ASCENT: Transformer-Based Aircraft Trajectory Prediction in Non-Towered Terminal Airspace

Alexander Prutsch   David Schinagl   Horst Possegger

{alexander.prutsch, david.schinagl, possegger}@tugraz.at

Institute of Visual Computing

Graz University of Technology, Austria

Project Page   Code

Motivation

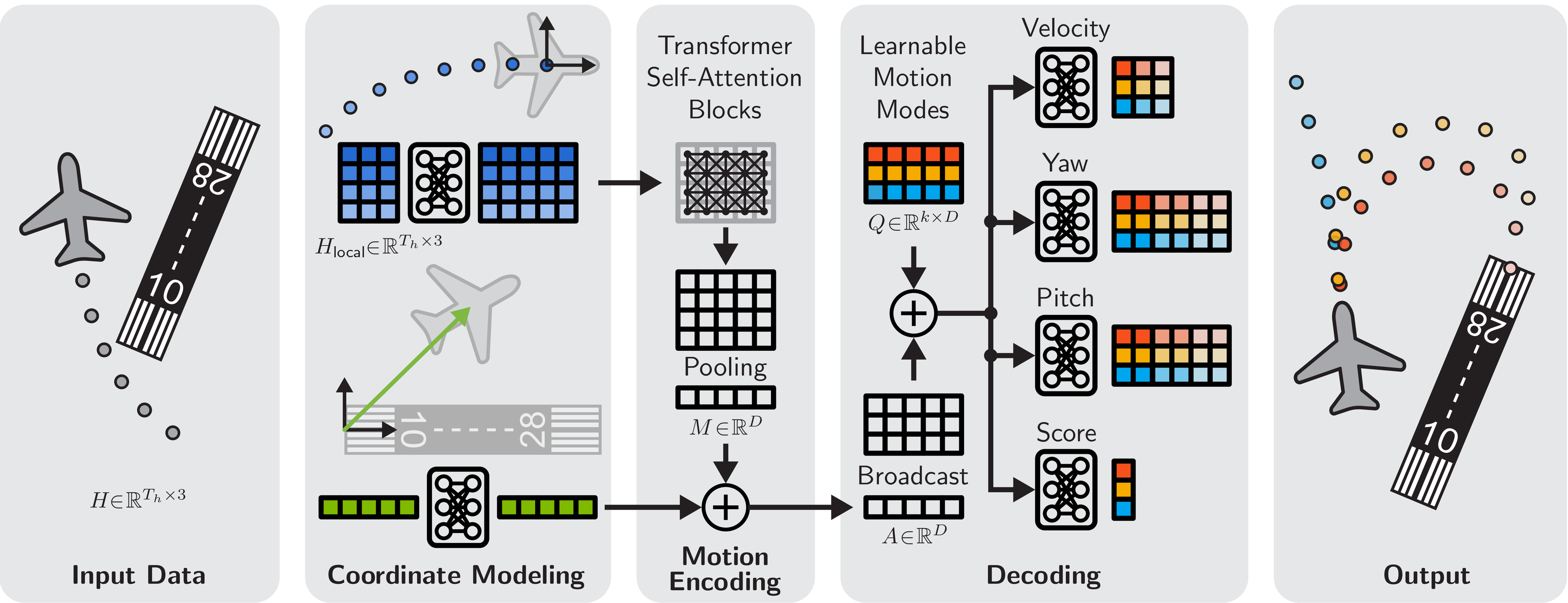
- **General Aviation** represents majority of aircraft, frequently operating between non-towered airports without active Air Traffic Control (ATC)
- **Accident rate** in General Aviation (especially near airports) is ∼30x higher than in Commercial Aviation—**Accurate trajectory prediction** is crucial for early conflict detection and improving airspace safety systems in these unmanaged areas
- Sophisticated prediction models from autonomous driving research cannot be directly applied due to **distinct domain differences**:
  - Aircraft do not strictly follow lanes; flight paths are defined by runways and airspace procedures
  - Aircraft operate in complex 3D space, whereas for vehicles 2D bird's-eye-view modeling is sufficient

Contributions

- Novel transformer-based architecture specifically tailored to the **unique challenges** of 3D aircraft trajectory prediction
- Achieves a new **state-of-the-art** on the widely used **TrajAir dataset** [4] across multiple evaluation settings, *e.g.*, input sequence length
- First results and cross-dataset evaluations on **TartanAviation** [5]
- Extensive ablation studies demonstrating the **effectiveness of the proposed model design**

