Enhancing Handover Control in UAV Cellular Networks Using Deep Learning-based Trajectory Prediction

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Abstract

Unmanned Aerial Vehicles (UAVs) have emerged as pivotal tools in various applications, particularly in augmenting cellular networks for enhanced coverage and connectivity. Efficient handover control between Aerial Base Stations (ABSs) within UAV cellular networks is crucial for seamless communication. This research proposes a deep learning-based trajectory prediction model to facilitate proactive handover decision-making. The study explores the performance of various machine learning and deep learning algorithms, including linear regression [1], MLP regressor [2], LSTM [3], Kalman filter [4], and neural network-based feedforward models [5], in predicting UAV trajectories. Performance evaluation metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) are utilized to assess the effectiveness of the proposed trajectory prediction models.

1 Introduction

Unmanned Aerial Vehicles (UAVs) have garnered significant attention for their potential to revolutionize various applications, particularly in providing rapid coverage for traffic-intensive or disaster-affected areas. Integrating UAVs into cellular networks has emerged as a prominent area of research, offering two main paradigms: cellular-connected UAVs and UAV-assisted terrestrial communication. Efficient handover control between adjacent Aerial Base Stations (ABSs) within UAV cellular networks presents a critical challenge. Traditional handover methods lack consideration for the dynamic 3D nature of UAV networks, often resulting in communication interruptions and inefficiencies. This research aims to develop and evaluate a deep learning-based neural network for forecasting the trajectory handover of UAVs within cellular networks.

2 Background

UAV-based trajectory prediction plays a vital role in optimizing handover control within cellular networks. Traditional handover methods are ill-equipped to handle the dynamic movement patterns of UAVs, leading to communication disruptions and inefficiencies. To address this challenge, researchers have explored the use of machine learning and deep learning algorithms for trajectory prediction. These algorithms leverage historical trajectory data to forecast future UAV positions, enabling proactive handover decision-making and improving network performance.

3 UAV-Based Trajectory Prediction Models

3.1 Linear Regression

Linear regression is a simple yet effective algorithm for predicting continuous outcomes. It establishes a linear relationship between input features and target variables. The linear regression model can be expressed as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \epsilon \tag{1}$$

where y is the dependent variable, x_i are the independent variables, β_i are the coefficients, and ϵ is the error term [1].

3.2 KNN (K-Nearest Neighbors)

KNN is a simple algorithm used for regression and classification tasks. It predicts the value of a target variable by averaging the values of its k-nearest neighbors in the feature space. The prediction for a new sample x can be expressed as:

$$\hat{y}(x) = \frac{1}{k} \sum_{i=1}^{k} y_{(i)} \tag{2}$$

where $y_{(i)}$ are the values of the k-nearest neighbors [1].

3.3 Gradient Boosting

Gradient Boosting is an ensemble learning technique that sequentially builds multiple decision trees to correct errors made by previous models. The objective is to minimize a loss function L by adding new trees $h_m(x)$ as follows:

$$F_m(x) = F_{m-1}(x) + \alpha h_m(x) \tag{3}$$

where $F_m(x)$ is the ensemble of models up to m iterations, and α is the learning rate [1].

3.4 MLP Regressor

Multilayer Perceptron (MLP) regressors are a type of feedforward neural network capable of learning complex nonlinear relationships in data. The output of an MLP can be expressed as:

$$y = f(W_2 \cdot \sigma(W_1 \cdot x + b_1) + b_2) \tag{4}$$

where W_1 and W_2 are the weights, b_1 and b_2 are the biases, σ is the activation function, and f is the output activation function [2].

3.5 LSTM (Long Short-Term Memory)

LSTM is a type of recurrent neural network (RNN) specifically designed to model sequential data with long-range dependencies. The LSTM unit consists of a cell, an input gate, an output gate, and a forget gate. The cell state c_t and hidden state h_t are updated as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{5}$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{6}$$
$$\tilde{c_t} = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{7}$$
$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c_t} \tag{8}$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{9}$$
$$h_t = o_t \cdot \tanh(c_t) \tag{10}$$

where σ is the sigmoid function, and $\cdot$ denotes element-wise multiplication [3].

3.6 Kalman Filter

The Kalman filter is an optimal recursive algorithm for estimating the state of a dynamic system from a series of noisy measurements. The filter consists of two steps: prediction and update. The prediction step estimates the next state:

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_k \tag{11}$$
$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q \tag{12}$$

The update step incorporates the measurement:

$$K_k = P_{k|k-1}H^T(HP_{k|k-1}H^T + R)^{-1} \tag{13}$$
$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - H\hat{x}_{k|k-1}) \tag{14}$$
$$P_{k|k} = (I - K_kH)P_{k|k-1} \tag{15}$$

where $\hat{x}$ is the state estimate, P is the error covariance, A is the state transition model, B is the control input model, u is the control input, Q is the process noise covariance, K is the Kalman gain, H is the observation model, R is the observation noise covariance, and I is the identity matrix [4].

