional maneuvering target tracking algorithms. This makes it difficult to meet the high-precision demands of modern maritime warfare.

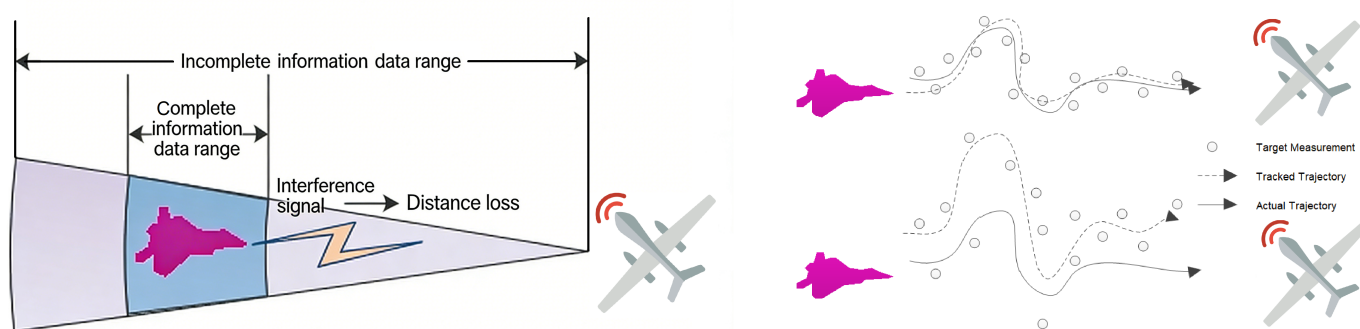


Figure 1. Impact of incomplete measurements on target tracking.

To address these issues, front-end anti-jamming techniques can be adopted to improve data quality. However, in practice, shipborne radar systems inevitably produce incomplete measurements. Therefore, it is necessary to enhance the robustness of tracking systems by improving downstream signal processing algorithms. Among various tracking methods, the Bayesian-theory-based IMM algorithm [2] is a mainstream approach for handling UAV maneuvers. Nevertheless, IMM relies on a fixed set of motion models, and its probability-weighted model switching mechanism suffers from inherent response latency.

Consequently, when the UAV performs aggressive maneuvers, the estimation accuracy of three-dimensional velocity deteriorates sharply.

To mitigate incomplete measurement issues, several approaches have been explored. Traditional interpolation-based methods (e.g., linear interpolation, spline interpolation, and Kalman smoothing) rely on strong smoothness assumptions and may fail to capture abrupt maneuvering dynamics, leading to trajectory distortion under highly maneuverable UAVs. Recent deep learning-based imputation methods improve reconstruction capability but typically require large-scale offline training data and may suffer from limited generalization in online shipborne radar scenarios with time-varying noise and missing patterns. Transformer-based [3] architectures have also been applied to sequence modeling; however, they introduce high computational and memory costs and are less suitable for real-time incremental processing of streaming radar measurements. In contrast, LSTM provides a lightweight recurrent structure with gated memory units, making it more suitable for online modeling of sequential radar measurements under limited data and real-time constraints.

To address these challenges, the main contributions of this paper are summarized as follows:

- (1) An online-trained LSTM-based incomplete-measurement compensation method is proposed. To address the problem of intermittent incomplete measurements in shipborne maritime radar measurements, the proposed method leverages historical states and current partial observations to compensate for incomplete measurements online, improving tracking continuity under incomplete measurements.
- (2) An LSTM-based model recognition method is proposed. To overcome the lag in response to aggressive maneuvers caused by probabilistic update delays in traditional IMM algorithms, the proposed method directly identifies UAV maneuver patterns from measurement data using LSTM, significantly improving the response speed and accuracy of three-dimensional velocity estimation.
- (3) A joint optimization framework integrating data compensation and model recognition is constructed. The two LSTM modules are collaboratively integrated into the tracking framework to enhance system robustness from two perspectives: “integrity of input data” and “timeliness of model recognition”, thereby forming a comprehensive maneuvering UAV tracking solution for shipborne UAV tracking in maritime environments.

The remainder of this paper is organized as follows. Section 2 reviews related work, focusing on model recognition methods for shipborne platform tracking of maneuvering UAV targets in maritime environments and incomplete-measurement compensation techniques. Section 3 presents the proposed online-trained LSTM-based incomplete-measurement compensation algorithm, as well as the LSTM-based model recognition method. Section 4 conducts simulation experiments under two typical scenarios—incomplete measurements and complete measurements—to verify the effectiveness of the online LSTM data compensation algorithm and the overall tracking performance achieved by combining online LSTM compensation with model recognition. Section 5 summarizes the entire work.

2. Related Work

2.1. Data Compensation Techniques for Incomplete Measurements

Research on data compensation has mainly been carried out along two directions: hardware-based and software-based approaches. Software compensation methods are widely favored for their cost-effectiveness and ease of implementation. Their core idea is to compensate for system errors through function fitting.

Function fitting aims to construct mapping relationships between input and output variables, and to perform data compensation based on criteria such as minimum variance. When there is only one input variable, the least squares method is commonly adopted [4,5]. To rapidly compensate for nonlinear error, an improved method combining power-function bases with direct solution strategies was proposed in [6]. Least squares was employed in [7] for temperature compensation of piezoresistive pressure sensors. When the reliability of different data sources varies, weighted least squares can be used. For example, the flatness measurement error of a space-target simulator was compensated for in [8] by constructing weights to fit the optimal plane.

When the number of input variables exceeds one, partial least squares (PLS) regression is commonly employed for fitting [9]. This method has been widely applied across diverse domains, including environmental prediction, industrial process modeling, and power system analysis [10–14]. However, such methods typically rely on predefined functional forms, and their adaptability to complex nonlinear relationships and dynamically changing environments remains limited. Moreover, conventional compensation methods face additional difficulties in strongly coupled systems with complex constraints [15]. From a broader perspective, incomplete measurements may also arise from communication constraints rather than sensing deficiencies. In such cases, maintaining information availability under communication denial can be interpreted as a form of implicit data compensation. A multi-UAV neighborhood interaction network with virtual nodes was constructed in [16] to preserve connectivity and control effectiveness. Furthermore, under stochastic disturbances and communication constraints, data-driven control provides an alternative paradigm for handling incomplete or unreliable information. For instance, a distributed event-triggered data-driven control framework for quadrotor UAVs was proposed in [17], integrating fault diagnosis and disturbance suppression while reducing communication burden. Nevertheless, achieving robust and accurate model recognition under incomplete measurements, especially in dynamic environments, remains an urgent challenge.

In recent years, as sensor systems grow more complex and data acquisition environments become increasingly uncertain, conventional compensation methods based on fixed functional forms have gradually revealed limitations in adaptability. Against this backdrop, deep learning—benefiting from strong nonlinear modeling capability and adaptive learning of complex data distributions—has been introduced into research on incomplete-measurement compensation in maneuvering target tracking. CNN-based approaches have been used to learn local correlations within matrices or sequences to effectively estimate missing-dimension data [18]. For missing data with pronounced temporal characteristics, RNN and their variants (e.g., GRU and LSTM) model the dynamic relationship between historical states and current observations, enabling time-series prediction and compensation [19]. Beyond recurrent architectures, recent studies have leveraged attention-based mechanisms and generative models for more flexible and accurate data imputation. For instance, Transformer-based models have been applied to capture long-range dependencies in sensor time series with missing entries [20], while conditional diffusion models have demonstrated superior performance in generating realistic missing values under complex noise patterns [21]. However, these methods generally require substantial computational resources and large-scale training data, making them less suitable for online shipborne radar scenarios.

To jointly capture spatial and temporal features, hybrid models that combine CNN and LSTM have been proposed and have achieved favorable performance in various time-series compensation tasks [22]. Beyond explicit missing-value filling, some studies encode missingness patterns so that neural networks retain sequence prediction capability even under incomplete inputs [23]. Moreover, for multidimensional sensor data with strong

spatiotemporal correlations, models integrating graph attention mechanisms with RNN have been employed to jointly exploit temporal dependencies and spatial associations [24]. In engineering applications, deep learning methods are also frequently combined with signal decomposition techniques; for instance, integrating empirical mode decomposition with LSTM has been shown to improve prediction performance for incomplete measurements in non-stationary signals [25]. This demonstrates that deep learning methods can learn intrinsic nonlinear data relationships without explicit modeling, exhibiting stronger adaptability and robustness in handling incomplete-measurement compensation problems in dynamic environments.

In maritime environments, incomplete measurements significantly affect target tracking and localization accuracy. To address challenges such as measurement outliers, time-varying noise, and intermittent signal loss faced by underwater vehicles in marine environments, a robust adaptive Kalman filter integrating IGGIII robust estimation with an improved Sage–Husa adaptive noise covariance estimator was proposed in [26]. To tackle the problem of short-term sensor failures, an LSTM neural network was employed in [27] to train a time-series prediction model offline and compensate for sensor observations online. The above studies demonstrate that deep learning methods have broad application prospects for incomplete-measurement compensation in marine environments. However, most existing studies focus on single scenarios or offline compensation, lacking real-time adaptability. For the incomplete-measurement problem for maneuvering UAV tracking by shipborne platforms in maritime environments, a unified method that balances real-time performance and model recognition capability is still lacking. In summary, the adaptability and real-time performance of existing incomplete-measurement compensation methods in complex marine environments still need to be improved. Recent efforts have begun to address these issues by, for example, integrating adaptive Kalman filtering with deep learning for state estimation under dynamic model conditions [28] or developing graph neural network-based methods for spatio-temporal modeling in multi-agent systems [29]. Nevertheless, how to achieve stable and continuous data compensation under incomplete measurement conditions during maneuvering target tracking remains a key challenge.

2.2. Model Recognition Methods for Maneuvering Target Tracking

The core challenge of maneuvering target tracking lies in the uncertainty of the target motion model. In complex and highly dynamic maritime environments, UAV targets often exhibit complicated maneuvering patterns, such as non-constant velocity and non-constant acceleration. To address the model mismatch problem, mainstream approaches can generally be categorized into two classes: model compensation methods and multi-model methods.

Model compensation aims to correct the parameters of a single-motion model through adaptive mechanisms. These include input-based estimation approaches that treat unknown maneuvers as deterministic inputs and estimate them from measurement data using least squares methods [30]. However, this strategy relies heavily on maneuver detection, which may introduce significant estimation latency and make it difficult to handle time-varying maneuvers. Strong tracking filtering (STF) improves robustness by introducing a decay factor to adaptively adjust the predicted covariance in real time, thereby forcing the filter to remain sensitive to state variations [31]. Although STF enhances robustness to some extent, its compensation mechanism does not sufficiently account for the target's intrinsic maneuvering characteristics, resulting in limited model-recognition capability.

