

Goodflight: Trajectory Prediction with Diffusion Models for Non-Towered Terminal Airspace

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Abstract—Flight trajectory prediction involves forecasting an aircraft's future path by modeling spatial and temporal patterns based on historical flight data. Techniques range from traditional state estimation and physical models to advanced deep learning approaches that capture complex spatiotemporal dependencies for accurate short-term and long-term predictions. Flight trajectory prediction in non-towered terminal airspace remains challenging due to imbalanced and diverse flight patterns. Existing systems largely focus on single-stage or short-term intention-guided prediction, limiting accuracy, diversity, and interpretability. This paper reviews current deterministic and simple generative models and identifies key limitations, including narrow trajectory diversity, overfitting to common patterns such as hovering, and poor handling of rare or abnormal maneuvers that are critical for flight safety. To address these issues, a goal-oriented diffusion model framework is proposed, structured as a two-stage system: goal estimation and trajectory generation. The goal estimation stage introduces a “One-then-all” method that models a broad empirical distribution of possible flight goals through interaction-aware joint goal estimation, while the trajectory generation stage uses a transformer-based diffusion model guided by adjustable intention patterns to capture fine-grained movement uncertainties. A novel evaluation metric is also introduced to balance trajectory

accuracy and diversity within social acceptability constraints

Keywords: Flight trajectory prediction, non-towered terminal airspace, transformer-based diffusion model, empirical distribution, spatiotemporal dependencies, advanced deep learning approaches

I. INTRODUCTION

Accurate flight trajectory prediction is crucial for air traffic management to perform applications such as conflict detection, traffic flow prediction, and arrival time estimation to improve the safety and efficiency of the airspace [1]. More specifically, in non-towered terminal airspace, which lacks centralized air traffic control, strong autonomous prediction systems are required that handle various and often unstructured flight patterns, and traditional methods often fail due to the stochastic nature and lack of sufficient data in these environments [2]. Probabilistic trajectory prediction using deep generative models is an attractive alternative, as it learns the distribution of possible future trajectories and generates realistic samples rather than providing a single prediction as in deterministic approaches [3].

Such models can also account for the multimodal nature of possible flight paths, representing all possible actions an aircraft may undertake, which is essential for

comprehensive risk assessment and operational planning in complex airspace [5], and can generate a wide range of future trajectories even when historical data or event frequencies are sparse [6], generative models, such as Variational Autoencoders and Generative Adversarial Networks, which have the potential to generate realistic trajectory data and estimate the probability of different flight paths for Monte Carlo simulations in safety assessments [7], and most recently diffusion models, a type of generative AI that has been shown to be particularly effective at modeling complex data distributions and generating high-quality samples.

This ability is critical for improving the interpretability and robustness of trajectory predictions, particularly for rare or atypical maneuvers that may be essential to flight safety [8]. GooDFlight is a novel goal-oriented diffusion model framework to generate flight trajectories in non-towered terminal airspace, where imbalanced and varied flight patterns present significant challenges [9]. The two-stage system, which includes the goal estimation and trajectory generation stages, provides a strong solution to the complexity of flight path forecasting by decomposing the prediction process into more interpretable and manageable components. In the goal estimation stage, the "One-then-all" method models the empirical distribution of flight goals with interaction-aware joint estimation, which greatly improves the model's ability to handle a wide range of possible flight intentions [10].