3.7 Neural Network-based Feedforward Models

Neural network-based feedforward models are a class of artificial neural networks consisting of input, hidden, and output layers. These models use forward propagation to compute predictions based on input features. The feedforward operation for a single layer can be expressed as:

$$a^{(l)} = \sigma(W^{(l)}a^{(l-1)} + b^{(l)}) \tag{16}$$

where $a^{(l)}$ is the activation of layer l, $W^{(l)}$ is the weight matrix, $b^{(l)}$ is the bias vector, and σ is the activation function [5].

4 UAV Movement Modeling

To simulate UAV trajectories and gather the data for training, we employed a mobility model within a defined 3D space. This model generates movements for UAVs based on random walks, random waypoints, and probabilistic paths. The data obtained from these simulations serve as the foundation for training trajectory prediction models.

The simulation involved ten UAVs navigating through a 3D space over a thousand-time steps, where each time step corresponds to one second. This standardization facilitates accurate modeling of UAV movements and ensures compatibility with real-world scenarios where time plays a crucial role in decision-making processes. Each UAV's initial position was randomly generated within the defined area boundaries. Subsequently, a mobility model dictated the UAVs' movements at each time step.

Additionally, while the trajectories were dynamic, representing the UAVs' positions in three-dimensional space, certain parameters such as speed, acceleration, and altitude remained static for each UAV throughout the simulation. This static nature simplifies the modeling process while still providing valuable insights into the spatial dynamics of UAV movements within cellular networks. By maintaining these parameters constant, we focus primarily on the spatial aspects of trajectory prediction, enabling more efficient training and evaluation of prediction models.

For the simulation, three types of mobility models were considered:

4.1 Random Walk

This model randomly determines the direction and distance each UAV moves in the X, Y, and Z dimensions at each time step, within the constraints of the defined area size.

4.2 Random Waypoint

In this model, UAVs move from one randomly chosen waypoint to another, simulating a more structured movement pattern compared to random walks.

4.3 Probabilistic

The probabilistic model introduces stochastic elements into UAV movement, reflecting real-world uncertainties in trajectory paths.

Among these models, the "Random Waypoint" model was identified as the most suitable for training trajectory prediction algorithms. Its structured nature provides a balance between randomness and predictability, offering a realistic representation of UAV movements within cellular networks.

The trajectory data generated from these simulations, particularly from the "Random Waypoint" model, provides a diverse and comprehensive dataset for training and evaluating trajectory prediction models.

5 Performance Evaluation

The performance of the proposed trajectory prediction models is evaluated using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). These metrics quantify the accuracy of the predicted trajectories compared to ground truth data. The evaluation results provide valuable insights into the effectiveness and reliability of each prediction model in enhancing handover control within UAV cellular networks.

