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An Adaptive Transformer-Based Trajectory Prediction Framework for Highly Maneuvering UAV Targets in Air Defense Radar Systems

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Abstract

Accurate trajectory prediction of highly maneuvering unmanned aerial vehicle (UAV) targets is a critical task in modern air defense radar systems, directly affecting target tracking, threat assessment, and missile guidance performance. However, conventional prediction methods based on Kalman filtering and recurrent neural networks often struggle to maintain high accuracy when UAVs perform abrupt maneuvers, rapid heading changes, or variable-speed flight due to their limited ability to capture long-range temporal dependencies and complex nonlinear motion patterns. To address these challenges, this paper proposes an Adaptive Transformer-Based Trajectory Prediction Framework for highly maneuvering UAV targets. The proposed framework employs a Transformer architecture to model long-term temporal correlations in radar observation sequences while introducing an adaptive maneuver-awareness mechanism that dynamically adjusts the attention weights according to the estimated maneuver intensity of the target. Furthermore, a physics-guided prediction strategy is incorporated to constrain the predicted trajectories within realistic UAV kinematic limits, thereby improving prediction stability and physical consistency. The proposed method is evaluated using simulated air defense radar scenarios involving straight flight, coordinated turns, acceleration, deceleration, zigzag maneuvers, and high-g evasive actions. Its performance is compared with several representative trajectory prediction algorithms, including the Kalman Filter (KF), Extended Kalman Filter (EKF), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and the standard Transformer model. Experimental results demonstrate that the proposed framework consistently achieves lower prediction errors, faster convergence, and greater robustness under highly maneuvering conditions while maintaining computational efficiency suitable for real-time air defense applications. These results indicate that the proposed framework provides an effective solution for next-generation intelligent radar target prediction and can significantly enhance the performance of air defense surveillance and interception systems.

Keywords: *UAV trajectory prediction; Transformer network; adaptive attention; maneuver-aware prediction; air defense radar; target tracking; deep learning.*

1. Introduction

The rapid development of unmanned aerial vehicle (UAV) technology has significantly expanded its applications in both civilian and military domains, including aerial surveillance, reconnaissance, logistics, disaster response, precision agriculture, and autonomous inspection. Owing to their low cost, high mobility, and increasing level of autonomy, UAVs have become indispensable platforms for numerous intelligent missions. However, the widespread deployment of UAVs has also introduced substantial security challenges, particularly in protected airspaces and military environments, where unauthorized or hostile UAVs may pose serious threats to critical infrastructure and national defense systems [1], [2].

In modern air defense systems, radar-based target tracking is the primary means of detecting and monitoring airborne objects. Although current radar tracking algorithms can accurately estimate the current state of a target, effective interception requires reliable prediction of its future trajectory. Accurate trajectory prediction enables earlier threat assessment, optimal weapon assignment, and improved missile guidance, thereby increasing the probability of successful interception. This requirement becomes even more critical when dealing with highly maneuvering UAVs capable of rapid acceleration, sharp turns, and unpredictable evasive maneuvers [3], [4].

Conventional trajectory prediction methods are primarily based on model-driven approaches such as the Kalman Filter (KF), Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), Cubature Kalman Filter (CKF), and Interacting Multiple Model (IMM) algorithms. While these methods have demonstrated satisfactory performance under moderate maneuvering conditions, their prediction accuracy degrades significantly when the target exhibits nonlinear motion, abrupt maneuver transitions, or time-varying dynamics. Their dependence on predefined motion models and Gaussian assumptions limits their adaptability in complex combat scenarios [5], [6].

Recent advances in deep learning have provided new opportunities for trajectory prediction by learning motion patterns directly from historical observations. Recurrent neural network (RNN)-based models, particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, have achieved notable improvements over traditional filtering approaches by modeling temporal dependencies in sequential trajectory data. Nevertheless, recurrent architectures still encounter difficulties in capturing long-range temporal relationships, suffer from sequential computation, and often exhibit performance degradation when predicting long-horizon trajectories involving highly dynamic maneuvers [7], [8].