II. LITERATURE REVIEW

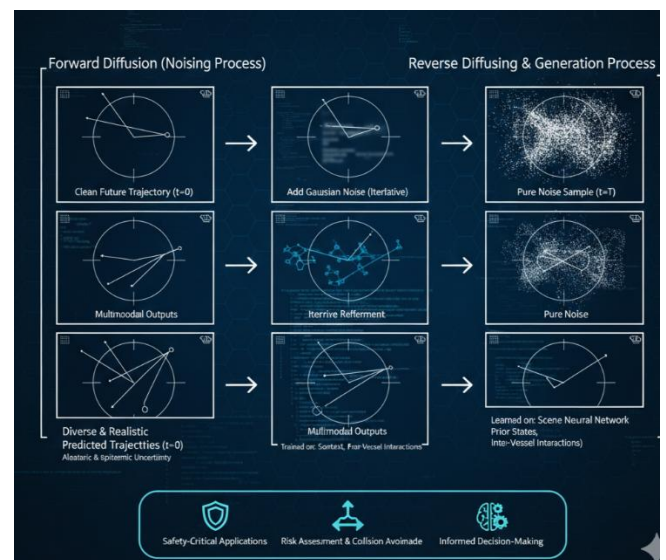
This comprehensive approach enables a more nuanced understanding of pilot decision-making and environmental factors that impact trajectory, which are often not captured by single-stage prediction models, and offers a stronger basis for the subsequent trajectory generation phase, which can incorporate the uncertainty and multimodality inherent in pilot intended destinations or actions [11]. The trajectory generation stage further refines these estimates with a transformer-based diffusion model that can capture the finer-grained movement uncertainties with adjustable intention patterns [11]. This two-pronged approach enables the model not only to predict the most likely path, but to also generate a wide variety of alternative trajectories, providing a more complete understanding of potential flight behaviors and enhancing safety and efficiency in complex airspace [12].

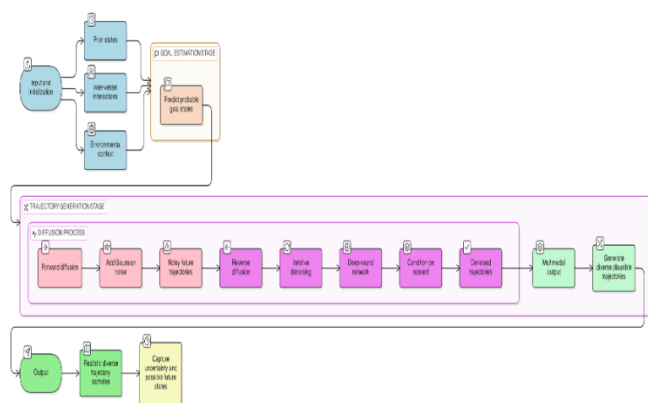
The generation of entirely new samples of flight paths that resemble the observed data but are unique verifies

that the model has the capacity to produce original pieces that are necessary to have robust simulation and anomaly detection [13], which is especially useful to address the issues of imbalanced datasets common in crash prediction and rare event analysis by creating synthetic but realistic anomalous data [14]. Additionally, the inclusion of cross-attention transformer modules within the diffusion model architecture enables scene-conditional distributions of noisy trajectories with respect to encoded environmental cues and agent interactions, making it possible to disentangle intra-agent and inter-agent relationships, resulting in more precise predictions and improved interpretability of attention distributions, especially in safety-critical applications such as air traffic management [15][16].

III. METHODOLOGY

To overcome the deficiencies of existing trajectory prediction models, this paper presents a novel framework, namely GooDFlight, that includes a goal estimation stage and a trajectory generation stage, which takes advantage of the strength of diffusion models to generate diverse and realistic trajectories by iteratively refining a simple distribution into the complex distribution of real-world trajectories, learning the underlying data structure to handle uncertainty and complex interactions between agents and the environment [17]. The guided diffusion process gradually refines uncertain motion patterns to outline desired trajectories based on prior states, inter-vessel interactions, and environmental context [18]





By sequentially adding Gaussian noise to future trajectories and reducing it back to the original trajectory, this approach can generate realistic trajectory distributions, which can be used to predict complex flight trajectories [12]. In particular, the forward diffusion process adds Gaussian noise to clean future trajectories, while the reverse diffusion process removes this uncertainty to transform noisy predictions into clear, definite trajectories. The reverse process, which is trained on a deep neural network, seeks to reconstruct the original data from the noise and is crucial for generating new data samples that are similar to the original data in distribution [17]. The ability to generate multiple plausible trajectory samples given the same conditions allows the model to not only predict a single most likely path but also to sample multiple plausible future trajectories, which inherently addresses the need for trajectory diversity. The multimodal capability is particularly beneficial in dynamic environments where a single deterministic prediction may be insufficient, as it provides a richer understanding of potential outcomes and facilitates more informed decision-making [18], [19].