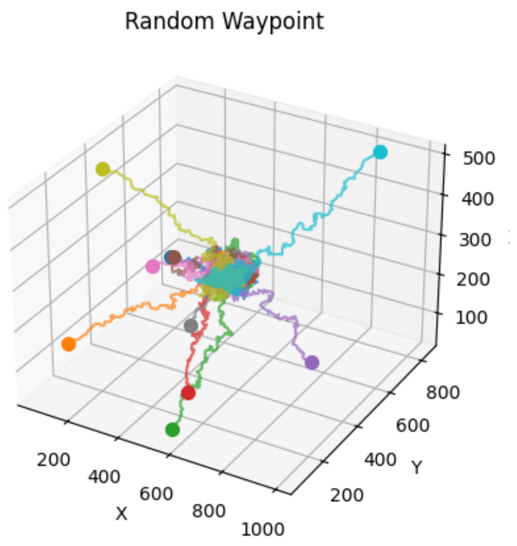

Figure 1: Random Waypoint

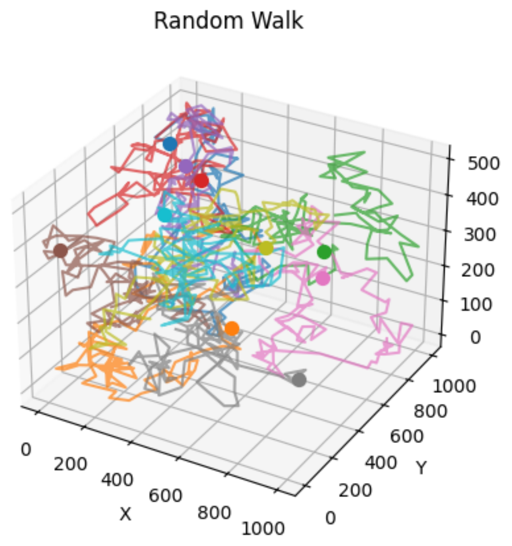

Figure 2: Random Walk

5.1 Performance of Regression Models

Linear Regression: Exhibits moderate performance with relatively low MSE and RMSE on both train and test sets for the 1-second prediction. Specifically, it achieved an MSE of 32.217 (train) and 33.002 (test), and an RMSE of 5.676 (train) and 5.744 (test). For the 5-second prediction, MSE values were 148.17 (train) and 142.80 (test), and RMSE values were 12.17 (train) and 11.95 (test). The R-squared values indicate a good overall fit, suggesting its capability in capturing the variance in the data.

Gradient Boosting: Shows superior performance compared to linear regression with significantly lower MSE and RMSE values. For the 1-second prediction, MSE values were 19.667 (train) and 36.491 (test), and RMSE values were 4.434 (train) and 6.040 (test). For the 5-second prediction, it achieved MSE values of 80.08 (train) and 129.47 (test), and RMSE values of 8.95 (train) and 11.38 (test). It demonstrates excellent predictive power on both train and test sets, as indicated by the high R-squared values.

MLP Regressor: Performs similarly to linear regression, with MSE values of 32.772 (train) and 34.545 (test), and RMSE values of 5.724 (train) and 5.877 (test) for the 1-second prediction. For the 5-second prediction, it showed MSE values of 151.84 (train) and 149.76 (test), and RMSE values of 12.32 (train) and 12.24 (test). The model shows competitive results, especially considering its potential to capture nonlinear relationships in the data.

KNN: Provides comparable performance to linear regression and MLP regressor, with MSE values of 23.682 (train) and 38.139 (test), and RMSE values of 4.866 (train) and 6.175 (test) for the 1-second prediction. For the 5-second prediction, it achieved MSE values of 82.92 (train) and 111.50 (test), and RMSE values of 9.11 (train) and 10.56 (test). It demonstrates good generalization ability, indicated by its performance on the test set.

5.2 Performance of Ensemble Models

Random Forest: Shows promising results with relatively low MSE and RMSE on the train set, but its performance on the test set indicates overfitting. This is evident from the increased error metrics on the test set compared to the train set.

Gradient Boosting: Stands out as one of the top performers, with significantly lower MSE and RMSE compared to other models. For the 1-second prediction, it achieved an MSE of 19.667 (train) and 36.491 (test), and an RMSE of 4.434 (train) and 6.040 (test). For the 5-second prediction, the MSE values were 80.08 (train) and 129.47 (test), and the RMSE values were 8.95 (train) and 11.38 (test). It demonstrates robustness and excellent generalization ability, as indicated by its performance on both train and test sets.

