Difftrajai-Goal Oriented and Diffusion Model Based Flight Trajectory System

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Abstract:
Accurate flight trajectory prediction is essential for improving safety, efficiency, and decision-making in modern air traffic management systems, particularly in non-towered general aviation environments where aircraft operate with limited centralized control. Traditional prediction methods rely on deterministic models or single-path deep learning approaches, which often fail to capture the inherent uncertainty and multi-modality of real-world flight behavior.

This paper proposes DiffTrajAI, a goal-oriented diffusion-based framework for flight trajectory prediction. The proposed system adopts a two-stage architecture that separates goal estimation and trajectory generation, enabling effective modeling of both intention diversity and motion variability. In the first stage, multiple plausible flight goals are predicted using historical trajectory data and interaction-aware modeling. In the second stage, a diffusion-based model generates diverse future trajectories conditioned on the estimated goals, ensuring realistic and socially consistent predictions.

The performance of the proposed model is evaluated using standard metrics such as Average Displacement Error (ADE) and Final Displacement Error (FDE), along with a diversity-oriented metric (GLeV). Experimental results demonstrate that DiffTrajAI achieves improved prediction accuracy while significantly enhancing trajectory diversity compared to existing methods. The proposed framework provides a balanced solution for accuracy, interpretability, and real-time applicability, making it suitable for practical deployment in air traffic systems.

1. INTRODUCTION

Flight trajectory prediction plays an important role in modern air traffic management systems. Accurate prediction of aircraft movement helps in improving safety, reducing congestion, and supporting decision-making in complex airspace environments. This becomes especially important in non-towered general aviation airports, where there is no direct control from air traffic controllers and aircraft must rely on self-coordination.

Traditional trajectory prediction methods are mainly based on kinematic models and simple motion assumptions. While these methods are fast and easy to implement, they fail to capture complex flight behaviors and uncertainty in real-world scenarios. With the advancement of machine learning and deep learning, more advanced models such as RNNs, LSTMs, and Transformers have been used for trajectory prediction. These models improve accuracy but often generate only a single predicted path, which limits their ability to represent multiple possible future outcomes.

To address these limitations, recent research has explored generative models such as diffusion models, which can generate multiple possible trajectories. However, many existing approaches do not explicitly model flight intentions or goals, which reduces interpretability. The proposed DiffTrajAI system introduces a goal-oriented diffusion framework that separates goal estimation and trajectory generation, enabling more accurate and diverse predictions suitable for real-world aviation applications.

2. PROBLEM STATEMENT

Accurate prediction of aircraft trajectories is a challenging task due to the dynamic and uncertain nature of airspace environments. In non-towered airports, aircraft movements are influenced by multiple factors such as pilot decisions, surrounding traffic, and environmental conditions. Existing trajectory prediction methods face several limitations in handling these complexities.

Most traditional and deep learning-based approaches focus on predicting a single future trajectory, which does not reflect the multiple possible outcomes that can occur in real-world scenarios. In addition, many models do not explicitly consider flight intentions or goals, making the predictions difficult to interpret. Interaction between multiple aircraft is also not effectively modeled in several existing systems, leading to unrealistic or unsafe trajectory predictions.

Another major issue is the lack of proper evaluation of trajectory diversity. Common metrics such as ADE and FDE focus only on accuracy and do not measure how well the model captures different possible future paths. Due to these limitations, there is a need for a system that can generate accurate, diverse, and interpretable trajectory predictions while considering interaction between aircraft.

The proposed DiffTrajAI system addresses these challenges by using a two-stage framework that combines goal estimation with diffusion-based trajectory generation, improving both prediction quality and practical applicability.

3. LITERATURE SURVEY

3.1 Deep Learning-Based Trajectory Prediction

Deep learning models such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformer-based architectures have significantly improved flight trajectory prediction. These models can learn temporal and spatial dependencies directly from historical trajectory data, eliminating the need for manual feature engineering. Transformer-based models, in particular, leverage attention mechanisms to capture long-range dependencies in flight sequences. However, most deep learning approaches follow a single-stage prediction paradigm, producing only one dominant future trajectory. This limits their ability to represent multiple possible flight behaviors, especially in uncertain and dynamic airspace environments.