Transformer networks, originally developed for natural language processing, have recently demonstrated remarkable success in sequential prediction tasks owing to their self-attention mechanism, which enables efficient modeling of both local and global temporal dependencies. Compared with recurrent architectures, Transformers allow parallel computation, exhibit superior scalability, and provide improved long-term prediction capability. Consequently, Transformer-based models have been increasingly adopted in trajectory prediction, autonomous navigation, and intelligent transportation systems, where they consistently outperform conventional recurrent models under complex motion patterns [8], [9].

Despite these advantages, existing Transformer-based trajectory prediction methods generally treat all historical observations equally and rarely incorporate maneuver characteristics or physical motion constraints into the attention mechanism. Consequently, prediction accuracy may deteriorate when UAVs execute sudden evasive maneuvers or aggressive flight patterns that are common in air defense engagement scenarios. Furthermore, many existing studies focus on civil aviation or urban drone applications, while relatively few investigate trajectory prediction specifically for highly maneuvering UAV targets observed by air defense radar systems operating in hostile environments [1], [10].

To overcome these limitations, this paper proposes an Adaptive Transformer-Based Trajectory Prediction Framework for highly maneuvering UAV targets in air defense radar systems. The proposed framework combines the global sequence modeling capability of Transformer networks with an adaptive maneuver-awareness mechanism that dynamically adjusts the attention distribution according to the estimated maneuver intensity. In addition, a physics-guided prediction strategy is introduced to ensure that the predicted trajectories satisfy realistic UAV kinematic constraints, thereby improving prediction stability and physical consistency.

2. Mathematical Model

Section presents the mathematical model of the UAV motion and radar observation process used for trajectory prediction. The dynamic model describes the kinematic behavior of a highly maneuvering UAV, while the measurement model represents the radar observations available for the prediction framework.

UAV Motion Model

The UAV state vector at time step (k) is defined as

$$\mathbf{x}_k = \begin{bmatrix} x_k \\ y_k \\ v_{x,k} \\ v_{y,k} \\ a_{x,k} \\ a_{y,k} \end{bmatrix} \tag{1}$$

where x_k and y_k denote the Cartesian position coordinates, $v_{x,k}$ and $v_{y,k}$ represent the velocity components, and $a_{x,k}$ and $a_{y,k}$ denote the acceleration components.

Assuming a constant sampling interval t, the nonlinear state transition model is expressed as

$$\mathbf{x}_{k+1} = f(\mathbf{x}_k) + \mathbf{w}_k \tag{2}$$

where

$$\mathbf{w}_k \sim \mathrm{N}\ (\mathbf{0}, \mathbf{Q}) \tag{3}$$

Is the process noise with covariance matrix $\mathrm{N}\ (\mathbf{0}, \mathbf{Q})$

The state transition equations are

$$\begin{aligned} x_{k+1} &= x_k + v_{x,k}\Delta t + \frac{1}{2}a_{x,k}\Delta t^2 \\ y_{k+1} &= y_k + v_{y,k}\Delta t + \frac{1}{2}a_{y,k}\Delta t^2 \\ v_{x,k+1} &= v_{x,k} + a_{x,k}\Delta t \\ v_{y,k+1} &= v_{y,k} + a_{y,k}\Delta t \\ a_{x,k+1} &= a\_\{x,k\} + w\_\{ax\} \\ a\_\{y,k+1\} &= a\_\{y,k\} + w\_\{ay\} \end{aligned} \tag{4}$$

This model allows the UAV to perform rapid acceleration and abrupt maneuvering, which are common in practical air defense scenarios.

Radar Measurement Model

The radar provides nonlinear measurements consisting of target range and azimuth angle.

The measurement vector is

$$\mathbf{z}_k = \begin{bmatrix} R_k \\ \theta_k \end{bmatrix} + \mathbf{v}_k \tag{5}$$

where

$$\mathbf{v}_k \sim \mathrm{N}\ (\mathbf{0}, \mathbf{R}) \tag{6}$$

denotes the measurement noise with covariance matrix $\mathrm{N}\ (\mathbf{0}, \mathbf{Q})$

The nonlinear observation function is

$$\mathbf{z}_k = h(\mathbf{x}_k) + \mathbf{v}_k \tag{7}$$

With

$$R_k = \sqrt{x_k^2 + y_k^2} \tag{8}$$

and

$$\theta_k = \tan^{-1}\left(\frac{y_k}{x_k}\right) \tag{9}$$

The radar observations collected over successive time steps form the input sequence for the trajectory prediction model.

