Flight Trajectory Prediction Based on Hybrid-Recurrent Networks

Cognitive Communications for Aeronautical Applications (CCAA) Workshop 2021
Cleveland, OH
June 21-23, 2021

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Outline

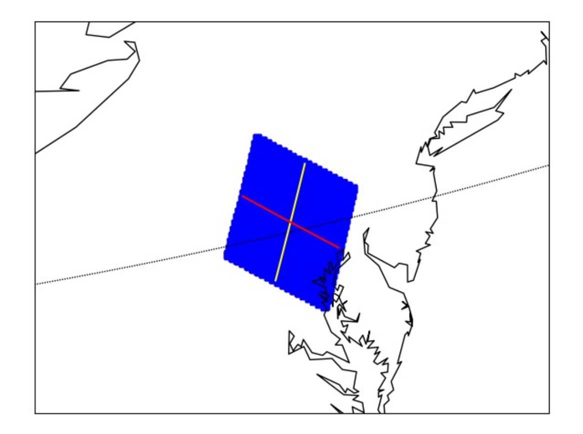
- Context
- Formulation
- Weather Data Selection
- Model Design Improvements
- Conclusions

Context

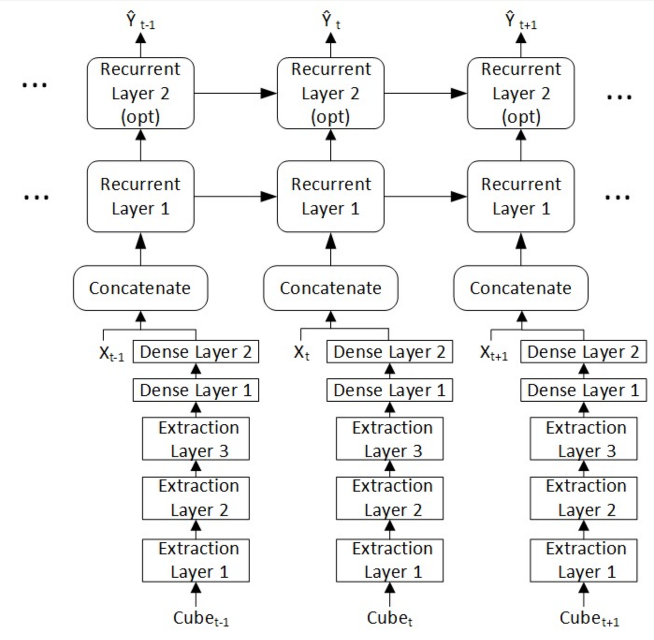
- Dynamic Spectrum Access
  - Anticipated proliferation and diversification of aircraft
  - Limited, static allocation of spectrum
  - NASA Glenn Research Center initiative for machine-learning solutions
  - Limitation of available, relevant data
- Predicted Trajectory as Data Input
  - Sector Identification
  - Channel estimation
  - Communication Demand Prediction

Formulation

- Challenge: Predicting 4D Deviations from Flight Plan
  - Longitude, Latitude, Altitude, Time
  - Varied by Convective Weather
  - Sequence-to-Sequence v. Time-Series Forecast
- Data Items
  - Flight Data: NASA Sherlock Data Warehouse
    - Flight Plans: Interpolated from navigation aids
    - Flight Trajectories: Interpolated from broadcast data
  - Weather Products: NASA Sherlock Data Warehouse, NOAA Portals
    - Varied spatial, temporal resolution
    - Continental Coverage: Parse into feature cubes along each flight plan
  - Collection: 379 Flights, 1/10/2019-1/24/2019, Los Angeles – New York
- Hybrid-Recurrent Structure
  - Sequence-to-Sequence paradigm