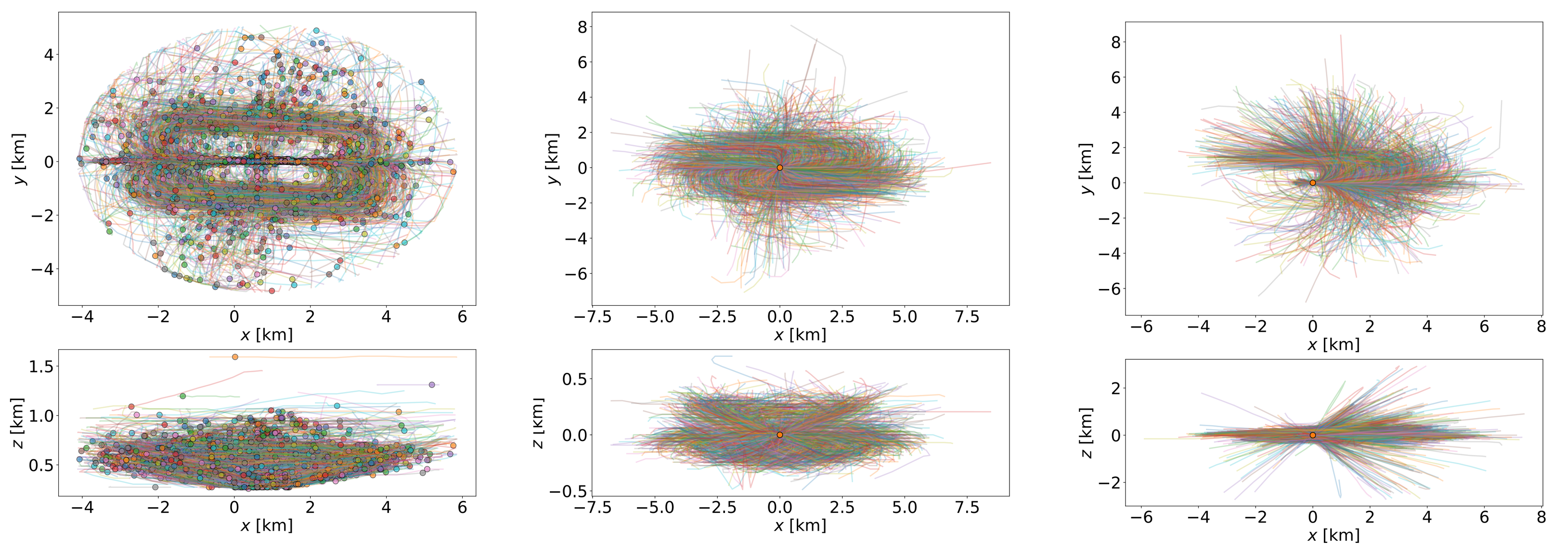
ASCENT: Aircraft Sequence Encoding Transformer

- **Agent-Centric Positional-Angular Coordinate Normalization** to learn local maneuvers (*e.g.*, turns and climbs) without global position bias
- To preserve global context (like runways), we use a **custom 3D positional embedding** using the 3D position along with the orientation angles
- **Motion encoder** outputs motion feature vector from observations
- To generate multi-modal predictions, the decoder broadcasts the encoded motion feature and adds k **learnable mode queries**. An MLP then decodes the probability scores for each candidate trajectory
- Instead of predicting raw 3D coordinates, the decoder forecasts **kinematic flight parameters** (speed, yaw and pitch)



Coordinate Normalization

Global Coordinates   Agent-centric Positional   Agent-centric Positional-Angular

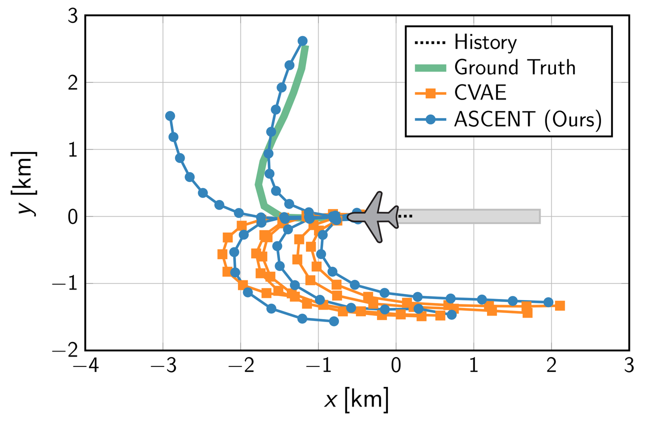


TrajAir Results

Input: 11 s Method	7Days-Avg minADE$_5$	minFDE$_5$
Constant Velocity	1.86	4.21
TransformerTF [1]	1.76	4.13
STG-CNN [3]	1.26	2.50
TrajAirNet [4]	0.78	1.55
ASCENT	**0.35**	**0.58**