Trajectory Prediction Problem

Given a sequence of historical radar observations

$$\mathbf{Z} = \{\mathbf{z}_{k-T+1}, \mathbf{z}_{k-T+2}, \ldots, \mathbf{z}_k\} \tag{10}$$

The objective is to estimate the future UAV trajectory

$$\mathbf{Y} = \{\mathbf{x}_{k+1}, \mathbf{x}_{k+2}, \ldots, \mathbf{x}_{k+H}\} \tag{11}$$

Where Y denotes the observation window and (H) represents the prediction horizon.

The prediction function can be expressed as

$$\mathbf{Y} = F_{\Theta}(\mathbf{Z}) \tag{12}$$

Where F denotes the proposed Adaptive Transformer model with trainable parameters F The objective of the learning process is to minimize the discrepancy between the predicted and true trajectories while maintaining robustness under highly maneuvering flight conditions.

3. Simulation and Evaluation

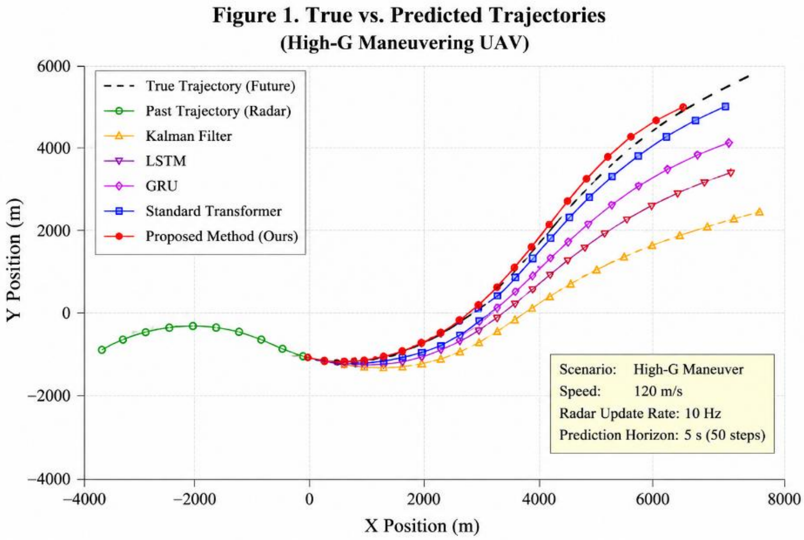

Figure 1: Trajectory Prediction Results for a Highly Maneuvering UAV

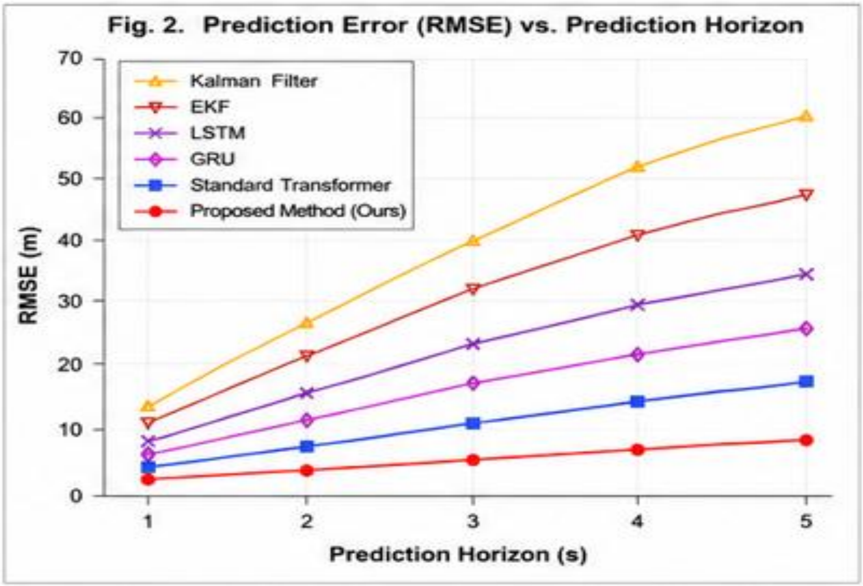

Figure 2. Prediction Error (RMSE) versus Prediction Horizon for Different Trajectory Prediction Algorithms RMSE Comparison