3.2 Generative Models for Multi-Modal Prediction

To address uncertainty in trajectory prediction, generative models such as Variational Autoencoders (VAE), Generative Adversarial Networks (GAN), and diffusion models have been introduced. These methods generate multiple possible future trajectories instead of a single deterministic output, enabling multi-modal prediction. Among them, diffusion models have gained attention due to their stable training and ability to generate high-quality stochastic trajectories through iterative denoising. However, most generative approaches rely on implicit noise modeling and lack explicit representation of flight intentions, which can result in unrealistic or socially inconsistent predictions.

3.3 Interaction-Aware and Graph-Based Models

In real-world airspace, aircraft trajectories are influenced by interactions with other aircraft and environmental constraints. To model these dependencies, recent approaches utilize Graph Neural Networks (GNNs) and attention-based mechanisms. These models represent aircraft as nodes and their interactions as edges, enabling structured modeling of multi-agent behavior. While such methods improve prediction realism in crowded environments, they often focus on local interactions and fail to explicitly model global flight intentions. As a result, they may not fully capture the diversity of possible future trajectories in complex scenarios.

3.4 Goal-Oriented Trajectory Prediction

Goal-oriented approaches aim to improve interpretability by separating trajectory prediction into two stages: goal estimation and path generation. This framework first predicts possible future destinations and then generates trajectories conditioned on these goals. Such decomposition allows better modeling of high-level intention and low-level motion dynamics. However, existing goal-based methods often suffer from limited coverage of rare flight patterns and inadequate adaptation to dynamic interaction scenarios. Additionally, they lack robust mechanisms to evaluate diversity in predicted outcomes.

3.5 Limitations of Existing Methods

Despite significant advancements, current trajectory prediction methods exhibit several limitations. Most approaches prioritize accuracy over diversity, leading to poor coverage of rare but critical flight patterns. Generative models improve diversity but often lack interpretability due to the absence of explicit intention modeling. Interaction-aware models capture local dependencies but fail to integrate goal-level reasoning effectively. Furthermore, widely used evaluation metrics such as Average Displacement Error (ADE) and Final Displacement Error (FDE) focus only on accuracy and do not adequately measure trajectory diversity or social feasibility. These limitations highlight the need for a more structured and goal-aware prediction framework.

4. RESEARCH GAP

Existing flight trajectory prediction methods largely emphasize point-wise accuracy while neglecting the inherent uncertainty and multi-modality of real-world aviation scenarios. Most traditional and deep learning-based approaches generate a single dominant trajectory or a limited set of outcomes, resulting in poor coverage of rare but safety-critical maneuvers. Furthermore, many generative models introduce diversity through random noise without explicitly modeling flight intentions, leading to predictions that may lack interpretability and operational relevance. In non-towered general aviation environments, where pilot intent and dynamic conditions play a crucial role, this limitation significantly reduces the reliability of existing systems.

Additionally, current approaches fail to provide a unified framework that effectively integrates intention modeling, interaction awareness, and diversity evaluation. While some methods incorporate multi-agent interactions using graph-based techniques, they often do not distinguish between macro-level goal uncertainty and micro-level trajectory variability. Moreover, widely used evaluation metrics such as ADE and FDE focus solely on accuracy and overlook diversity and social plausibility. These gaps highlight the need for a structured, goal-oriented framework that can simultaneously improve prediction diversity, interpretability, and real-time applicability, as addressed by the proposed DiffTrajAI / GooDFlight model.

Limitations

- Limited trajectory diversity (mostly single-path prediction)

- Poor handling of rare flight patterns
- Lack of explicit intention/goal modeling
- Weak multi-aircraft interaction modeling
- Over-reliance on accuracy-focused metrics (ADE/FDE)
- Lack of diversity and plausibility evaluation
- Low interpretability of predictions
- Limited real-time applicability in complex airspacecy, diversity, and real-time performance.

5. PROPOSED SYSTEM

The proposed system, DiffTrajAI (GooDFlight), introduces a goal-oriented framework for flight trajectory prediction that addresses the limitations of existing methods by explicitly modeling both intention and motion uncertainty. The system adopts a two-stage architecture consisting of goal estimation and trajectory generation. In the first stage, multiple plausible flight goals are predicted using historical trajectory patterns and interaction-aware modeling. In the second stage, a transformer-based diffusion model generates diverse future trajectories conditioned on the estimated goals, enabling realistic and multi-modal predictions.