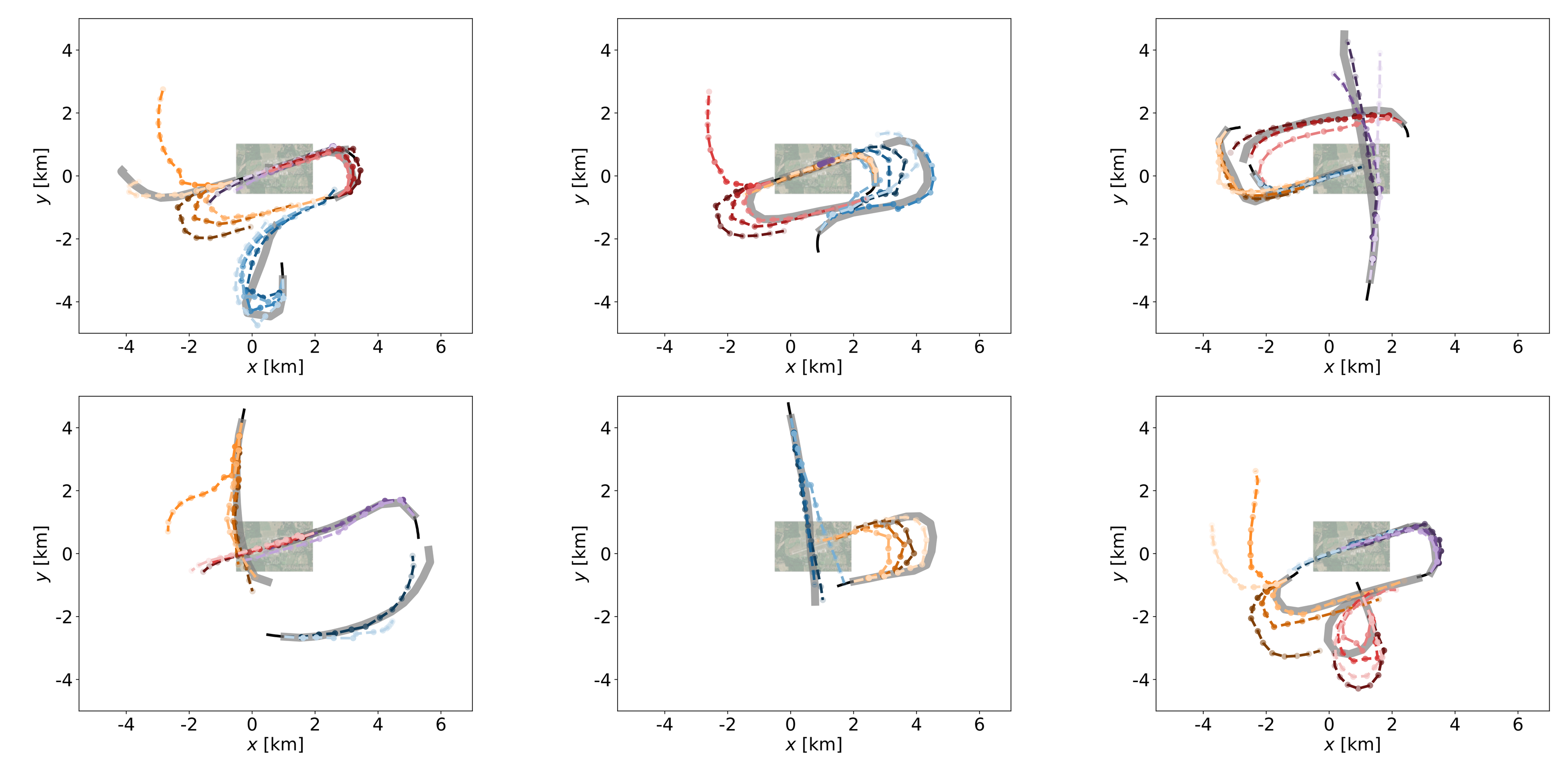
Input: 16 s Method	7Days-Avg minADE$_5$	minFDE$_5$
Constant Velocity	1.70	4.08
TrajAirNet [4]	0.75	1.47
MID [2]	0.61	1.13
Expert-Traj [9]	0.57	1.06
LBA [10]	0.50	0.92
ATP [8]	0.49	0.89
CoATP (Abs. Loc.) [7]	0.50	0.88
ASCENT	**0.33**	**0.59**