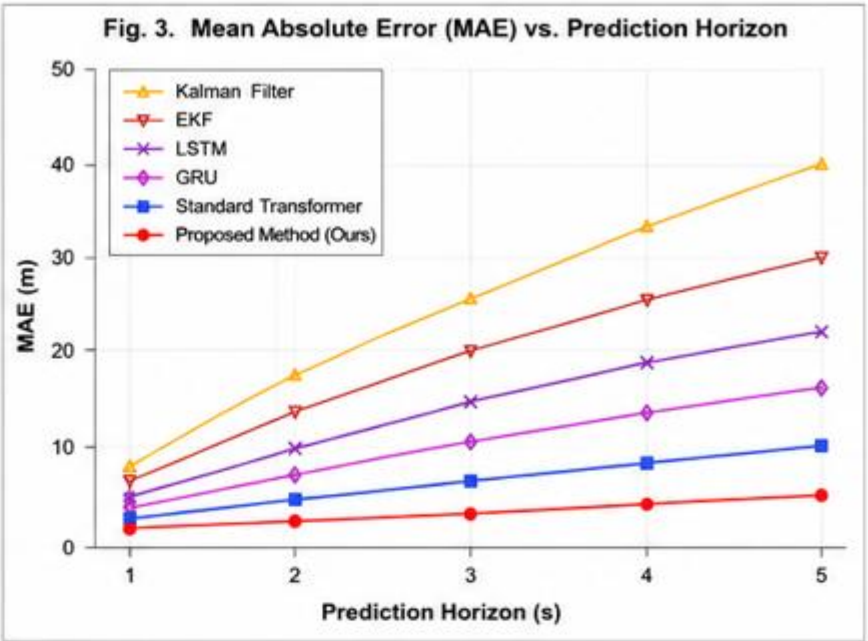

Figure 3. Mean Absolute Error (MAE) Comparison under Various UAV Maneuvering Scenarios