Due to the limited capability of single-model approaches in compensating for target maneuvers, multi-model methods address this issue more systematically through the parallel operation of a set of predefined models and probability-weighted fusion. Among them,

the IMM algorithm [32] is a representative approach. By combining and selecting among different motion models to match the optimal target dynamics, IMM can improve both robustness and tracking accuracy. Extensive studies have further enhanced IMM performance by optimizing the model set [33], incorporating strong tracking filtering models with parameter adaptation [34], adaptively adjusting the Markov transition matrix [35], and leveraging historical measurement information to update transition probabilities in an adaptive manner [36]. More recently, adaptive IMM approaches have been proposed to handle maneuvering targets by adaptively adjusting the Markov transition matrix in real time [37]. In the field of underwater unmanned systems, IMM has also been employed to address navigation and tracking problems in complex environments. A hybrid interactive multi-model-aided INS/DVL-integrated navigation scheme for autonomous underwater vehicles (AUVs) was proposed in [38] to address the issues of outliers and observation noise in DVL measurements. However, IMM-based methods inherently rely on a recursive update mechanism of model probabilities, which tends to cause response lag when the target undergoes abrupt maneuvers. Furthermore, their performance is highly dependent on the completeness of the preset model set, making it difficult to cover the complex and variable maneuvering patterns of maneuvering targets.

With the rapid development of deep learning, neural network-based methods have also been introduced into maneuvering target tracking. Related UAV studies have also shown that deep learning can improve pose estimation and motion understanding in aerial platforms, further supporting its applicability to dynamic-state modeling tasks [39]. Early studies primarily relied on RNN and LSTM to perform trajectory prediction and tracking. Existing research indicates that LSTM can effectively capture long-term temporal dependencies in trajectory prediction tasks for highly maneuvering targets, such as missiles, and shows superior performance over traditional IMM methods under motion-model uncertainty [40]. Subsequently, researchers began exploring hybrid approaches that integrate deep learning with classical filtering frameworks. For instance, an RNN-enhanced IMM-KF method was proposed, in which neural networks are used to adaptively adjust the process noise and measurement noise parameters of the filter [41]. Building on this, meta-learning concepts were introduced to develop a model-agnostic meta learning-based neural network-assisted Kalman filtering framework, enabling rapid adaptation to different state-space models under limited training samples [42]. Some studies have integrated feed-forward networks, recurrent networks, and attention mechanisms within a unified neural architecture to construct an end-to-end deep learning tracking filter, achieving a unified formulation of motion modeling, adaptive filtering strategies, and the overall tracking framework [43]. In addition, the combination of CNN and LSTM has been applied to target motion prediction, where spatial and temporal features are jointly modeled to enable high-accuracy and low-power target tracking [44]. Related recurrent alternatives, such as GRU-based trajectory prediction models, have also shown promising performance in real-time UAV motion modeling due to their relatively lightweight gating structure [45].

Beyond recurrent architectures, graph neural networks (GNNs) have recently been introduced to capture spatial-temporal interactions among multiple maneuvering targets, enabling more accurate tracking in dense target scenarios [46]. Temporal convolutional networks (TCNs) have likewise been explored for trajectory prediction because they support parallel sequence modeling and long effective receptive fields [47]. Nevertheless, RNN/LSTM-based methods still have limited capability in modeling global maneuvering patterns over long time horizons. In parallel, deep state-space models have also been introduced into tracking tasks, where trainable neural transition and observation functions are used to better capture complex target dynamics and measurement uncertainty [48]. To address this limitation, Transformer architectures based on attention mechanisms have

been introduced into maneuvering target tracking [49,50]. Recent online Transformer-based tracking models have further demonstrated the potential of causal attention and memory mechanisms for long-horizon tracking in streaming scenarios [51]. Although not designed specifically for maneuvering target tracking, deep learning-based perception frameworks in autonomous driving further illustrate the capability of unified neural pipelines for real-time dynamic scene understanding [52]. Deep learning-based tracking frameworks have also been extended to marine environments. For instance, a framework comprising a CNN-based ship detector, a nonlinear state augmentation (NSA) filter, and a dual-criterion bounding box similarity index (BBSI) was proposed in [53] to mitigate performance degradation in traditional multi-target tracking methods for marine radar images, thereby effectively modeling ship motion patterns and enhancing tracking stability and accuracy in complex marine environments. Furthermore, diffusion models have emerged as a powerful generative tool for maneuvering target tracking under incomplete measurements, with recent work demonstrating their ability to generate plausible target states when observations are missing [54].

Meanwhile, traditional model-driven approaches continue to evolve. For example, adaptive IMM-UKF improves robustness under nonlinear maneuvers and sensor interruptions by adjusting model transition probabilities online; however, its overall performance remains constrained by the design of the model set and parameter tuning [55].

In summary, existing methods remain inadequate in terms of model recognition real-time performance and adaptability to complex maneuvers. Especially for maritime UAV tracking, achieving fast and accurate model recognition under incomplete measurements is an urgent challenge. To address this, this study introduces a dual-LSTM collaborative network for joint optimization of model recognition and data compensation, thereby enhancing maneuvering target tracking performance.

3. Proposed Method

This section focuses on two pervasive issues in the process of maritime UAV tracking, namely model mismatch and incomplete measurements, and investigates intelligent target tracking methods based on deep learning. Within conventional multi-model tracking frameworks, the Interactive Multiple Model Extended Kalman Filter (IMM-EKF) improves adaptability to UAV maneuvers to some extent through parallel model execution and probability-weighted fusion. However, its tracking performance still heavily depends on the accuracy of model probability updates and the completeness of measurement data. When UAV maneuver patterns become complex or shipborne sensor measurement information is limited, traditional methods exhibit inherent limitations in both model selection and state estimation. To address these challenges, this study introduces LSTM-based modules to fully exploit the temporal characteristics embedded in historical measurement data, and proposes a two-branch framework consisting of a model recognition module and an incomplete-measurement compensation module, both built upon LSTM networks, to enhance the persistent tracking capability of shipborne platforms for airborne UAVs.

First, Section 3.1 reviews the EKF and the IMM tracking framework, providing the theoretical foundation for subsequent developments. Then, in Section 3.2, to cope with potential incomplete-measurement scenarios that may occur when shipborne radar detects airborne UAVs under complex sea conditions, an online-trained LSTM-based incomplete-measurement compensation method is proposed. This method does not rely on large-scale datasets; instead, it utilizes recent historical measurements to model measurement increments, thereby enabling online prediction and compensation of incomplete measurements. By feeding the compensated measurements into the tracking algorithm, the continuity and stability of state estimation can be maintained under incomplete-measurement conditions

caused by factors such as sea clutter or signal occlusion, thereby offering reliable data support for maneuvering target tracking of airborne UAVs. Finally, on the premise that measurement data exhibit continuous temporal characteristics under both incomplete measurements and complete conditions, Section 3.3 proposes an LSTM-based model recognition method. By performing temporal modeling on the UAV's historical three-dimensional position observations, the method enables adaptive identification of the probability distribution over candidate motion models. During practical tracking, when the available historical observations are insufficient, the system employs the conventional IMM-EKF to estimate the UAV state. Once the accumulated time-series data reach a predefined length, the model probability vector produced by the LSTM network is activated to replace or correct the model probabilities computed via the likelihood function in IMM-EKF, thereby improving the accuracy and timeliness of model selection.

3.1. Overview of IMM-EKF

IMM-EKF is a hybrid estimation algorithm that effectively addresses the problem of maneuvering target tracking, which is also applicable to maritime UAV tracking. It combines the capability of the EKF to handle nonlinear systems with the adaptability of the IMM framework to multiple motion modes. The core principle of IMM-EKF is as follows: a set of predefined motion models (e.g., constant velocity, constant acceleration, turning models) is run in parallel using EKF, and their outputs are dynamically fused based on model likelihood probabilities. This allows the algorithm to maintain robust tracking performance even when the target's motion model switches. The following provides a detailed explanation of its two core components.

3.1.1. Extended Kalman Filter (EKF)

Assume that the state-space model of the shipborne radar system is described by the following equations:

$$\mathbf{X}_{k+1} = \mathbf{F}_k \mathbf{X}_k + \mathbf{W}_k \quad (1)$$

$$\begin{aligned} \mathbf{Z}_{k+1} &= \begin{bmatrix} r_{k+1} \\ \alpha_{k+1} \\ \beta_{k+1} \\ v_{k+1} \end{bmatrix} + \mathbf{V}_{k+1} = h(\mathbf{X}_{k+1}, \mathbf{X}_{k+1}^r) + \mathbf{V}_{k+1} \\ &= \begin{bmatrix} \sqrt{(x_{k+1}^t - x_{k+1}^r)^2 + (y_{k+1}^t - y_{k+1}^r)^2 + (z_{k+1}^t - z_{k+1}^r)^2} \\ \arctan\left(\frac{y_{k+1}^t - y_{k+1}^r}{x_{k+1}^t - x_{k+1}^r}\right) \\ -\arcsin\left(\frac{z_{k+1}^t - z_{k+1}^r}{\sqrt{(x_{k+1}^t - x_{k+1}^r)^2 + (y_{k+1}^t - y_{k+1}^r)^2 + (z_{k+1}^t - z_{k+1}^r)^2}}\right) \\ \frac{(x_{k+1}^t - x_{k+1}^r)(\dot{x}_{k+1}^t - \dot{x}_{k+1}^r) + (y_{k+1}^t - y_{k+1}^r)(\dot{y}_{k+1}^t - \dot{y}_{k+1}^r) + (z_{k+1}^t - z_{k+1}^r)(\dot{z}_{k+1}^t - \dot{z}_{k+1}^r)}{\sqrt{(x_{k+1}^t - x_{k+1}^r)^2 + (y_{k+1}^t - y_{k+1}^r)^2 + (z_{k+1}^t - z_{k+1}^r)^2}} \end{bmatrix} + \mathbf{V}_{k+1} \quad (2) \end{aligned}$$

where $\mathbf{F}_k$ is the UAV state transition matrix at time step k , whose specific values are determined by the adopted motion model. $\mathbf{W}_k$ represents the process noise, and $\mathbf{X}_k$ denotes the target state information. For a shipborne radar system, $\mathbf{X}_k$ consists of the three-dimensional position, velocity, and acceleration of the UAV. $h(\mathbf{X}_{k+1}, \mathbf{X}_{k+1}^r)$ denotes the measurement equation, and $\mathbf{X}_{k+1}^r$ represents the shipborne radar state information. r_{k+1} , α_{k+1} , β_{k+1} , and v_{k+1} correspond to the UAV's radial distance, radial velocity, azimuth angle, and elevation angle, respectively. $\mathbf{V}_{k+1}$ is the measurement noise.

For shipborne radar systems, however, the relationship between the measurements and the UAV's dynamic parameters is nonlinear. For nonlinear filtering problems, no exact optimal solution exists. A common approach is to linearize the nonlinear system and then apply linear filtering theory to obtain a suboptimal solution. The method that uses a first-order Taylor series expansion to linearize the nonlinear system and applies KF for state estimation is referred to as the EKF.