Input: 40 s Method	111Days minADE$_{20}$	minFDE$_{20}$
Constant Velocity	1.85	4.16
TransformerTF [1]	1.67	3.94
STG-CNN [3]	1.37	2.35
TrajAirNet [4]	0.79	1.58
MID [2]	0.55	0.87
Expert-Traj [9]	0.55	0.72
GooDFlight [6]	0.29	0.39
ASCENT	**0.19**	**0.26**



Output trajectory prediction horizons are *120 s*

Qualitative Results (TrajAir)



Black: *11 s* input; Gray: *120 s* ground truth; Colored: Predictions

Ablation Study (TrajAir)

Decoder Architecture	Coordinate System	Normalization Pos.	Normalization Ang.	Pos. Embed.	Flight Parameter Prediction	7Days-Avg mADE$_5$	mFDE$_5$
CVAE Baseline	Local	✓	✓	✗	✗	0.68	1.33
Mode Queries	Local	✓	✓	✗	✗	0.52	0.98
CVAE Baseline	Global	–	–	–	–	0.48	0.82
CVAE Baseline	Local	✓	✓	✓	✗	0.44	0.80
Mode Queries	Global	–	–	–	–	0.38	0.60
Mode Queries	Local	✓	✗	✓	✗	0.36	0.60
Mode Queries	Local	✓	✓	✓	✗	**0.35**	0.60
Mode Queries	Local	✓	✗	✓	✓	0.37	**0.58**
Mode Queries	Local	✓	✓	✓	✓	**0.35**	**0.58**

TartanAviation Results

Input: 11 s Method	KBTP S1 mADE$_5$	KBTP S1 mFDE$_5$	KBTP S2 mADE$_5$	KBTP S2 mFDE$_5$	KAGC S1 mADE$_5$	KAGC S1 mFDE$_5$	KAGC S2 mADE$_5$	KAGC S2 mFDE$_5$
Constant Velocity	1.83	3.91	1.77	3.80	1.77	3.78	1.86	3.96
ASCENT	**0.36**	**0.60**	**0.32**	**0.56**	**0.47**	**0.72**	**0.50**	**0.75**

Cross Dataset Experiments

Train Dataset	Test Dataset	minADE$_5$	minFDE$_5$
TrajAir 111days	TartanAv. KBTP S1*	0.33	0.58
TrajAir 111days	TartanAv. KBTP S2*	0.36	0.60
TartanAv. KBTP S1	TrajAir 111days	0.32	0.57
TartanAv. KBTP S2	TrajAir 111days	0.33	0.57

*Filtered to trajectories within the 5 km TrajAir recording radius around the airport

References & Acknowledgments

[1] F. Giuliari et al. "Transformer Networks for Trajectory Forecasting". *ICPR*. 2021.
[2] T. Gu et al. "Stochastic Trajectory Prediction via Motion Indeterminacy Diffusion". *CVPR*. 2022.
[3] A. Mohamed et al. "A Social Spatio-Temporal Graph Convolutional Neural Network for Human Trajectory Prediction". *CVPR*. 2020.
[4] J. Patrikar et al. "Predicting Like A Pilot: Dataset and Method to Predict Socially-Aware Aircraft Trajectories in Non-Towered Terminal Airspace". *ICRA*. 2022.
[5] J. Patrikar et al. "Image, Speech, and ADS-B Trajectory Datasets for Terminal Airspace Operations". *Scientific Data* (2025).
[6] S. Yang et al. "GooDFlight: Goal-Oriented Diffusion Model for Flight Trajectory Prediction". *IEEE Transactions on Aerospace and Electronic Systems* (2025).
[7] Y. Yin et al. "Context-Aware Aircraft Trajectory Prediction With Diffusion Models". *ITSC*. 2023.
[8] Y. Yin et al. "Aircraft Trajectory Prediction in Terminal Airspace With Intentions From Local History". *Neurocomputing* (2025).
[9] H. Zhao and R. Wildes. "Where Are You Heading? Dynamic Trajectory Prediction With Expert Goal Examples". *CVPR*. 2021.
[10] Y. Zhong et al. "Aware of the History: Trajectory Forecasting with the Local Behavior Data". *ECCV*. 2022.

This work received funding from the Take Off programme under the project SAFER (894164). Take Off is a research, technology and innovation funding programme of the Republic of Austria, Federal Ministry for Climate Action, Environment, Energy, Mobility, Innovation and Technology. The Austrian Research Promotion Agency (FFG) has been authorised for the programme management.