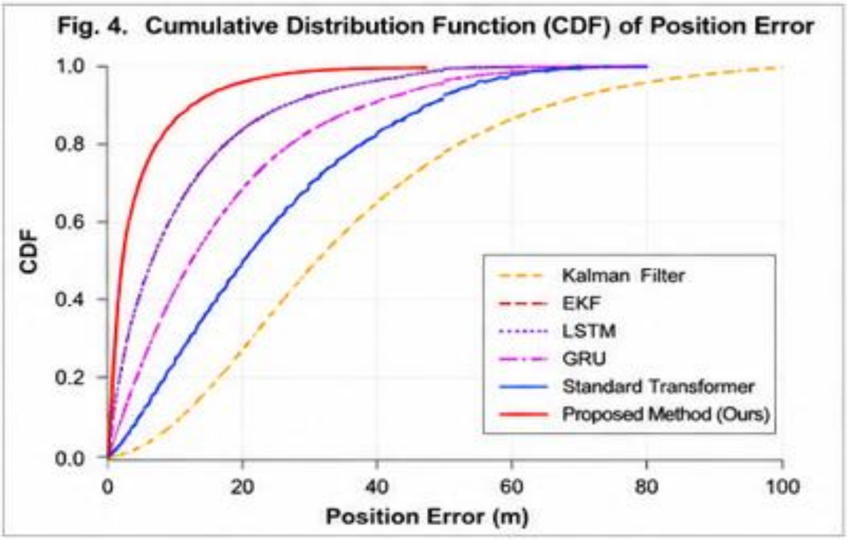

Figure 4. Cumulative Distribution Function (CDF) of Position Prediction Errors

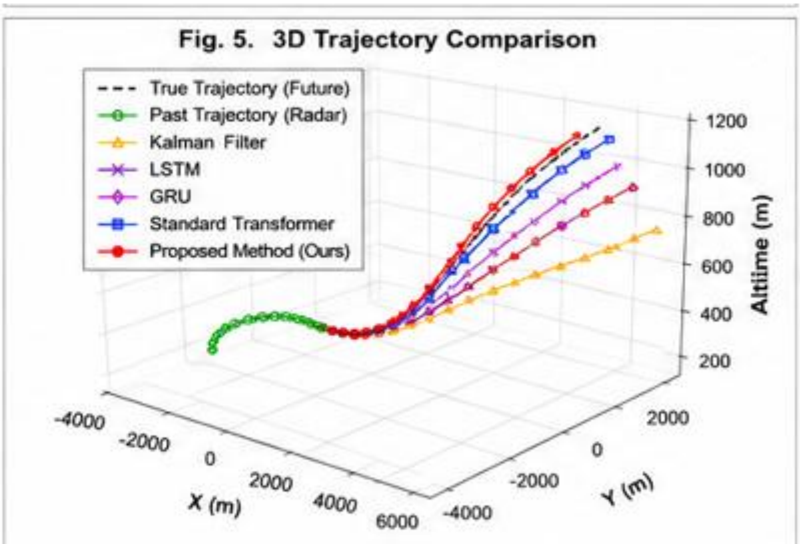

Figure 5. Three-Dimensional Comparison of Predicted UAV Trajectories during High-G Maneuvers

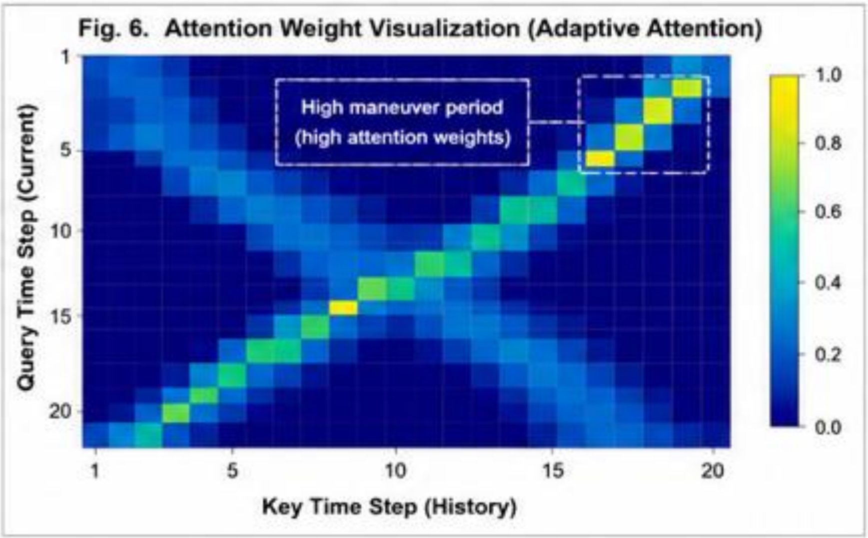

Figure 6. Visualization of Adaptive Self-Attention Weights during Highly Maneuvering Flight