For shipborne radar tracking systems for airborne UAV targets, the main steps of the EKF algorithm are as follows:

- (1) State Prediction

$$\mathbf{X}_{k+1|k} = \mathbf{F}_k \mathbf{X}_{k|k} \quad (3)$$

where $\mathbf{X}_{k|k}$ is the estimated state for the target tracking at time k , and $\mathbf{X}_{k+1|k}$ is the predicted state at time $k + 1$.

- (2) Covariance Prediction

$$\mathbf{P}_{k+1|k} = \mathbf{F}_k \mathbf{P}_{k|k} \mathbf{F}_k^T + \mathbf{Q}_k \quad (4)$$

where $\mathbf{P}_{k+1|k}$ is the predicted covariance at time $k + 1$, $\mathbf{P}_{k|k}$ is the estimated covariance at time k , and $\mathbf{Q}_k$ is the process noise covariance.

- (3) Measurement Prediction

$$\mathbf{Z}_{k+1|k} = h(\mathbf{X}_{k+1|k}, \mathbf{X}_{k+1}^r) \quad (5)$$

- (4) Kalman Gain Calculation

$$\mathbf{K}_{k+1} = \mathbf{P}_{k+1|k} \mathbf{H}_{k+1,EKF}^T \mathbf{S}_{k+1}^{-1} \quad (6)$$

$$\mathbf{S}_{k+1} = \mathbf{H}_{k+1,EKF} \mathbf{P}_{k+1|k} \mathbf{H}_{k+1,EKF}^T + \mathbf{R}_{k+1} \quad (7)$$

$$\mathbf{H}_{k+1,EKF} = \left. \frac{\partial h(\mathbf{X}_{k+1}, \mathbf{X}_{k+1}^r)}{\partial \mathbf{X}_{k+1}} \right|_{\mathbf{X}_{k+1} = \mathbf{X}_{k+1|k}} \quad (8)$$

where $\left. \frac{\partial h(\mathbf{X}_{k+1}, \mathbf{X}_{k+1}^r)}{\partial \mathbf{X}_{k+1}} \right|_{\mathbf{X}_{k+1} = \mathbf{X}_{k+1|k}}$ denotes the operation of partial derivatives.

- (5) State Update

$$\mathbf{X}_{k+1|k+1} = \mathbf{X}_{k+1|k} + \mathbf{K}_{k+1} (\mathbf{Z}_{k+1} - \mathbf{Z}_{k+1|k}) \quad (9)$$

- (6) Covariance Update

$$\mathbf{P}_{k+1|k+1} = (\mathbf{I} - \mathbf{K}_{k+1} \mathbf{H}_{k+1,EKF}) \mathbf{P}_{k+1|k} \quad (10)$$

where $\mathbf{I}$ is the identity matrix.

It can be observed that the first-order EKF covariance prediction formula is similar to that of the standard KF. By retaining third- or fourth-order terms in the Taylor series expansion, third- or fourth-order EKFs can be obtained, which often provide improved estimation performance. However, higher-order EKFs require longer computation times, and the improvement in estimation accuracy is not always substantial. Therefore, from a

practical engineering perspective, first-order EKF is commonly adopted for state filtering in shipborne radar systems for UAVs.

3.1.2. Interactive Multiple Model (IMM)

For maritime UAV tracking, when using a single-model adaptive filtering algorithm, the filter typically requires prior knowledge to match the UAV's maneuvering characteristics. As a result, it often exhibits poor tracking accuracy when facing UAVs with highly variable maneuver structures or dynamic parameters. To address this limitation, the IMM approach was proposed. IMM is a Markov transition-probability-based adaptive estimation algorithm that assumes transitions among independent models follow a finite-state Markov chain with known transition probabilities. By accounting for interactions among multiple models, maneuvering target tracking of airborne UAVs is achieved. The algorithm can be divided into four main steps:

(1) State Interaction

Let the posterior probability density function and weight of the i -th submodel at time step k be $\mathcal{N}(\mathbf{X}_k; \mathbf{X}_{k|k}^i, \mathbf{P}_{k|k}^i)$ and $\mu_{k|k}^i$, respectively, and let π denote the Markov transition matrix. Interaction operations are performed among all submodels to obtain the input state $\mathbf{X}_{k|k}^{i,0}$ and covariance $\mathbf{P}_{k|k}^{i,0}$ for each submodel:

$$\mathbf{X}_{k|k}^{i,0} = \sum_{j=1}^l \mu_{k|k}^{ij} \mathbf{X}_{k|k}^j \quad (11)$$

$$\mathbf{P}_{k|k}^{i,0} = \sum_{j=1}^l \mu_{k|k}^{ij} \left(\mathbf{P}_{k|k}^j + (\mathbf{X}_{k|k}^{j,0} - \mathbf{X}_{k|k}^j)(\mathbf{X}_{k|k}^{j,0} - \mathbf{X}_{k|k}^j)^T \right) \quad (12)$$

$$\mu_{k|k}^{ij} = \frac{\pi_{ij} \mu_{k|k}^j}{\sum_{j=1}^l \pi_{ij} \mu_{k|k}^j} \quad (13)$$

where l is the total number of submodels, $\mu_{k|k}^{ij}$ represents the transition weight from the j -th to the i -th submodel, and π_{ij} is the Markov transition probability from the j -th submodel to the i -th submodel.

(2) Submodel State Filtering

Each submodel's target tracking information $\mathbf{X}_{k+1|k+1}^i$ and $\mathbf{P}_{k+1|k+1}^i$ are obtained using nonlinear filtering methods such as EKF.

(3) Model Probability Update

Nonlinear filtering algorithms such as EKF are employed to obtain submodel measurement predictions $\mathbf{Z}_{k+1|k}^i$ and new information covariance $\mathbf{S}_{k+1}^i$, thereby calculating the likelihood function Λ_{k+1}^i .

$$\Lambda_{k+1}^i = \mathcal{N}(\mathbf{Z}_{k+1}; \mathbf{Z}_{k+1|k}^i, \mathbf{S}_{k+1}^i) \quad (14)$$

The submodel weights are then updated using the likelihood function:

$$\mu_{k+1|k+1}^i = \frac{\Lambda_{k+1}^i \sum_{j=1}^l \pi_{ij} \mu_{k|k}^j}{\sum_{m=1}^l \left(\Lambda_{k+1}^m \sum_{j=1}^l \pi_{mj} \mu_{k|k}^j \right)} \quad (15)$$

(4) State Fusion Output

Weighted fusion of model weights and state information from each submodel is performed to obtain the fused state $\mathbf{X}_{k+1|k+1}$ and covariance $\mathbf{P}_{k+1|k+1}$.

$$\mathbf{x}_{k+1|k+1} = \sum_{i=1}^l \mu_{k+1|k+1}^i \mathbf{x}_{k+1|k+1}^i \quad (16)$$

$$\mathbf{P}_{k+1|k+1} = \sum_{i=1}^l \mu_{k+1|k+1}^i \left(\mathbf{P}_{k+1|k+1}^i + (\mathbf{x}_{k+1|k+1} - \mathbf{x}_{k+1|k+1}^i)(\mathbf{x}_{k+1|k+1} - \mathbf{x}_{k+1|k+1}^i)^T \right) \quad (17)$$

3.2. Incomplete-Measurement Compensation Based on Online-Trained LSTM

In shipborne radar tracking of maneuvering UAVs, measurement data often suffer from incomplete measurements due to factors such as sea surface multipath interference, low-altitude occlusion, or system resource constraints, undermining the reliance of multi-model tracking algorithms on continuous temporal information. Although offline training of neural networks can effectively improve recognition and tracking accuracy, it typically requires a large number of UAV trajectory samples for training. Moreover, the training process must carefully account for sample characteristics, data diversity, outlier samples, and training costs. Directly applying deep learning networks based on offline learning concepts still presents numerous challenges that require consideration and resolution.

To accelerate deep learning adoption, online learning approaches are considered for algorithm design. Online learning requires minimal training data, focusing solely on the impact of recent historical information on the system, making implementation significantly less complex than offline learning. Naturally, its accuracy typically falls short of offline methods. Nevertheless, if online learning demonstrates performance advantages over traditional methods, it still holds practical value. Since shipborne radar measurements of maneuvering UAVs exhibit strong temporal continuity and nonlinear dynamic characteristics, LSTM is adopted in this work because its memory-cell mechanism can effectively model long-term temporal dependencies under intermittent measurement interruptions while maintaining relatively low computational complexity for online learning. Motivated by this, this section proposes an LSTM-based incomplete-measurement compensation method for shipborne radar detection of airborne UAVs and integrates the compensated measurements into the target tracking system to achieve state estimation of airborne UAVs.

This section constructs the compensation model using an LSTM network followed by a fully connected layer. When incomplete measurements occur in the measurements, historical full-dimensional measurements are used to compensate for the current incomplete measurements. Since the data exhibit non-uniform time intervals, the method draws inspiration from the conventional least squares fitting concept by computing the slopes between adjacent historical data points and uses these slope values as the network inputs:

$$\Delta_k = \frac{\mathbf{Z}_{k+1} - \mathbf{Z}_k}{t_{k+1} - t_k} \quad (18)$$

where $\mathbf{Z}$ denotes the original measurement vector, and Δ is the modified input. It can be observed that Δ represents the measurement variation per unit time, which contains both temporal and state information, whereas $\mathbf{Z}$ only reflects state information. Δ is analogous to the slope information in one-dimensional fitting. The historical measurement data is segmented to form a training set. The input–output relationship of the training samples can be expressed as:

$$\begin{aligned} \text{LSTM}(\Delta_1, \Delta_2, \dots, \Delta_n) &\rightarrow \Delta_{n+1} \\ &\vdots \\ \text{LSTM}(\Delta_{k-n+1}, \Delta_{k-n+2}, \dots, \Delta_k) &\rightarrow \Delta_{k+1} \end{aligned} \quad (19)$$

where k denotes the length of historical training data, requiring $k + 1$ historical data points for acquisition; and n represents the length of the data input to the network. Considering the temporal correlation among samples during online learning, the network model is illustrated in Figure 2. It trains historical data change information online using squared loss. During the output phase, it utilizes recent data change information combined with the latest hidden state information $h_{1,m-n}$ and $h_{2,m-n}$ to obtain the latest data change quantity information. It compensates for incomplete measurements of airborne UAVs based on the following formula:

$$Z_{now} = Z_{k+1} + \Delta_{estimate}(t_{now} - t_{m+1}) \quad (20)$$

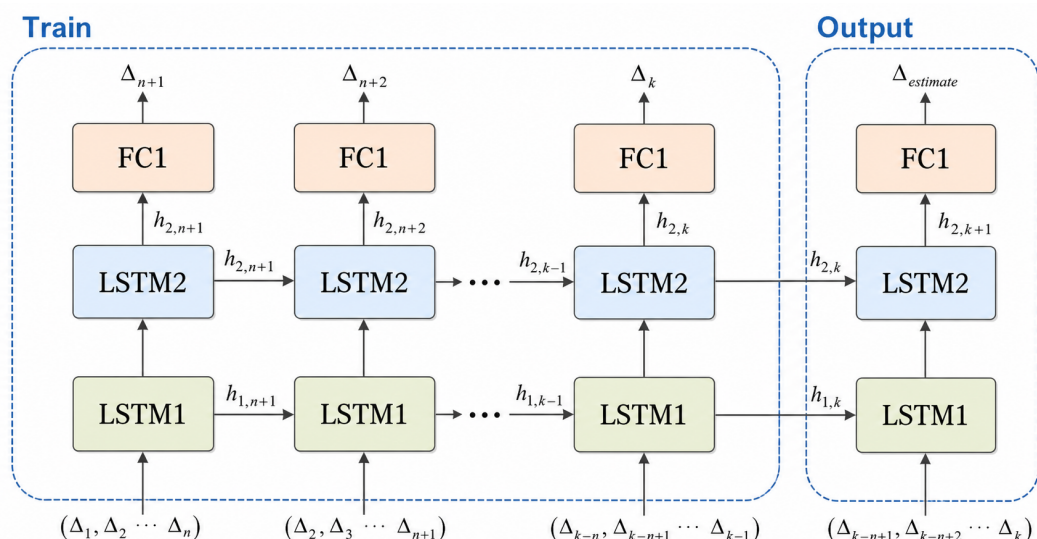


Figure 2. Network model for incomplete-measurement compensation.