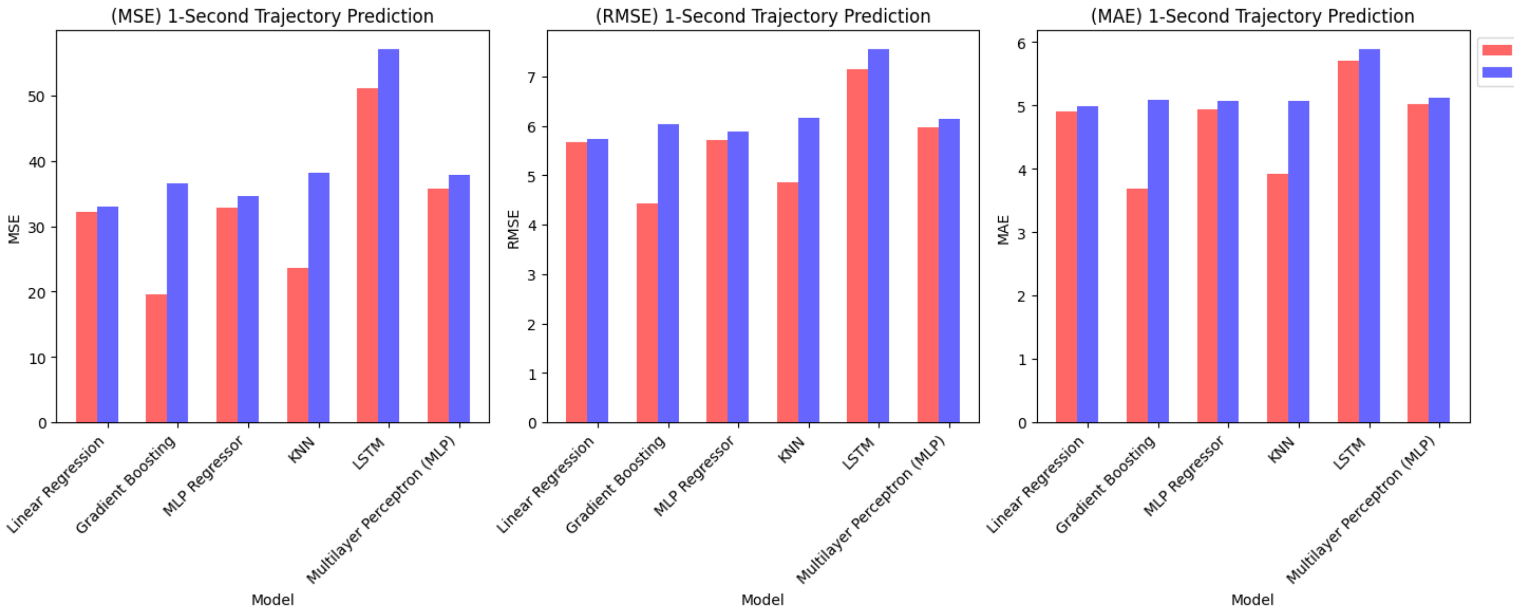

Figure 3: 1-second trajectory predictions

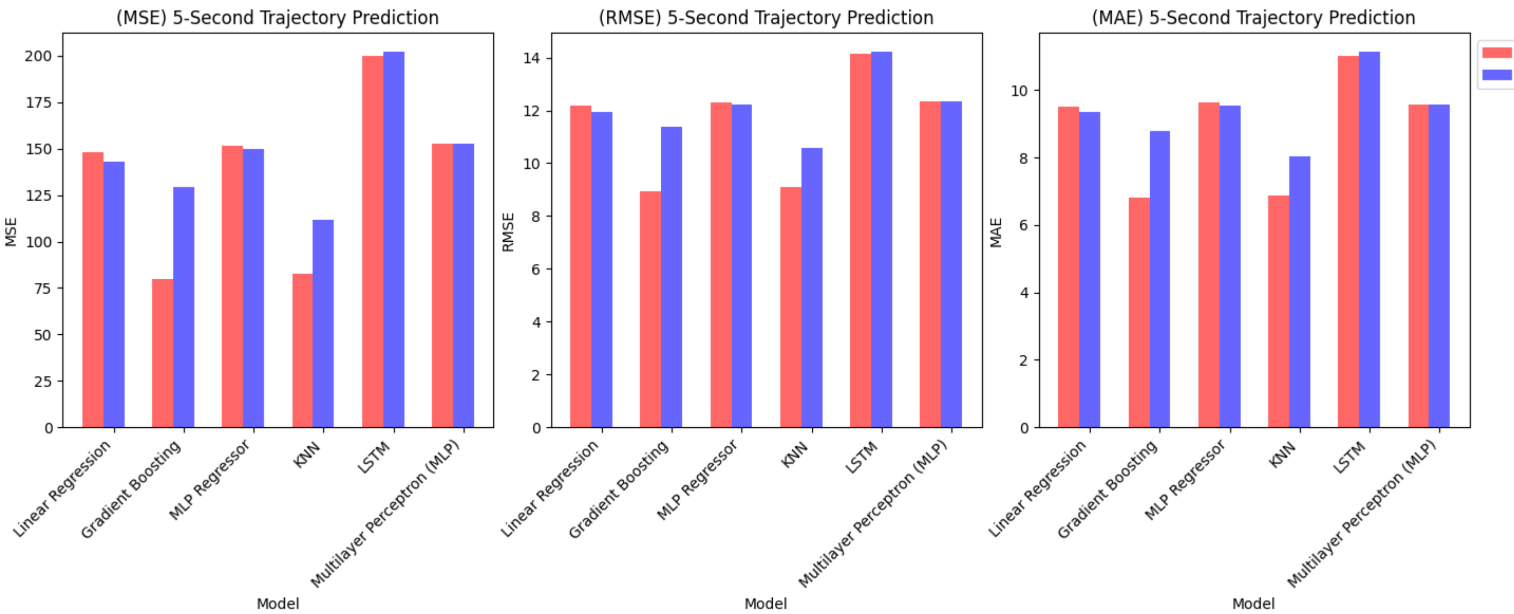

Figure 4: 5-second trajectory predictions

5.3 Performance of Deep Learning Models

LSTM: Performs reasonably well, exhibiting MSE values of 51.188 (train) and 57.099 (test), and RMSE values of 7.154 (train) and 7.556 (test) for the 1-second prediction. For the 5-second prediction, it achieved MSE values of 199.81 (train) and 202.21 (test), and RMSE values of 14.14 (train) and 14.22 (test). While it falls short in achieving the superior performance seen in ensemble methods like Gradient Boosting, it still shows good results.