Collection of a Single Feature Cube



Hybrid-Recurrent General Structure

Weather Data Selection: Setup

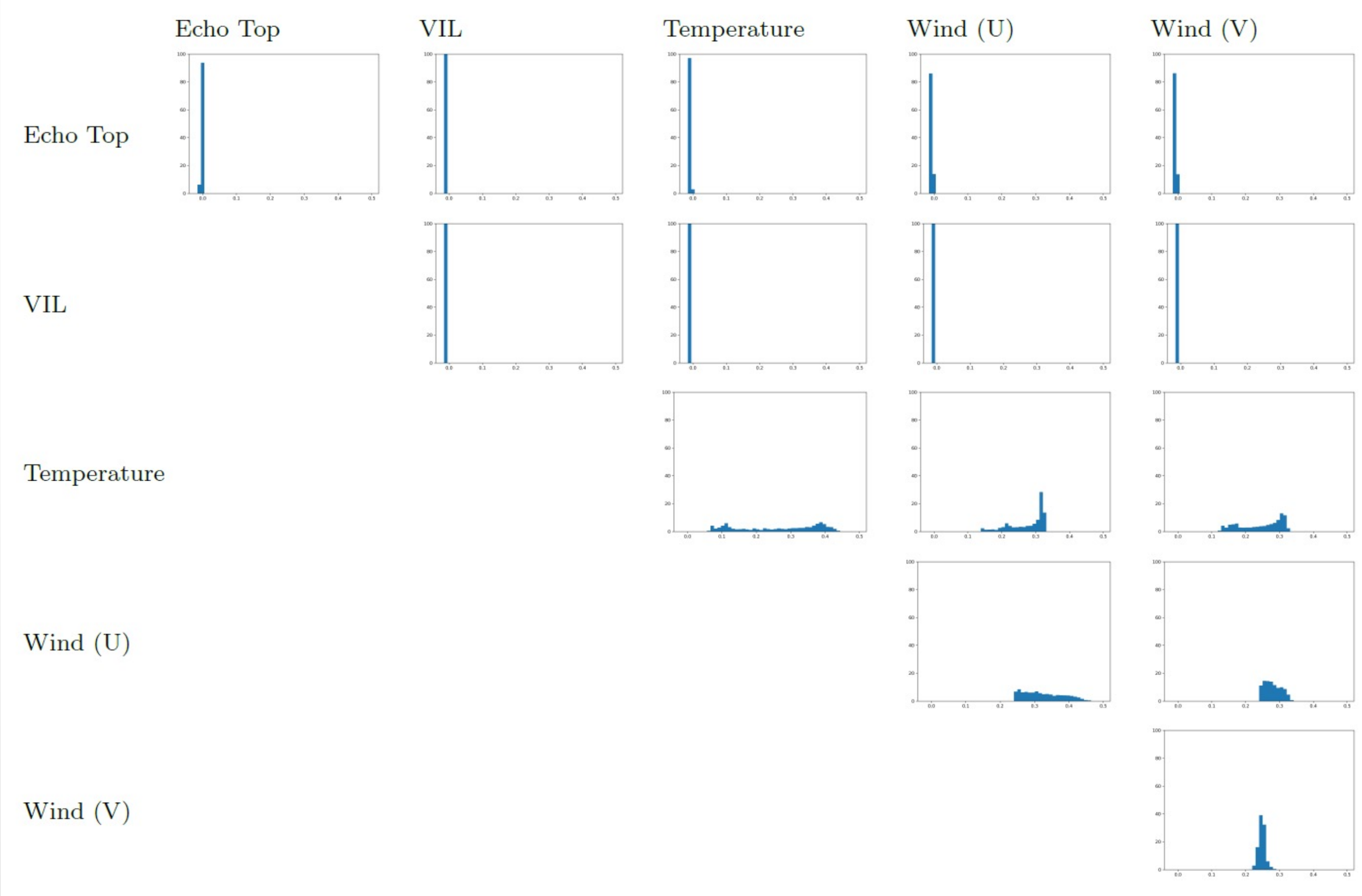
- Variables of Interest
  - CIWS: Vertically Integrated Liquid
  - HRRR: Wind Speed (U/V), Temperature
- Correlation Analysis to determine combinations of 2 products
- CNN-LSTM network, 1 recurrent layer
- Comparison against Echo Top as Baseline

Overview of Weather Products in Existing Literature
Highlighted Products/Databases Used in Research

Weather Database	**Used in**	**Relevant Variables**		**Update Period**	**Resolution**
Corridor Integrated Weather Service (CIWS)	[5]	Vertically Integrated Liquid (VIL) Echo Top		Current 2.5 Min Forecast 5 Min	1.85 km (1 nmi)
North American Mesoscale (NAM)	[6]	Humidity Wind Speed (U)	Temperature Wind Speed (V) Air Pressure	6 Hours	12 km (6.48 nmi)
Rapid Refresh (RAP) High Resolution Rapid Refresh (HRRR)	[2]	Humidity Wind Speed (U)	Temperature Wind Speed (V) Air Pressure	1 Hour	RAP 13 km (7.01 nmi) HRRR 3 km (1.61 nmi)

Weather Data Selection: Results

- Limitations
  - Cropped, transformed data between sources
  - No padding/shifting, limited coefficients
- Trends
  - Low correlation of all products
  - Sparsity of Echo Top and VIL
- Products for training
  - Echo Top + VIL
  - Echo Top + Temperature
  - VIL + Temperature
  - Temperature + V Wind



Normalized (0,1) Histograms
Each histogram ranges (0, 0.5) on the x-axis of Cross-Correlation Coefficients