The LSTM network structure used for incomplete-measurement compensation is depicted in Figure 3.

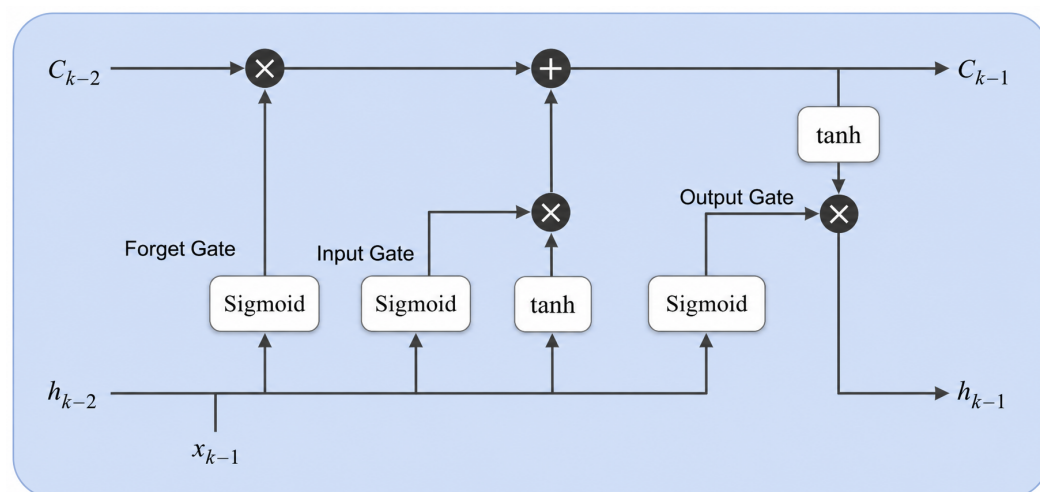


Figure 3. Structure of the LSTM network.

Once the model is capable of compensating for incomplete measurements, the compensated measurement data can be directly fed into the multi-model target tracking algorithm of the shipborne platform to enable state estimation of airborne UAVs under incomplete measurement conditions. Meanwhile, the proposed method preserves the temporal conti-

nuity of the measurement data, providing stable inputs for subsequent LSTM-based model recognition.

3.3. Model Recognition Based on LSTM

While the aforementioned incomplete-measurement compensation method ensures the temporal continuity of measurement data, the overall performance of the IMM-EKF algorithm remains heavily dependent on the accuracy and timeliness of model probability updates. To overcome the shortcomings of traditional methods in this aspect and fully leverage the temporal nature of the data, this section designs a model recognition method based on the LSTM. Since UAV maneuvering behaviors are strongly correlated with temporal trajectory evolution, LSTM is employed to capture long-term maneuver-related temporal features from historical motion sequences through its gated recurrent structure. By modeling the temporal characteristics of airborne UAV historical measurement data, it directly identifies the probability of the UAV's current maneuvering model, thereby assisting in shipborne multi-model target tracking. The adopted recognition framework is illustrated in Figure 4.

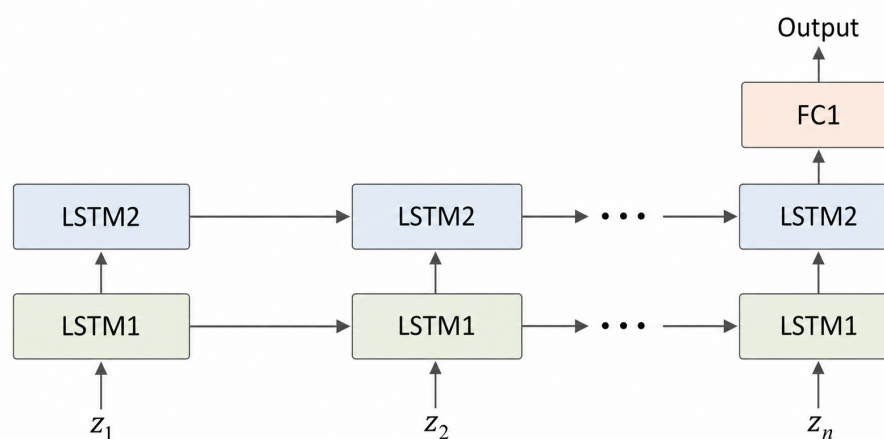


Figure 4. LSTM-based model recognition network.

Since the model probability ranges from 0 to 1, and the sum of probabilities equals 1, the activation function softmax can be used to constrain the output. Since the output result is the probability vector of the UAV model, this vector represents the weights of each sub-model. Considering that the UAV motion model can be inferred from its trajectory information, the input sequence of the network consists of the UAV's three-dimensional position in the geographic coordinate system. This information can be extracted from the shipborne inertial navigation system (INS) and shipborne radar measurements. The UAV's three-dimensional position at time step k can be expressed as:

$$\begin{bmatrix} x_k \\ y_k \\ z_k \end{bmatrix} = \begin{bmatrix} x_{k,p} + r_k \cos \alpha_k \cos \beta_k \\ y_{k,p} + r_k \sin \alpha_k \cos \beta_k \\ z_{k,p} + r_k \sin \beta_k \end{bmatrix} \quad (21)$$

where $x_{k,p}$, $y_{k,p}$, and $z_{k,p}$ denote the three-dimensional position of the shipborne radar platform, obtained from the shipborne INS. The radial distance information r_k , azimuth α_k , and elevation angle β_k can be acquired through shipborne radar detection.

The output is a model probability vector defined over the same predefined candidate model set as the existing multi-model tracking algorithm. When the number of models is l , the output dimension is l . In practice, the true model probabilities are generally unknown. Moreover, to satisfy real-time requirements in engineering applications, the

number of candidate motion models is limited, and the true UAV motion may not be exactly included in the predefined model set. Although the predefined model set cannot fully cover all possible UAV motions, a reliable reference trajectory is still required to evaluate which candidate models are most consistent with the actual motion. For this reason, GPS measurements are introduced offline for label construction. In the collected experiments, GPS data provide the most reliable and relatively complete description of the UAV's actual motion, whereas radar measurements are affected by noise, missing observations, and clutter, making them less suitable for direct supervisory label generation. Specifically, the GPS data are used to characterize the UAV's actual motion at each time frame, and each candidate model in the predefined model set is matched against this GPS-referenced motion to obtain a matching score. The resulting matching probabilities are then used as supervisory labels for network training. In this way, the labels and the IMM output are defined over the same model space, but the labels are not obtained by recursively updating IMM posterior probabilities from radar measurements. As a result, they may still be limited by the completeness of the predefined model set, but they do not inherit the temporal update bias of IMM probability recursion. It should also be noted that GPS information is used only offline for label generation and is not provided to the network during deployment. The network input consists only of measurements from the shipborne inertial navigation system (INS) and shipborne radar.

After constructing the supervisory labels, the dataset is standardized before network training. To reflect the diversity across samples, the mean and variance of each dimension are recorded, and the data are normalized as follows:

$$\begin{bmatrix} \tilde{x}_k \\ \tilde{y}_k \\ \tilde{z}_k \end{bmatrix} = \begin{bmatrix} \frac{(x_k - \bar{x})}{\sigma_x} \\ \frac{(y_k - \bar{y})}{\sigma_y} \\ \frac{(z_k - \bar{z})}{\sigma_z} \end{bmatrix} \quad (22)$$

The model recognition network fundamentally computes model probabilities for each submodel, which can be viewed as a classification problem. Therefore, cross-entropy can be employed as the loss function to achieve parameter estimation.

$$Loss = \sum_{i=1}^l \sum_{j=1}^g Q_i(j) \ln \left(\frac{1}{P_i(j)} \right) \quad (23)$$

Among these, $Q_i(j)$ represents the true probability of the j -th submodel in the i -th batch of data, while $P_i(j)$ denotes the predicted probability of the j -th submodel in the i -th batch of data. When any pair of i and j satisfies $Q_i(j) = P_i(j)$, $Loss$ assumes the minimum value.

When real shipborne radar measurements are insufficient, additional simulated data can be generated to construct a sufficient dataset. Specifically, real UAV trajectory data is obtained using GPS information, and Gaussian white noise is added to these real measurements to simulate shipborne radar measurements. Although Gaussian noise cannot fully characterize complex maritime interference such as sea clutter and multipath effects, it provides a controllable simulation framework for validating the effectiveness of the proposed method under incomplete-measurement conditions. To ensure that the simulated measurements closely approximate the real maritime environment, the noise level is set based on the shipborne radar's actual detection accuracy. The network is trained using this simulated data, and the trained network is then utilized to obtain data recognition results, which are employed to assist UAV tracking.

The LSTM network requires sufficient temporal data to perform reliable model recognition. Therefore, when the available observation sequence is shorter than a predefined threshold, the proposed LSTM-EKF framework degenerates to the conventional IMM-EKF

algorithm to ensure stable UAV tracking. Once sufficient temporal context is available, the LSTM module is activated to generate model probability outputs, which are used to refine the model probability vector within the IMM framework for target tracking. The overall workflow of the LSTM-EKF algorithm is illustrated in Figure 5. This switching mechanism is implemented as a hard threshold strategy on the sequence length, ensuring that the LSTM is only activated under reliable temporal conditions and thereby avoiding unstable predictions under incomplete observations. In this hybrid design, IMM-EKF provides robust baseline tracking, while LSTM offers adaptive refinement of model probabilities when temporal information becomes sufficiently informative, forming a complementary framework with adaptive activation rather than independent alternatives.