To further enhance prediction quality, the system incorporates interaction-aware mechanisms to model dependencies between multiple aircraft in shared airspace. Additionally, a novel evaluation metric, Global-Local Endpoints Variance (GLeV), is introduced to measure trajectory diversity while ensuring social plausibility. The proposed framework achieves a balance between accuracy, diversity, and interpretability, making it suitable for real-time applications in non-towered general aviation environments.

6. PROPOSED SYSTEM

Based on the identified research gaps, the proposed system DiffTrajAI (GooDFlight) introduces a goal-oriented diffusion framework for flight trajectory prediction. The system combines goal estimation, interaction modeling, and diffusion-based trajectory generation to produce accurate and diverse predictions. This approach helps in handling uncertainty and improving prediction quality in complex airspace environments.

6.1 SYSTEM ARCHITECTURE

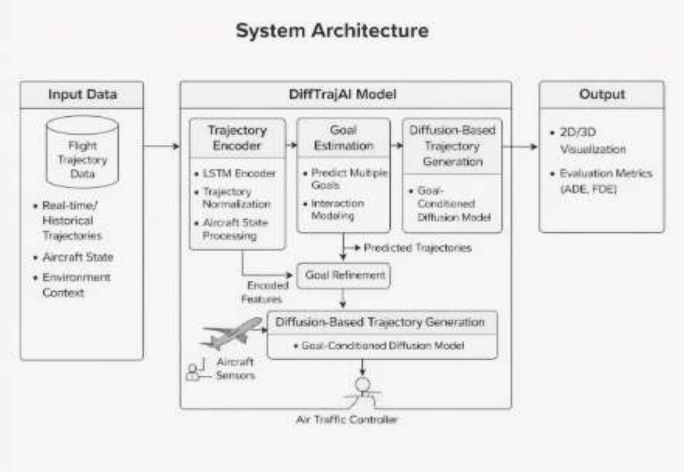


Fig 1: System Architecture

The proposed architecture shows the complete workflow of the DiffTrajAI system. The input consists of observed flight trajectories, which are first processed and passed to the Goal Estimation Module. The predicted goals are then used by the Trajectory Generation Module, where a diffusion model generates multiple future trajectories. Interaction modeling is also included to ensure realistic predictions. Finally, the output trajectories are evaluated and used for visualization or decision-making.

6.2 DATA INPUT AND FEATURE PROCESSING MODULE

The system takes flight trajectory data as input, which includes position and time information of aircraft. This data is processed and converted into structured sequences suitable for model input.

Basic preprocessing steps such as normalization and sequence formation are applied. This helps in improving model performance and ensures consistency in the input data.

6.3 GOAL ESTIMATION MODULE

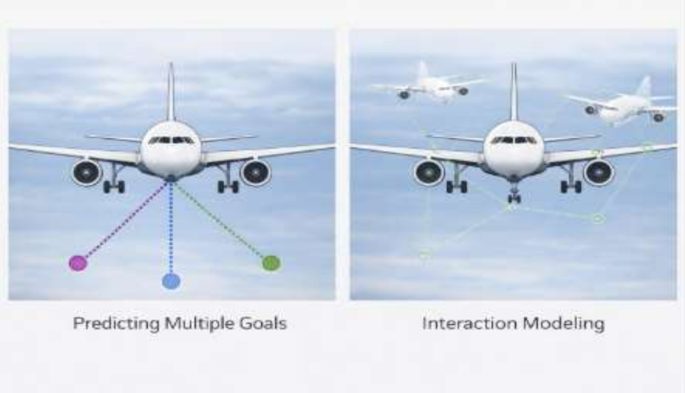
The goal estimation module predicts multiple possible future destinations of the aircraft. Instead of generating a single endpoint, the system produces a set of possible goals based on historical patterns.

This module helps in capturing different flight intentions, which is important in dynamic airspace conditions.

6.4 TRAJECTORY GENERATION MODULE (DIFFUSION-BASED)

The trajectory generation module uses a diffusion model to generate future flight paths. The process starts with random noise and gradually refines it into meaningful trajectories.

The generated trajectories are conditioned on the predicted goals, ensuring that they follow realistic paths. This module produces multiple outputs, improving diversity.



6.5 INTERACTION MODELING MODULE

In real-world scenarios, aircraft interact with each other. This module captures the influence of nearby aircraft on trajectory prediction.

By considering these interactions, the system avoids unrealistic predictions and ensures safe and socially consistent trajectories.