Multilayer Perceptron (MLP): Shows performance similar to LSTM, with MSE values of 35.751 (train) and 37.851 (test), and RMSE values of 5.979 (train) and 6.152 (test) for the 1-second prediction. For the 5-second prediction, it achieved MSE values of 152.80 (train) and 152.86 (test), and RMSE values of 12.36 (train) and 12.36 (test). While it demonstrates the capability to capture complex patterns, it does not outperform other models.

5.4 Model Generalization and Overfitting

Several models exhibit signs of overfitting, particularly Random Forest, where there is a notable increase in error metrics on the test set compared to the train set. This suggests the need for regularization techniques or hyperparameter tuning to improve generalization. Gradient Boosting stands out for its ability to generalize well to unseen data, as evidenced by its consistent performance on both train and test sets.

5.5 Implications for Future Research

Further investigation into ensemble methods like Gradient Boosting could yield insights into their robustness and generalization ability in trajectory prediction tasks. Exploring advanced deep learning architectures or ensemble techniques tailored for trajectory prediction may lead to improved performance and more accurate models. Investigating feature engineering techniques and data preprocessing methods could enhance the predictive power of existing models, especially in capturing the intricate spatial dynamics of UAV trajectories.

5.6 Future Directions

Incorporating domain-specific knowledge or additional contextual features into the modeling process could enhance the accuracy and interpretability of trajectory prediction models. Conducting comparative studies with larger and more diverse datasets can provide a comprehensive understanding of the strengths and limitations of different modeling approaches in UAV trajectory prediction tasks. Overall, the results highlight the importance of selecting appropriate modeling techniques and the potential for ensemble methods like Gradient Boosting to achieve superior performance in UAV trajectory prediction tasks.

6 Future Work

In our ongoing research, we are committed to enhancing the performance and versatility of our trajectory prediction models. One avenue for improvement involves introducing variability in altitude, speed, and acceleration parameters within individual UAVs, reflecting the diverse scenarios encountered in real-world applications. By incorporating dynamic attributes for these parameters, our models will be better equipped to adapt to a wider range of environmental conditions and operational requirements.

Furthermore, we plan to explore advanced machine learning techniques and algorithms to refine the accuracy and efficiency of our predictions. Leveraging state-of-the-art methodologies such as reinforcement learning, and attention mechanisms holds promise for achieving superior performance in trajectory forecasting tasks.

Through these efforts, we aim to develop robust and adaptive UAV trajectory prediction models capable of addressing the evolving challenges and demands of modern aerial communication networks.

7 Conclusion

In conclusion, our research demonstrates the feasibility and effectiveness of employing a range of machine learning and deep learning-based trajectory prediction models to enhance handover control in UAV cellular networks. Through a comprehensive evaluation of various algorithms, including linear regression, Gradient Boosting, MLP regressor, KNN, LSTM, and Kalman filter, we have shown significant advancements in predicting UAV trajectories.

Our findings reveal that among the tested models, Gradient Boosting exhibits superior performance in trajectory prediction, significantly surpassing traditional methods like linear regression and MLP regressor. It achieves lower MSE, RMSE, and MAE values, indicating higher accuracy and better predictive capabilities. These models enable proactive handover decision-making, leading to seamless connectivity and improved network performance in UAV cellular networks.

Furthermore, our study highlights the importance of selecting appropriate modeling techniques and demonstrates the potential for ensemble methods like Gradient Boosting to achieve superior performance in UAV trajectory prediction tasks. This approach addresses the limitations of traditional handover methods by leveraging the advanced capabilities of machine learning and deep learning, offering a promising solution to the critical challenge of efficient handover control in UAV networks.

Overall, our research contributes to the advancement of aerial communication networks by providing practical insights and methodologies for optimizing UAV movement modeling and handover control strategies. With further refinement and validation, our proposed approach has the potential to revolutionize the deployment and operation of UAVs in cellular networks, paving the way for enhanced connectivity and coverage in various applications.

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