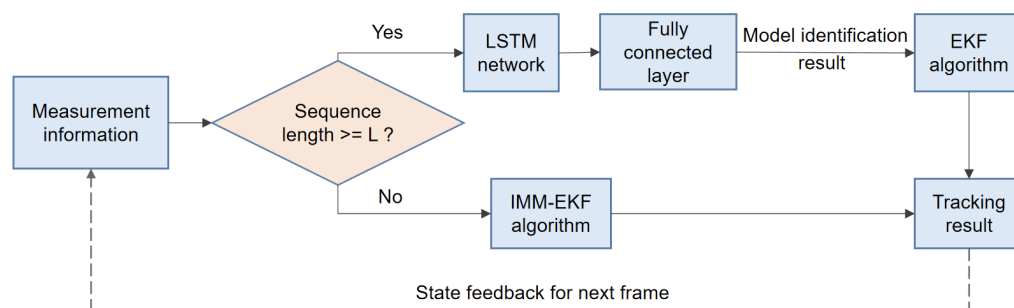


Figure 5. Maneuvering target tracking algorithm based on LSTM. In the experiments, $L = 10$.

The LSTM-EKF algorithm enables the LSTM network to automatically learn UAV motion patterns from historical observations and dynamically adjust model probabilities based on temporal information, thereby effectively capturing nonlinear characteristics of UAV motion. Compared with IMM-EKF, LSTM-EKF demonstrates stronger adaptability and robustness when dealing with unknown or complex maneuvering targets. In addition, by updating the state estimation using the model probability vector output by the LSTM network, LSTM-EKF reduces reliance on the predefined model set in conventional approaches, thereby improving tracking adaptability and estimation accuracy for UAV tracking by shipborne platforms.

It should be noted that the proposed LSTM module is only used for auxiliary model probability estimation, while the underlying state prediction and update process still follows the conventional IMM-EKF framework. In other words, the LSTM does not directly generate measurement inputs for the EKF, but only refines the model probability vector for IMM-based model selection, so the standard EKF measurement-update formulation remains unchanged. Since the adopted LSTM network has a lightweight structure with a short sequence length and a small hidden dimension, the additional inference overhead under the current network configuration remains limited for practical tracking scenarios. Moreover, before LSTM activation, the IMM-EKF framework continuously maintains baseline target tracking capability, thereby preserving tracking continuity during the transition stage.

4. Experiments

Since the model recognition method requires complete measurements, this study first tests the shipborne radar's measurement fitting capability and tracking performance for airborne UAVs under incomplete measurements. Subsequently, based on the complete measurements, the model recognition and tracking performance of the algorithm are tested, and the overall performance of the algorithm is evaluated.

To further clarify the applicability of the proposed framework, we provide a discussion on the experimental scenarios and their representativeness. The experimental scenarios

considered in this work mainly focus on representative maritime UAV tracking conditions, including incomplete measurements, maneuvering trajectories, and shipborne radar observation uncertainty. Although only several typical scenarios are evaluated in this study, the proposed framework is not restricted to a specific trajectory pattern or sea condition. Since the proposed LSTM-based compensation and model recognition methods primarily learn temporal measurement dependencies, the framework is expected to maintain applicability under different sea-clutter levels, maneuver intensities, and target trajectory patterns, provided that the measurement characteristics remain temporally correlated.

4.1. Performance Evaluation of Data Compensation Under Incomplete Measurement Conditions

To verify the effectiveness of the proposed data compensation method in UAV tracking by shipborne platforms, simulation experiments are conducted on a set of scenario data to evaluate the related algorithms. In this scenario, the incomplete measurements are compensated online using an LSTM network, and the compensated measurement data is fed into the traditional multi-model filtering algorithm IMM-VB-EKF for target state estimation. The relative geometry between the UAV and the shipborne platform in this scenario is shown in Figure 6.

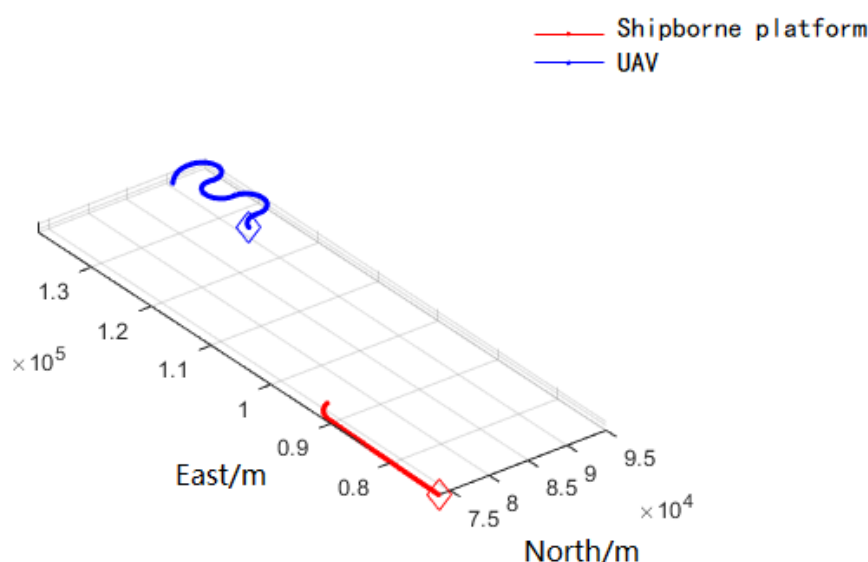


Figure 6. Relative posture of UAV and shipborne platform.

In this scenario, the UAV trajectory has an average sampling interval of 0.03 s, with a total of 3638 frames sampled. During the first 50% of the frame length, the UAV trajectory is uninterrupted. In the latter 50% of frames, the UAV trajectory is disrupted. During this disruption phase, measurement quality is affected by severe sea clutter and intentional electronic interference. An anti-jamming processing module is employed to mitigate part of the interference effects; however, due to residual jamming and sensor limitations, only a portion of the range measurements can be successfully recovered, while the remaining measurements are treated as missing or partially observed data. Consequently, the measurements in this stage consist of 50% three-dimensional observations (range plus azimuth and elevation angles) and 50% two-dimensional observations (azimuth and elevation angles only). The anti-jamming success coefficient follows a uniform distribution between 0 and 1. A threshold is set based on the success rate; when the coefficient exceeds this threshold, the frame is considered successfully anti-jammed. The algorithm is evaluated using Monte Carlo simulations with 10 simulation iterations. The length of the historical sequence data for the network is set to 10. This value also serves as the sequence length threshold in the switching mechanism illustrated in Figure 5. This value was selected as a trade-off between

temporal dependency modeling and online adaptation capability. Shorter sequences were insufficient to capture maneuver continuity, whereas excessively long sequences increased online training latency and reduced responsiveness to abrupt maneuver changes. Before the sequence length threshold is reached, the system continues target tracking using the conventional IMM-EKF framework, thereby avoiding interruption during the initial data accumulation stage. After applying the differencing operation, the effective historical data length of the LSTM model becomes 9, and the input dimension is set to 5. The measurements compensated by the LSTM model are then fed into the IMM-VB-EKF algorithm (LSTM-IMM-VB-EKF) for UAV tracking.

The eight algorithms evaluated include the baseline IMM-EKF without fitting, 1D fitting IMM-EKF, 2D fitting IMM-EKF, adaptive fitting IMM-EKF, 1D fitting IMM-VB-EKF, 2D fitting IMM-VB-EKF, adaptive fitting IMM-VB-EKF, and LSTM-IMM-VB-EKF. For a fair comparison, all filters employ a model set consisting of 25 models for UAV tracking. Based on the constructed maneuvering motion model characteristics, the specific models used in this section are defined in Table 1.

The model set is constructed to capture heterogeneous maneuvering behaviors of UAVs in three-dimensional space. Specifically, constant velocity (CV), coordinated turn (CT), and constant acceleration (CA) models are combined to represent different motion patterns. To characterize varying levels of maneuvering intensity, coordinated turn models are parameterized using a set of discrete turn rates, which represent different angular motion strengths ranging from mild to aggressive maneuvers. Both positive and negative turn rates are included to account for symmetric turning behaviors in opposite directions. In addition, CT dynamics are applied across different motion planes (XY, XZ, and YZ), further enriching the spatial diversity of the model set. This multi-model configuration enhances the flexibility and robustness of the IMM framework in handling complex and time-varying UAV trajectories.

The initial state of each submodel can be set using the initial measurement information. The specific formulation is as follows:

$$\begin{cases} x_0^t = r_0 \cos \beta_0 \cos \alpha_0 + x_0^r \\ \dot{x}_0^t = v_0 \cos \beta_0 \cos \alpha_0 + \dot{x}_0^{r'} \\ \ddot{x}_0^t = 0 \\ y_0^t = r_0 \cos \beta_0 \sin \alpha_0 + y_0^r \\ \dot{y}_0^t = v_0 \cos \beta_0 \sin \alpha_0 + \dot{y}_0^{r'} \\ \ddot{y}_0^t = 0 \\ z_0^t = r_0 \sin \beta_0 + z_0^r \\ \dot{z}_0^t = v_0 \sin \beta_0 + \dot{z}_0^r \\ \ddot{z}_0^t = 0 \end{cases} \quad (24)$$

where $(r_0, v_0, \alpha_0, \beta_0)$ denotes the initial shipborne radar measurement, (x_0^r, y_0^r, z_0^r) represents the initial shipborne radar position, and $(\dot{x}_0^r, \dot{y}_0^r, \dot{z}_0^r)$ denotes the initial shipborne radar velocity. The left-hand side of the equation corresponds to the initial state of the UAV.

During the testing process, the root mean square error is used to evaluate the tracking performance of each algorithm. In practical maritime combat scenarios, the velocity tracking results of the shipborne radar tracking system are transmitted to the weapon system to assist in guidance. Therefore, in the performance comparison, this study mainly focuses on the comparison of velocity tracking results. Figure 7 presents the fitted results of the range measurements, while Figure 8 illustrates the tracking performance of the UAV's three-dimensional velocity. Since the LSTM-based compensation strategy is conceptually derived

from the 1D fitting approach, the comparison mainly focuses on these two categories of methods. The RMSE used in this paper is computed over all time steps, which inherently reflects the cumulative estimation error of the tracking process over the entire trajectory. For clarity, Table 2 summarizes the estimated results of three-dimensional velocity tracking and range measurement reconstruction across all algorithms. The results indicate that the LSTM-based fitting accuracy achieves a 33.4% improvement over the 1D fitting method. In terms of three-dimensional velocity estimation, the LSTM-IMM-VB-EKF algorithm yields improvements of 23.6%, 37.0%, and 0.4% compared with the 1D fitting IMM-EKF, and 16.2%, 34.9%, and 5.7% compared with the 1D fitting IMM-VB-EKF, respectively. These results validate the effectiveness of the proposed LSTM-based incomplete-measurement compensation method for shipborne radar detection of airborne UAVs.

Table 1. Detailed information of the model set.