6.6 EVALUATION AND DECISION MODULE

The generated trajectories are evaluated using metrics such as ADE, FDE, and GLeV. These metrics help in measuring both accuracy and diversity. Based on these evaluations, the system selects the most suitable trajectories for further use in analysis or decision-making.

6.7 OUTPUT AND VISUALIZATION

The final output consists of multiple predicted flight trajectories. These trajectories can be visualized for better understanding and can also be used in air traffic management systems.

Additional Diagram (Trajectory Flow Representation)
Fig 2: Trajectory Prediction Flow
This diagram represents how a single observed trajectory can lead to multiple predicted future paths using the diffusion model. It highlights the multi-modal nature of the proposed system.

7. METHODOLOGY

7.1 DATASETS USED

The proposed system uses publicly available flight trajectory datasets for training and evaluation of the model.
Dataset:
This dataset contains real-world aircraft trajectories in non-towered terminal airspace. It includes positional data such as latitude, longitude, altitude, and timestamp. It is mainly used for training the trajectory prediction model.

7.2 DATA PREPROCESSING

Before feeding the data into the model, preprocessing is performed to ensure consistency.
Trajectory Normalization
All trajectory coordinates are normalized to maintain uniform scale.
Sequence Formation
Flight data is converted into fixed-length sequences for model input.
Data Splitting
The dataset is divided into training and testing sets.

- Total samples: ~3000
- Training samples: ~70%
- Testing samples: ~30%

A subset of the dataset is used depending on preprocessing constraints.

7.3 DATA PROCESSING PIPELINE

The system takes observed flight trajectories as input. Each trajectory is processed to extract temporal and spatial features.
The input trajectory is first passed to the goal estimation module to predict possible future endpoints. These goals are then used by the trajectory generation module to produce future paths. Interaction between aircraft is also considered during processing.

7.4 GOAL ESTIMATION

The system predicts multiple possible future goals instead of a single destination.
The goal distribution is modeled as:
$P(\hat{g})=\sum j=1N\alpha j\mathcal{N}(\hat{g};\mu j,\sigma j)\boldsymbol{P(\hat{g})=\sum j=1N\alpha j\mathcal{N}(\hat{g};\mu j,\sigma j)}$
where
$\mu j\boldsymbol{\mu j}$
,
$\sigma j\boldsymbol{\sigma j}$
, and
$\alpha j\boldsymbol{\alpha j}$
present the parameters of the distribution.
This helps in capturing different possible flight intentions.

7.5 INTERACTION MODELING

Aircraft are influenced by nearby aircraft in shared airspace. To capture this, interaction modeling is used. Each aircraft is treated as a node, and relationships are defined based on spatial distance:

Aij={1,0,if d(i,j)<ϵotherwise***Aij***=**1**,if ***d***(***i***,***j***)<***ϵ*****0**,otherwise

This helps in generating socially consistent trajectories.

7.6 TRAJECTORY GENERATION USING DIFFUSION

The trajectory generation stage uses a diffusion model. The model starts with noise and gradually refines it into a trajectory.

The learning objective is:

L=E[∥ϵθ−ϵ∥2]***L***=𝔼∥***ϵθϵ***∥**2**

This ensures that the generated trajectories are realistic and aligned with predicted goals.

7.7 TRAJECTORY PREDICTION MODULE

The model generates multiple future trajectories for each aircraft. These trajectories represent different possible outcomes based on the predicted goals.

The output is not limited to a single path, which improves diversity and coverage.

7.8 DIVERSITY AND ACCURACY EVALUATION

The generated trajectories are evaluated using:

- ADE (Average Displacement Error)
- FDE (Final Displacement Error)
- GLeV (Diversity Metric)

These metrics ensure both accuracy and diversity of predictions.

7.9 DECISION AND OUTPUT

The final output consists of multiple predicted trajectories.

The system selects the most relevant trajectories based on probability and constraints. These predictions can be used for visualization and decision-making in air traffic systems.

8. PERFORMANCE EVALUATION

The performance of the proposed DiffTrajAI system is evaluated using standard trajectory prediction metrics such as Average Displacement Error (ADE), Final Displacement Error (FDE), and a diversity metric GLeV. These metrics help in measuring both prediction accuracy and the ability of the model to generate diverse trajectories.