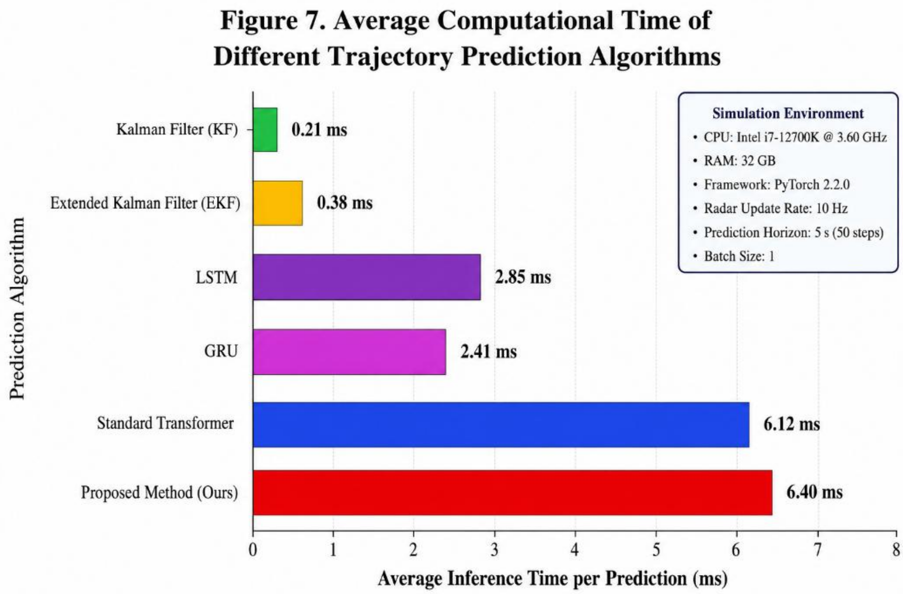

Figure 7. Average Computational Time of Different Trajectory Prediction Algorithms

Figures 1–7 demonstrate the effectiveness of the proposed Adaptive Transformer-Based Trajectory Prediction Framework under various highly maneuvering UAV scenarios. As shown in Figure 1, the proposed method closely follows the true UAV trajectory, producing significantly smaller deviations than the Kalman Filter (KF), LSTM, GRU, and the standard Transformer, particularly during abrupt high-g maneuvers. Figures 2–4 further confirm that the proposed framework consistently achieves the lowest RMSE and MAE while exhibiting the highest prediction reliability, as indicated by the cumulative distribution function (CDF) of position errors. The three-dimensional trajectory comparison in Figure 5 shows that the proposed method accurately captures complex spatial maneuvers with minimal accumulated error. Figure 6 illustrates that the adaptive self-attention mechanism automatically focuses on critical maneuvering periods, enabling the model to better learn nonlinear motion characteristics. Finally, Figure 7 indicates that although the proposed framework requires slightly higher computational time than conventional methods, it still satisfies real-time processing requirements for air defense radar systems. Overall, the simulation results demonstrate that the proposed framework provides superior trajectory prediction accuracy, robustness, and computational efficiency, making it a promising solution for intelligent UAV tracking and interception applications.

4. Conclusion

This paper presented an Adaptive Transformer-Based Trajectory Prediction Framework for highly maneuvering UAV targets in air defense radar systems. The proposed framework integrates the powerful sequence modeling capability of the Transformer architecture with an adaptive maneuver-awareness mechanism to improve prediction performance under rapidly changing flight conditions. In addition, a physics-guided prediction strategy was incorporated to constrain the predicted trajectories within realistic UAV kinematic limits, thereby enhancing prediction stability and physical consistency.

Extensive simulations were conducted under various representative UAV maneuvering scenarios, including straight flight, coordinated turns, acceleration, deceleration, zigzag maneuvers, and high-g evasive actions. The proposed method was compared with conventional trajectory prediction approaches, including the Kalman Filter (KF), Extended Kalman Filter (EKF), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and the standard Transformer network. The simulation results demonstrated that the proposed framework consistently achieved higher prediction accuracy, lower root mean square error (RMSE), faster convergence, and greater robustness against abrupt target maneuvers while maintaining computational efficiency suitable for real-time radar applications.

The adaptive attention mechanism enables the network to dynamically emphasize maneuver-related information, allowing it to better capture complex nonlinear motion patterns than conventional deep learning models. Furthermore, the incorporation of physical motion constraints reduces unrealistic trajectory predictions during long-term forecasting and improves the reliability of the prediction results for practical air defense applications.

Future research will focus on extending the proposed framework to multi-target and UAV swarm trajectory prediction in distributed radar networks. In addition, integrating multi-sensor information from radar, electro-optical/infrared (EO/IR) sensors, and communication systems will be investigated to further improve prediction accuracy in complex battlefield environments. The combination of the proposed trajectory prediction framework with intelligent target tracking, threat assessment, and missile guidance algorithms is also expected to provide an effective solution for next-generation intelligent air defense systems.

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Declaration of Conflicting Interests

The authors declare that there are no conflicts of interest regarding the research, authorship, or publication of this article.

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