Model	Description
Model 1	CV model on all X, Y, and Z axes
Model 2	The XY plane follows a CT model with a turn rate of 0.01 rad/s, while the Z axis follows a CA model.
Model 3	The XY plane follows a CT model with a turn rate of -0.01 rad/s, while the Z axis follows a CA model.
Model 4	The XY plane follows a CT model with a turn rate of 0.02 rad/s, while the Z axis follows a CA model.
Model 5	The XY plane follows a CT model with a turn rate of -0.02 rad/s, while the Z axis follows a CA model.
Model 6	The XY plane follows a CT model with a turn rate of 0.03 rad/s, while the Z axis follows a CA model.
Model 7	The XY plane follows a CT model with a turn rate of -0.03 rad/s, while the Z axis follows a CA model.
Model 8	The XY plane follows a CT model with a turn rate of 0.04 rad/s, while the Z axis follows a CA model.
Model 9	The XY plane follows a CT model with a turn rate of -0.04 rad/s, while the Z axis follows a CA model.
Model 10	The XY plane follows a CT model with a turn rate of 0.05 rad/s, while the Z axis follows a CA model.
Model 11	The XY plane follows a CT model with a turn rate of -0.05 rad/s, while the Z axis follows a CA model.
Model 12	The XY plane follows a CT model with a turn rate of 0.06 rad/s, while the Z axis follows a CA model.
Model 13	The XY plane follows a CT model with a turn rate of -0.06 rad/s, while the Z axis follows a CA model.
Model 14	The XZ plane follows a CT model with a turn rate of 0.02 rad/s, while the Y axis follows a CA model.
Model 15	The XZ plane follows a CT model with a turn rate of -0.02 rad/s, while the Y axis follows a CA model.
Model 16	The XZ plane follows a CT model with a turn rate of 0.04 rad/s, while the Y axis follows a CA model.
Model 17	The XZ plane follows a CT model with a turn rate of -0.04 rad/s, while the Y axis follows a CA model.
Model 18	The XZ plane follows a CT model with a turn rate of 0.06 rad/s, while the Y axis follows a CA model.
Model 19	The XZ plane follows a CT model with a turn rate of -0.06 rad/s, while the Y axis follows a CA model.
Model 20	The YZ plane follows a CT model with a turn rate of 0.02 rad/s, while the X axis follows a CA model.
Model 21	The YZ plane follows a CT model with a turn rate of -0.02 rad/s, while the X axis follows a CA model.
Model 22	The YZ plane follows a CT model with a turn rate of 0.04 rad/s, while the X axis follows a CA model.
Model 23	The YZ plane follows a CT model with a turn rate of -0.04 rad/s, while the X axis follows a CA model.
Model 24	The YZ plane follows a CT model with a turn rate of 0.06 rad/s, while the X axis follows a CA model.
Model 25	The YZ plane follows a CT model with a turn rate of -0.06 rad/s, while the X axis follows a CA model.

However, the range reconstruction accuracy of the LSTM-based method is still inferior to that of the adaptive fitting method, indicating that the online-trained LSTM approach has limited capability in further improving range measurement accuracy. An analysis of the range variation trends over a large number of samples shows that first-order linear and second-order polynomial functions are sufficient to characterize the short-term range dynamics in most cases. This implies that 1D and 2D fitting methods have the ability to compensate for range information of airborne UAVs in the majority of maritime scenarios. This also explains why online fitting-based approaches cannot significantly enhance the compensation accuracy. Further improvements would require incorporating more accurate prior information, such as systematic measurement errors and measurement correlations, to achieve higher compensation precision.

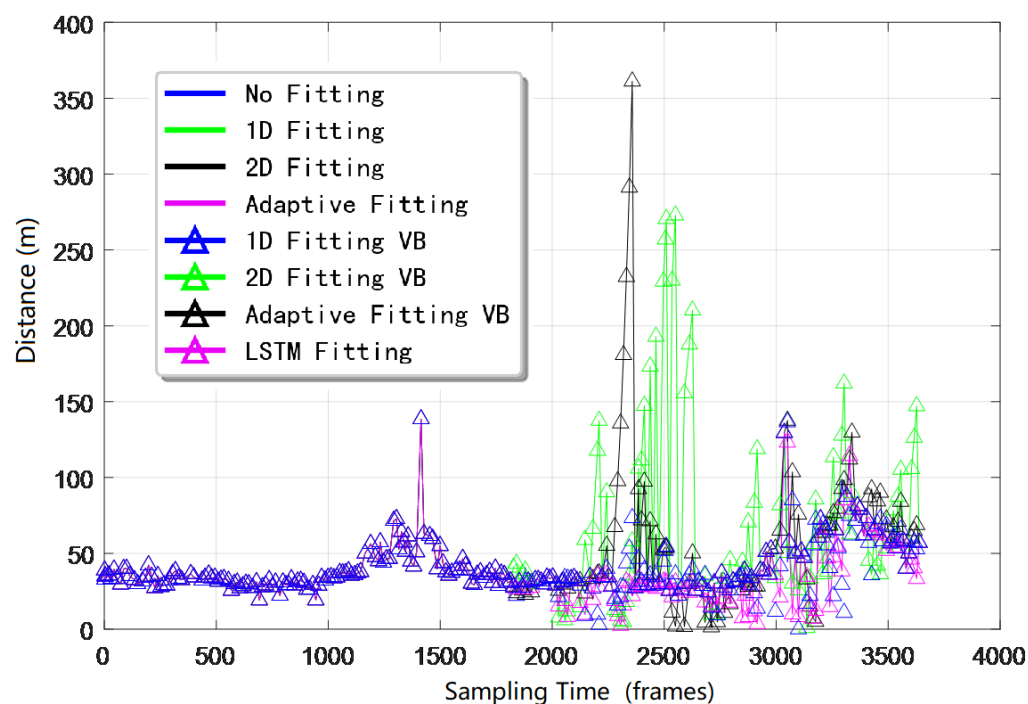


Figure 7. Fitted range measurements.

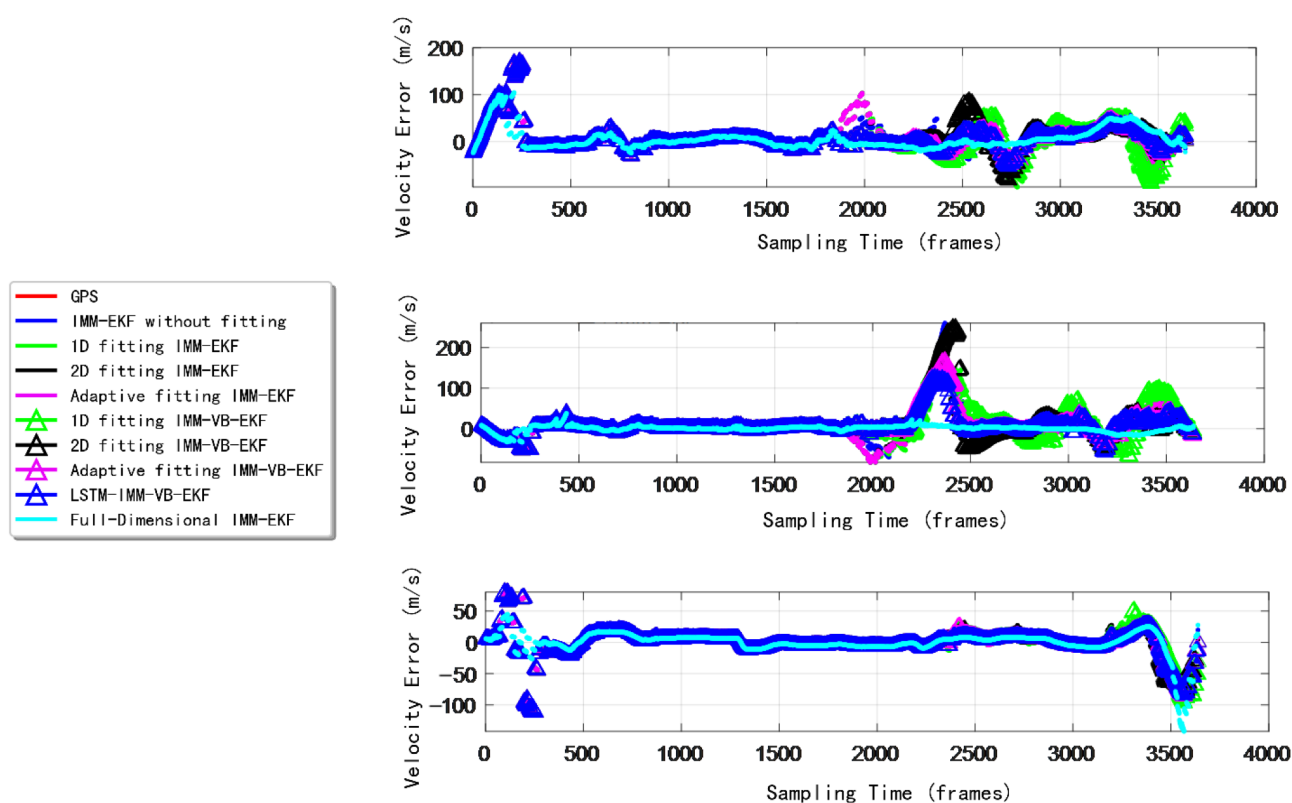


Figure 8. Velocity estimation errors in different directions by different algorithms. Top: Northward tracking results; Middle: Eastward tracking results; Bottom: Ground-speed tracking results.

Table 2. RMSE of three-dimensional velocity and range estimation with data compensation.

Algorithm	Northward Velocity		Eastward Velocity		Ground Velocity		Distance Information	
	(m/s)	Improvement (%)	(m/s)	Improvement (%)	(m/s)	Improvement (%)	(m)	Improvement (%)
IMM-EKF without fitting	31.7	0	41.45	0	22.08	0	44.27	0
1D fitting IMM-EKF	37.78	−19.2	41.33	0.3	22.72	−2.9	66.2	−49.5
2D fitting IMM-EKF	34.37	−8.4	38.61	6.9	22.68	−2.7	59.09	−33.5
Adaptive fitting IMM-EKF	34.66	−9.3	35.38	14.6	22.55	−2.1	42	5.1
1D fitting IMM-VB-EKF	34.46	−8.7	39.98	3.5	24.02	−8.8	66.2	−49.5
2D fitting IMM-VB-EKF	32.09	−1.2	46.04	−11.1	23.04	−4.3	59.09	−33.5
Adaptive fitting IMM-VB-EKF	28.82	9.1	31.17	24.8	22.76	−3.1	42	5.1
LSTM-IMM-VB-EKF	28.87	8.9	26.05	37.2	22.65	−2.6	43.44	1.9
Full-dimensional IMM-EKF	21.45	32.3	7.84	81.1	19.67	10.9	—	—

The proposed LSTM-based incomplete-measurement compensation method can effectively recover the UAV range information under measurement loss conditions and, within the traditional IMM-VB-EKF tracking framework, improve the state estimation accuracy in most cases. Since the compensation module is relatively independent of the subsequent model recognition algorithm, the compensated measurement data can be directly used as the input for the model recognition algorithm. Based on this, the next section further investigates the application of the LSTM network in maneuvering model recognition for shipborne platform UAV tracking.