Weather Data: Results & Closing Thoughts

- Trends
  - Echo Top as nominal, singular product
  - V Wind provided best vertical error
  - No tested combination of products significantly improved accuracy
  - Notable degradation in VIL

Prediction Results of Selected Weather Product
Reported based on Trajectory-wise Errors

Product(s)	Horizontal Error (μ/σ in nmi)	Vertical Error (μ/σ in ft)	Improvement over Echo Top ($\mu_{Horiz}/\sigma_{Horiz}$ as percent)	Improvement over Echo Top (μ_{Vert}/σ_{Vert} as percent)
Echo Top	50.017 48.854	1160.07 1420.26	0 0	0 0
VIL	55.171 67.276	1230.23 1514.95	-10.304 -37.708	-6.048 -6.667
TMP	52.983 60.901	1130.72 1399.41	-5.931 -24.659	2.530 1.468
U Wind (E/W)	50.560 54.588	1128.17 1420.57	-1.085 -11.738	2.749 -0.022
V Wind (N/S)	50.167 51.376	1097.16 1390.80	-0.299 -5.164	5.422 2.074
ET + VIL	50.670 57.596	1118.72 1365.45	-1.305 -17.895	3.564 3.859
ET + TMP	50.194 51.937	1156.50 1424.41	-0.354 -6.312	0.307 -0.292
VIL + TMP	52.520 65.513	1248.81 1558.70	-5.005 -34.101	-7.650 -9.748
TMP + V Wind	49.578 51.764	1128.25 1430.29	0.877 -5.957	2.743 -0.707

Model Design: Setup

- Architecture Changes
  - Weather Extraction Mechanism: CNN v. Self-Attention v. hybrid
  - Recurrent Mechanism: LSTM v. GRU v. IndRNN
  - Recurrent Depth
- Trained on Echo Top feature cubes
- Comparison against CNN-LSTM (1 layer) as baseline

Default Parameters of Hybrid-Recurrent Models

Parameter Description	**Parameter Value**
Convolution Kernel Sizes	[6x6, 3x3, 1x1]
Convolution Stride Lengths	[2, 2, 1]
Convolution Filter Sizes	[1, 2, 4]
Attention Output Dimensions	[128, 36, 36]
Dense Layer Sizes	LSTM, GRU: [16, 3] IndRNN: [16, 97]
Recurrent Input Size	6
Recurrent Hidden Layers	100 Cells
Recurrent Depth	GRU, LSTM: 1 or 2 Layers IndRNN: 2 or 3 Layers
Optimizer Learning Rate	2×10^{-4}
Training Duration	500 Epochs

Model Design: Results & Closing Thoughts

- Trends
  - Poor Performance of IndRNN
  - Notable improvement in self-attention models
  - Unclear: selection between LSTM and GRU, 1 and 2 recurrent layers

Prediction Results of Trained Hybrid-Recurrent Models
Reported based on Trajectory-wise Errors

Model	Horizontal Error (μ/σ in nmi)	Vertical Error (μ/σ in ft)	Improvement over Flight Plan (μ_{Horiz}/μ_{Vert} as percent)	Improvement over CNN-LSTM1lay (μ_{Horiz}/μ_{Vert} as percent)
CNN – LSTM1lay	63.558 26.891	1160.27 1500.83	39.592 64.013	0 0
CNN-LSTM2lay	60.9995 29.2265	1167.39 151.46	42.0241 63.7919	4.0260 -0.6135
CNN-GRU1lay	59.895 28.056	1120.04 1399.75	43.074 65.261	5.763 3.468
CNN-GRU2lay	47.2278 22.9868	1156.16 1332.40	55.1131 64.1404	25.6938 0.3548
CNN-IndRNN2lay	119.131 63.130	1219.99 1682.68	-13.226 62.161	-87.436 -5.146
CNN-IndRNN3lay	122.6245 61.8804	1219.86 1682.68	-16.5463 62.1645	-92.9320 -5.1355
CNN+SA-LSTM1lay	59.325 29.585	1178.57 1546.38	43.615 63.445	6.660 -1.576
SA-LSTM1lay	40.945 23.797	804.73 1054.89	61.084 75.041	35.579 30.644

Conclusions & Looking Forward

- 4D Trajectory prediction may serve as a multifaceted data product for dynamic spectrum allocation
- Research assesses the usefulness of available data and deep learning mechanisms for prediction.
  - Echo Top remains recommended as a holistic, singular product. No combinations of data can be recommended at this time.
  - The incorporation of self-attention has greatly improved model accuracy.
- Continued research
  - Additional weather products: air pressure
  - Model generalization: account for seasonality of data
  - Model tuning: architecture and optimizer hyperparameters
  - Data generalization: selection of additional flights with varied headings, durations, coverages of the continental United States.

Questions?

Thank you!