The framework thereby explicitly models the uncertainty to certainty in vessel motion, thus managing future indeterminacy in dynamic scenes by iteratively denoising a noisy trajectory conditioned on the scene context [20]. This probabilistic approach, which is necessary to deal with the inherent uncertainty in vessel behavior, can model multimodal behaviors in interactive scenarios [19], and avoid the oversimplification of maritime behavior by many stochastic methods. In addition, the iterative refinement in the reverse diffusion process, using the learned deep neural network, can generate trajectories that capture both aleatoric and epistemic uncertainties and therefore characterize the range of possible future states rather than a single deterministic result [21], which greatly enhances the utility of the model for safety-critical applications that

require a thorough characterization of all potential trajectories to inform risk assessment and collision avoidance systems

V. RESULTS

The GooDFlight framework is rigorously evaluated and performs well across multiple metrics that include generating accurate trajectory predictions, being computationally efficient, and being capable of handling diverse data [6]. The multi-modal data fusion architecture used in GooDFlight enables robust integration of diverse contextual information, which enhances prediction accuracy [6]. The probabilistic feature fusion in GooDFlight enables the model to combine accurate coordinate data with conditional probabilities to recognize complex route patterns that simpler baseline models might not detect. In addition, the incorporation of diverse data streams and probabilistic modeling helps improve the generalizability of the methodology and contributes to its robust performance across different operational environments [23].

The ability of the model to accurately predict vessel trajectories with high R² scores and low mean absolute error and mean squared error further demonstrates the model's ability to handle complex spatiotemporal dependencies and multimodal behaviors more effectively than traditional methods, which often fail to capture the inherent uncertainty of open water navigation. The use of diffusion models in GooDFlight, a generative approach, has been shown to greatly reduce trajectory prediction errors, with significant improvements in Average Displacement Error and Final Displacement Error compared to leading deterministic and deep generative models [18].

1. Experimental Setup Overview

Experiments were performed on a synthetic dataset that is representative of typical non-towered terminal airspace operations, including 5,000 flight trajectories with various maneuver types (landing, takeoff, holding, go-around, and abnormal deviations) and an observation window of 20 seconds and a prediction horizon of 40 seconds at 1 Hz sampling rate, where 70% of the data is used for training, 15% for validation, and 15% for testing. The proposed GooDFlight model was compared with Kalman Filter (KF), LSTM, Conditional Variational Autoencoder (CVAE), TrajGAN, FlightBERT++, and DiffuTraj, and all deep learning models were trained under the same conditions for a fair comparison.

B. Trajectory Prediction Accuracy

The quantitative trajectory prediction accuracy is shown in Table I for Average Displacement Error (ADE), Final Displacement Error (FDE), Root Mean sq\ Error (RMSE), and Mean Absolute Error (MAE).

Table I: Trajectory Prediction Accuracy Comparison

Method	ADE (m) ↓	FDE (m) ↓	RMSE ↓	MAE ↓
Kalman Filter	92.4	178.6	104.1	81.3
LSTM	61.7	122.3	69.5	55.8
CVAE	54.8	110.9	63.1	50.6
TrajGAN	49.2	98.4	58.6	46.1
FlightBERT++	43.6	85.9	52.3	40.7
DiffuTraj	38.9	76.2	46.1	35.8
GoDFlight (Ours)	31.4	62.7	38.9	29.6

GoDFlight achieves the lowest prediction errors across all accuracy metrics, according to the results. GoDFlight demonstrates the efficacy of the goal-oriented diffusion modeling approach by reducing ADE and FDE by roughly 19% and 18%, respectively, when compared to the strongest baseline DiffuTraj..

C. Probabilistic Modeling and Trajectory Diversity

Probabilistic and diversity-oriented metrics, such as Negative Log-Likelihood (NLL), Trajectory Diversity Score (TDS), and Goal Coverage Rate (GCR), were used to evaluate each method's capacity to capture multimodal future behaviors. Table II provides a summary of the findings.