4.2. Performance Evaluation of Model Recognition under Complete Measurement Conditions

After compensating for incomplete measurements, this section selects a real S-maneuver scenario dataset composed of complete measurement data to evaluate the model recognition network for shipborne UAV tracking. The dataset consists of 10 measured trajectories and 100 simulated trajectories, with 10 simulated trajectories generated from each measured trajectory by adding zero-mean Gaussian white noise to the corresponding GPS data. The standard deviations of the noise range from 50 to 500 m for distance, 1 to 10 m/s for velocity, and 0.1° to 0.5° for azimuth and elevation angles. Each measured trajectory contains approximately 1000–4000 frames. To prevent data leakage, each measured trajectory and its associated simulated trajectories are treated as one group. The ten trajectory groups are randomly divided into training and testing sets at a ratio of 8:2. Each trajectory is then segmented into input samples using a sliding window of 10 consecutive frames. The training set is used to optimize the network parameters and the testing set is used only for final performance evaluation.

Based on the spatial dimensions and the number of candidate models, the input and output dimensions are set to 3 and 25, respectively. For computational efficiency, the hidden layer dimension can be set to 2^n . Accordingly, this study sets this parameter to 32 as a trade-off between maneuver feature representation capability and computational efficiency. This lightweight configuration also helps reduce the risk of overfitting when only recent historical measurements are available. This setting is also consistent with commonly adopted configurations in prior sequence-modeling studies, where moderate hidden dimensions are typically used to balance expressive capacity and computational efficiency. Subsequently, MATLAB-based target tracking code is used to extract the per-frame model probability vectors from the UAV GPS measurements, shipborne platform GPS/INS information, and UAV radar measurements. These data are then processed to generate standardized training and testing datasets. The network is trained using the training dataset to optimize its parameters, while the testing dataset is fed into the trained network to obtain the model recognition results. Finally, the model recognition results are imported into the MATLAB target tracking algorithm to perform UAV state estimation. Since the proposed method is developed as a lightweight enhancement to the IMM-EKF framework, the current experiments mainly compare with IMM-family baselines to ensure

a consistent filtering backbone and fair evaluation under the considered shipborne radar setting, while comparisons with other recent deep learning architectures are left for future work. To verify the effectiveness of the proposed network, its model recognition accuracy is compared with that of the IMM-EKF algorithm using a model recognition error metric, which is defined as follows:

$$Error_{model} = \sqrt{\frac{\sum_{i=1}^{25} (Q(i) - P(i))^2}{25}} \quad (25)$$

Figure 9 displays the model recognition error results for the IMM-EKF and LSTM-EKF algorithms. The Root Mean Square Error (RMSE) indicates that the LSTM-EKF algorithm achieves a 27.9% improvement in model recognition accuracy.

The model recognition results are fed into the target tracking algorithm to compare the tracking performance of the IMM-EKF and LSTM-EKF. Figure 10 shows the velocity estimation error curves of the two algorithms in three dimensions, and Table 3 lists the corresponding RMSE statistical results and improvement rates. As shown in Table 3, the RMSE values for the three-dimensional velocities estimated by the IMM-EKF algorithm are 22.95 m/s, 10.26 m/s, and 8.24 m/s, respectively, while those estimated by the LSTM-EKF algorithm are 19.33 m/s, 9.28 m/s, and 8.84 m/s, respectively. Compared with the IMM-EKF algorithm, the LSTM-EKF achieves improvements of 15.8%, 9.5%, and -7.3% in three-dimensional velocity tracking accuracy. Overall, the LSTM-EKF demonstrates superior velocity tracking performance in this scenario.

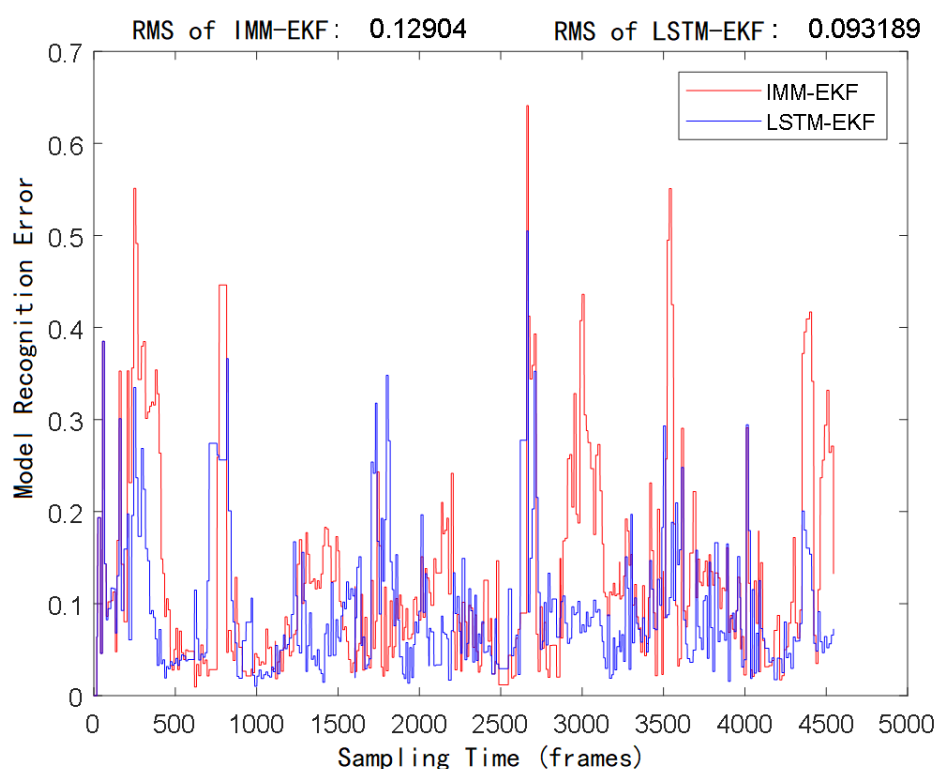


Figure 9. Model recognition error of IMM-EKF and LSTM-EKF.

Subsequently, this study conducts a further analysis of the model probability results. Firstly, the GPS, IMM-EKF, and LSTM-EKF algorithms are employed to statistically analyze the model probability distribution at the measurement update frames. Table 4 presents the model probability results for 2362 measurement update frames, where 10^{-7} represents the probability protection threshold. When the actual model weight of a UAV exceeds 0.01, that model is considered valid; otherwise, it is deemed unused. Statistical analysis reveals

that when the model probability exceeds 0.01, the IMM-EKF and GPS algorithms primarily employ identical models, whereas the LSTM-EKF algorithm exhibits deviations from the GPS approach.

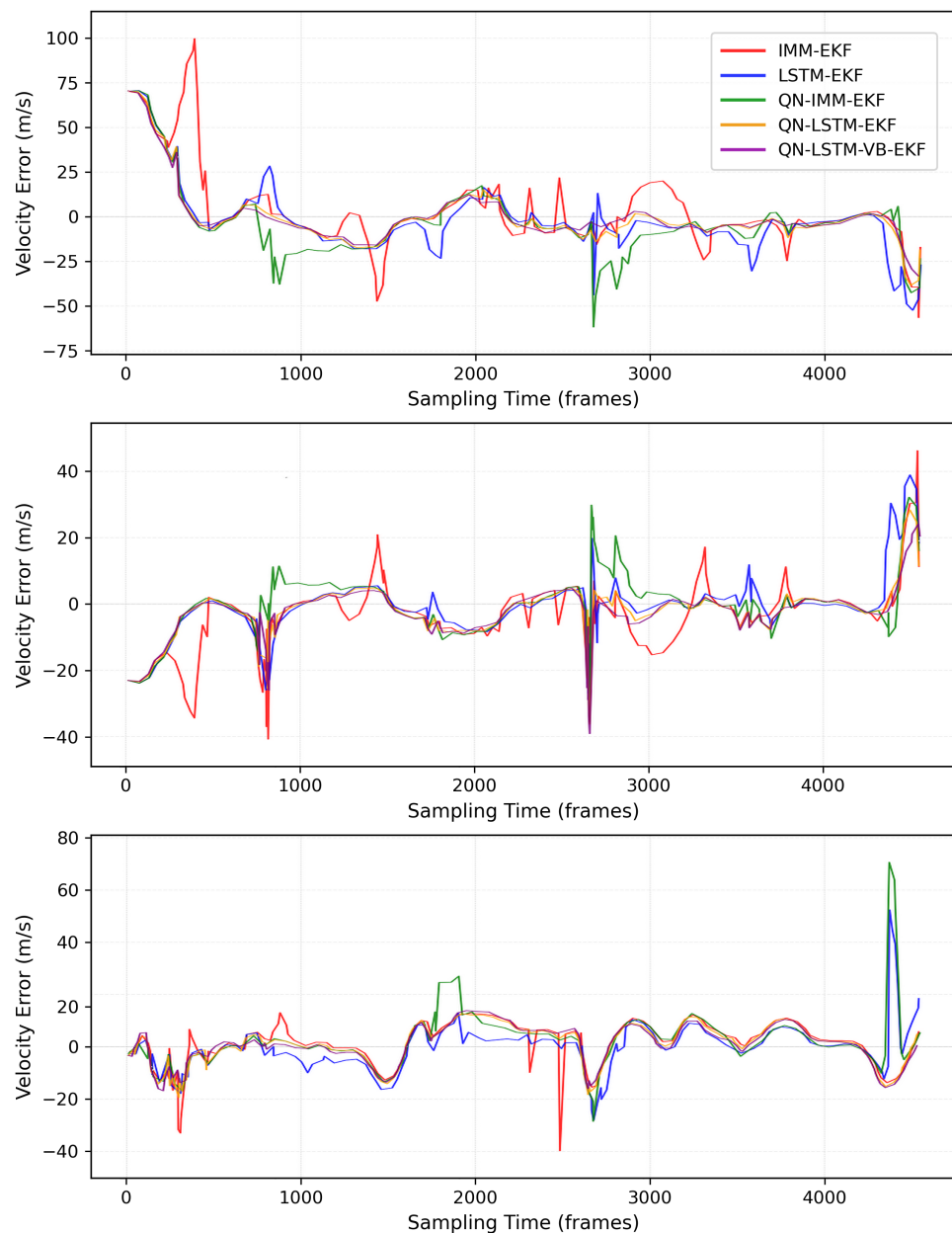


Figure 10. Velocity estimation errors in different directions by different algorithms. **(Top):** Northward tracking results; **(Middle):** Eastward tracking results; **(Bottom):** Ground-speed tracking results.