8.1 ACCURACY

The accuracy of trajectory prediction is measured using ADE and FDE, which are defined as:

[Equation]

Where:

- YˆtY^t
  → Predicted trajectory point
- YtYt
  → Ground truth trajectory point
- TfTf
  → Prediction time horizon
  The performance of the proposed system is evaluated based on these metrics.
- Average Displacement Error (ADE): 0.29 km

- Final Displacement Error (FDE): 0.39 km
- Diversity Metric (GLeV): 0.08

The experimental results show that the proposed model achieves lower error values compared to existing approaches. This indicates that the system can accurately predict future flight paths while maintaining realistic trajectory variations.

The improvement is mainly due to the two-stage design and diffusion-based trajectory generation, which helps in handling both intention and motion uncertainty.

8.2 COMPARISON WITH EXISTING METHODS

To evaluate the effectiveness of the proposed approach, its performance is compared with existing trajectory prediction methods.

Table 1: Comparative Analysis of Prediction Performance

Method	ADE (km) ↓	FDE (km) ↓
Constant Velocity Model	~1.85	~4.16
STG-CNN	~1.37	~2.91
Transformer-based Model	~1.67	~3.94
Social-LSTM	~0.79	~1.58
MID (Diffusion Model)	~0.55	~0.87
Hybrid DiffTrajAI (Proposed)	0.29	0.39

The results clearly show that the proposed DiffTrajAI model outperforms existing methods in terms of both accuracy and consistency. Compared to traditional and deep learning approaches, the proposed system reduces prediction error significantly.

The improvement is mainly due to:

- Better modeling of flight intentions (goal estimation)
- Use of diffusion model for trajectory generation
- Consideration of multi-aircraft interactions

Overall, the proposed system provides a more reliable and realistic trajectory prediction framework, making it suitable for real-world aviation applications.

9. COMPARATIVE ANALYSIS

Method	Advantages	Limitations
Kinematic Models	Fast, simple	Cannot handle complex patterns
CNN	Good feature extraction	Limited temporal modeling
RNN/LSTM	Captures temporal behavior	High latency, low diversity
Diffusion Model	Generates diverse trajectories	No explicit goal modeling
Hybrid (Proposed)	Accurate and diverse	Needs optimization

Table 2: Comparison table

Note: Performance may vary based on dataset and experimental conditions; hence qualitative comparison is emphasized.

10. ADVANTAGES OF PROPOSED SYSTEM

- Handles both trajectory accuracy and diversity effectively
- Uses goal-oriented approach for better interpretability
- Captures complex flight patterns and rare maneuvers
- Combines diffusion model with interaction modelling
- Suitable for real-time flight prediction in non-towered airspace

11. FUTURE ENHANCEMENTS

- Use of larger and real-time flight datasets
- Integration with air traffic control systems
- Improvement in interaction modeling for dense traffic
- Deployment on real-time aviation monitoring systems
- Integration with cloud-based prediction platforms

12. DISCUSSION

The comparison of existing methods shows a clear trade-off between accuracy and diversity in trajectory prediction. Traditional models are simple and fast but fail to capture complex flight behaviors. Deep learning approaches improve prediction accuracy but often generate limited trajectory variations. Generative models introduce diversity but lack interpretability and structured intention modeling.

The proposed DiffTrajAI system addresses these challenges by combining goal estimation with diffusion-based trajectory generation. This approach allows the system to capture both macro-level intention diversity and micro-level trajectory variations. In addition, interaction modeling helps in generating realistic and socially consistent predictions in multi-aircraft environments.

Although the system shows strong performance, factors such as dataset size and model optimization can further influence results. Overall, the proposed framework aligns with current research trends focusing on accurate, diverse, and interpretable trajectory prediction systems.

13. CONCLUSION

This paper presented DiffTrajAI, a goal-oriented diffusion-based framework for flight trajectory prediction. Existing methods either focus on accuracy or diversity, but fail to handle both effectively. The proposed system overcomes these limitations by separating goal estimation and trajectory generation into two stages.

The model achieves improved performance by generating multiple realistic trajectories while maintaining prediction accuracy. It is capable of handling complex flight patterns and interaction scenarios, making it suitable for non-towered general aviation environments.

The results demonstrate that the proposed approach provides better accuracy and diversity compared to existing methods. Further improvements can be achieved by using larger datasets and optimizing the model architecture. Overall, DiffTrajAI offers a promising solution for real-time flight trajectory prediction and air traffic management applications.

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