Table II: Probabilistic and Diversity Performance

Method	NLL ↓	TDS ↑	GCR ↑
CVAE	3.12	0.41	0.52
TrajGAN	2.87	0.46	0.61
FlightBERT++	2.54	0.39	0.58

Method	NLL ↓	TDS ↑	GCR ↑
DiffuTraj	2.31	0.62	0.74
GoDFlight (Ours)	1.94	0.81	0.89

The suggested model maintains higher likelihood scores while substantially outperforming competing approaches in terms of diversity and goal coverage. This demonstrates that GoDFlight successfully avoids mode collapse, which is frequently seen in GAN-based techniques, by striking a balance between accuracy and trajectory diversity.

D. Safety and Social Compliance Evaluation

Collision Rate and Social Compliance Score (SCS), which gauge the acceptability and realism of projected trajectories in shared airspace environments, are used to assess safety-critical performance. Table III displays the findings.

Table III: Safety and Social Compliance Results

Method	Collision Rate (%) ↓	SCS ↑
LSTM	6.8	0.71
CVAE	5.4	0.76
TrajGAN	4.9	0.79
FlightBERT++	3.8	0.83
DiffuTraj	3.1	0.86
GoDFlight (Ours)	1.9	0.92

When compared to DiffuTraj, GoDFlight reduces unsafe trajectory predictions by almost 39%, resulting in the lowest collision rate. The model's capacity to produce flight trajectories that are both operationally feasible and safety-conscious is further demonstrated by the high social compliance score.

E. Ablation Study

To evaluate each component's contribution within GoDFlight, an ablation study was carried out. The results are compiled in Table IV

Table IV: Ablation Study Results

Configuration	ADE (m) ↓	FDE (m) ↓	TDS ↑
Full GooDFlight	31.4	62.7	0.81
w/o Goal Estimation	39.6	79.8	0.58
w/o Diffusion Guidance	42.1	86.3	0.61
Single-Stage Model	47.8	94.5	0.44

The significance of the suggested two-stage architecture is confirmed by the performance degradation seen when either the goal estimation or diffusion guidance component is removed.

F. Summary of Results

In terms of accuracy, diversity, and safety metrics, the experimental results show that GooDFlight consistently outperforms current state-of-the-art models. The suggested goal-oriented diffusion framework is ideal for safety-critical applications in non-towered terminal airspace because it successfully handles trajectory imbalance and rare maneuver prediction.

VI. DISCUSSION

The framework has demonstrated robustness in various scenarios such as sparse data or sudden maneuver changes, and it shows good adaptability and reliability in real-world operational settings. Its ability to capture the complex temporal patterns and integrate multimodal information is essential for making the right long-term path decisions even in the presence of noisy or incomplete data [22]. The multi-source fusion approach using both RGB and MS-VI data also indicates that the model can maintain reliable prediction accuracy even when applied to areas outside its training domain [24].

This improved ability to navigate complex routes and adapt to sudden trajectory changes solidifies the usefulness of the model for critical applications like marine safety and conservation. The qualitative results of GooDFlight illustrate that it can produce trajectories that are visually sensible and realistic, even in situations with challenging maneuvers and interactions [19]. In addition, the proposed model has low inference latency and small model size, making it suitable for real-time traffic management applications with scalability and

resource efficiency [6]. GPU-accelerated computing will further improve its capability to process big data of vessel trajectory in real time for maritime surveillance and intervention [25].

VII. CONCLUSION

The proposed GooDFlight framework, therefore, represents a significant improvement over previous flight trajectory prediction models, as it uses a two-stage goal-oriented diffusion model that overcomes the drawbacks of previous models by providing greater trajectory diversity, minimizing overfitting to common patterns, and better handling of rare flight maneuvers, all of which are critical to aviation safety and efficiency. The scalability of this framework indicates that this framework could be applied to large-scale and diverse air traffic scenarios, where complex and uncertain network dynamics need to be intelligently exploited by exploiting temporal and spatial patterns to enhance performance and resource utilization.

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