To compare the model accuracy employed by different algorithms, this study statistically validates this metric based on sample diversity. During this process, the accuracy of model probabilities is disregarded, focusing instead on whether the correct model is utilized. Under these conditions, the model usage discrepancy of an algorithm can be defined as:

$$Diff_{model} = \sum_{i=1}^{25} |Q(i) - P(i)|$$

$$Q(i) = \begin{cases} 1 & \text{if GPS model probability} \geq 0.01 \\ 0 & \text{otherwise} \end{cases}$$

$$P(i) = \begin{cases} 1 & \text{if algorithm model probability} \geq 0.01 \\ 0 & \text{otherwise} \end{cases} \quad (26)$$

This metric effectively reflects algorithmic bias in model utilization, particularly in scenarios with large model sets and dispersed probability distributions for airborne UAV tracking. It enables quantitative analysis of different model recognition methods' behavioral characteristics from the perspective of "whether models are correctly employed".

Table 3. RMSE of three-dimensional velocity estimation without data compensation

Algorithm	Northward Velocity		Eastward Velocity		Ground Velocity	
	(m/s)	Improvement (%)	(m/s)	Improvement (%)	(m/s)	Improvement (%)
IMM-EKF	22.95	0	10.26	0	8.24	0
LSTM-EKF	19.28	15.8	9.28	9.5	8.84	−7.3
IMM-VB-EKF	20.41	11.1	8.8	14.2	7.41	10.1
QN-IMM-EKF	19.85	13.5	8.58	16.4	11.2	−35.1
QN-LSTM-EKF	16.85	26.6	7.56	26.3	7.47	9.9
QN-IMM-VB-EKF	20.64	10.1	8.88	13.5	7.38	10.4
QN-LSTM-VB-EKF	15.91	30.7	7.02	31.6	7.33	11.1

Figure 11 presents the results of model usage discrepancy between the IMM-EKF and LSTM-EKF algorithms. It can be observed that the LSTM-EKF does not significantly reduce the model misapplication rate. In some measurement update frames, both algorithms exhibit poor model usage performance, with the worst-case scenario potentially misapplying up to 12 models.

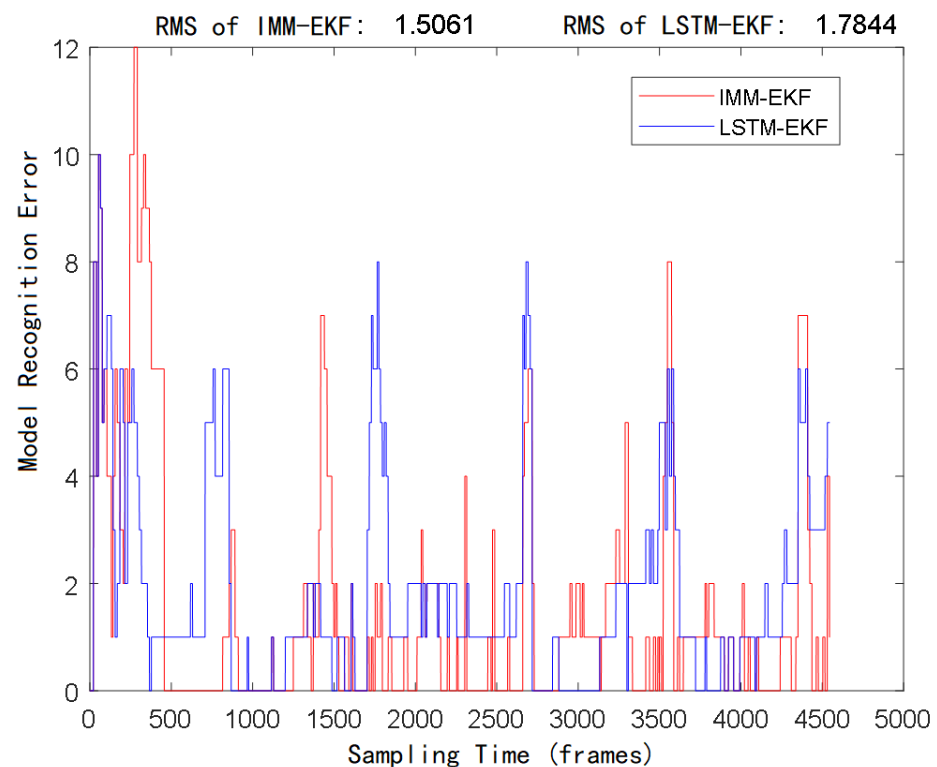


Figure 11. Model usage discrepancy.

During the update process, the sensitivity of the probability threshold of the LSTM-EKF algorithm is relatively high. When the threshold setting value changes slightly ($10^{-7} \rightarrow 10^{-6} \rightarrow 10^{-5}$), the three-dimensional velocity undergoes a noticeable change (decrease exceeding 10%). Analysis of the GPS and LSTM-EKF algorithm model utilization results reveals that the LSTM-EKF algorithm exhibits higher weights for ineffective models. To validate the impact of these ineffective model weights on tracking accuracy, the weights of ineffective models were reinitialized based on the IMM-EKF and LSTM-EKF algorithm model utilization results. The model weights were renormalized, and the identified ineffective model weights were set to 10^{-7} , which was selected to suppress numerically negligible model contributions while preserving stability during probability normalization and recursive filtering updates. The algorithm results were then tested. The velocity estimation errors of the three-dimensional velocity at this moment are shown in Figure 10. It can be observed that the reweighted IMM-EKF algorithm (QN-IMM-EKF) achieved three-dimensional velocity tracking accuracy improvements of 13.5%, 16.4%, and -35.1% compared to the IMM-EKF algorithm. The three-dimensional velocity tracking accuracy of the LSTM-EKF algorithm with secondary assignment (QN-LSTM-EKF) improved by 26.6%, 26.3%, and 9.9%, respectively, compared to the IMM-EKF algorithm. The LSTM-EKF algorithm with secondary assignment demonstrated a more pronounced enhancement in three-dimensional velocity tracking accuracy.

Table 4. Model probability results for 2362 frames.

	GPS	IMM-EKF	LSTM-EKF
Model 1	1×10^{-7}	1×10^{-7}	0.0041
Model 2	0.00002	0.00005	0.0128
Model 3	1×10^{-7}	1×10^{-7}	0.0050
Model 4	0.026	0.0301	0.0538
Model 5	1×10^{-7}	1×10^{-7}	0.0018
Model 6	0.7090	0.6741	0.6057
Model 7	1×10^{-7}	1×10^{-7}	0.0013
Model 8	0.2615	0.2886	0.3066
Model 9	1×10^{-7}	1×10^{-7}	0.0005
Model 10	0.0035	0.0071	0.0045
Model 11	0.0004	0.0006	0.00003
Model 12	1×10^{-7}	1×10^{-7}	0.0002
Model 13	1×10^{-7}	1×10^{-7}	0.00006
Model 14	1×10^{-7}	1×10^{-7}	0.0001
Model 15	1×10^{-7}	1×10^{-7}	0.0001
Model 16	1×10^{-7}	1×10^{-7}	0.00007
Model 17	1×10^{-7}	1×10^{-7}	0.0001
Model 18	1×10^{-7}	1×10^{-7}	0.00008
Model 19	1×10^{-7}	1×10^{-7}	0.0002
Model 20	1×10^{-7}	1×10^{-7}	0.00007
Model 21	1×10^{-7}	1×10^{-7}	0.0005
Model 22	1×10^{-7}	1×10^{-7}	0.0003
Model 23	1×10^{-7}	1×10^{-7}	0.0002
Model 24	1×10^{-7}	1×10^{-7}	0.0016
Model 25	1×10^{-7}	1×10^{-7}	0.00008

Models greater than 0.01; GPS: 4, 6, 8; IMM-EKF: 4, 6, 8; LSTM-EKF: 2, 4, 6, 8.

Subsequently, the VB algorithm and the QN-LSTM-EKF algorithm were combined to evaluate tracking performance. The experimental results are collectively presented in Figure 10.

For clarity, Table 3 summarizes the three-dimensional velocity tracking results across all algorithms. It can be observed that under this set of scenarios, the QN-LSTM-VB-EKF algorithm exhibits the best estimation performance. Its three-dimensional velocity tracking

results surpass those of the IMM-EKF algorithm by over 10% in all dimensions, with an overall improvement in velocity tracking accuracy of 24.5%.

4.3. Computational Complexity Analysis

Compared with the conventional IMM-EKF framework, the additional computational cost of the proposed method mainly comes from the introduction of two LSTM-based modules, namely the incomplete-measurement compensation network and the model recognition network. These modules introduce extra recurrent computations for temporal feature extraction and sequence modeling.

However, the overall computational burden remains moderate. First, both LSTM networks operate on low-dimensional measurement sequences. The compensation network only processes recent measurement increments, while the model recognition network uses short-term three-dimensional trajectory observations as input. Second, the sequence length adopted in the experiments is relatively short, which limits the computational cost during online inference. In addition, the proposed framework does not employ computationally intensive structures such as deep Transformer architectures or large-scale attention mechanisms.

From the implementation perspective, the proposed method preserves the original IMM-based filtering framework and only introduces lightweight neural-network inference operations during the measurement compensation and model recognition stages. Therefore, although the proposed framework increases computational complexity compared with traditional IMM-based methods, the increase is acceptable for real-time shipborne UAV tracking applications. The proposed framework was evaluated on an NVIDIA GeForce RTX 4080 SUPER GPU. With a batch size of 1, the average inference time for one input sequence was approximately 0.3 ms. Since the frame period of the practical radar system is typically greater than 50 ms, the inference latency is substantially shorter than the available processing interval, indicating that the proposed model can satisfy the real-time requirements of the considered radar tracking system.

Overall, the proposed method achieves improved maneuver responsiveness and tracking accuracy under incomplete-measurement conditions with only a moderate increase in computational cost, demonstrating a favorable trade-off between tracking performance and computational efficiency.

5. Conclusions

This study addresses the problem of maritime UAV tracking. First, to tackle the potential issue of incomplete measurements in shipborne radar measurements and to improve the practical applicability of the model, an online-trained LSTM-based incomplete-measurement compensation method is proposed. This approach provides relatively complete and continuous measurement inputs for subsequent target tracking and model recognition.

Building upon this, a maneuvering UAV model-recognition method based on LSTM networks is developed. By modeling the temporal dependencies of historical UAV measurements, this method adaptively identifies the probabilities of candidate motion models. Considering that, in practical applications, measurement data may be either complete or partially compensated, the designed network is capable of operating robustly under varying data integrity conditions.

To address the challenge of obtaining model probabilities directly, GPS data are employed to construct an approach for deriving optimal model probabilities, providing reliable training outputs for the model-recognition network. Experimental results demonstrate the effectiveness and feasibility of the proposed algorithm in complex maritime environ-

ments, while also indicating that the method has potential for further optimization and performance improvement under different operational scenarios.

Future work will further investigate the robustness and generalization of the proposed method under more diverse and extreme maritime environments, including different sea-clutter levels, measurement loss rates, maneuvering profiles, and stronger sensor interference conditions. In addition, the effects of different hyperparameter settings, such as sequence length, hidden layer size, and the number of network layers, will be systematically evaluated, and comparisons with other recent deep learning architectures will also be included.

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