Flight Trajectory Prediction Based on Hybrid-Recurrent Networks

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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

• Hybrid-Recurrent Structure
  • Sequence-to-Sequence paradigm
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

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

- Limitations
  - Cropped, transformed data between sources
  - No padding/shiftning, 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
  • Notable degradation in VIL
  • V Wind associated with best vertical error
  • No tested combination of products significantly improved accuracy

• Looking Forward
  • Additional products: air pressure (HRRR)
  • Considerations for seasonal changes

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

<table>
<thead>
<tr>
<th>Product(s)</th>
<th>Horizontal Error (µ/σ in nmi)</th>
<th>Vertical Error (µ/σ in ft)</th>
<th>Improvement over Echo Top (µ_{horiz}/σ_{horiz} as percent)</th>
<th>Improvement over Echo Top (µ_{vert}/σ_{vert} as percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Echo Top</td>
<td>50.017</td>
<td>1160.07</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>VIL</td>
<td>55.171</td>
<td>1230.23</td>
<td>-10.304</td>
<td>-6.648</td>
</tr>
<tr>
<td>TMP</td>
<td>52.983</td>
<td>1130.72</td>
<td>-5.931</td>
<td>-24.659</td>
</tr>
<tr>
<td>U Wind (E/W)</td>
<td>50.560</td>
<td>1128.17</td>
<td>-1.085</td>
<td>-11.738</td>
</tr>
<tr>
<td>V Wind (N/S)</td>
<td>50.167</td>
<td>1097.16</td>
<td>-0.299</td>
<td>-5.164</td>
</tr>
<tr>
<td>ET + VIL</td>
<td>50.670</td>
<td>1118.72</td>
<td>-1.305</td>
<td>-5.805</td>
</tr>
<tr>
<td>ET + TMP</td>
<td>50.194</td>
<td>1156.50</td>
<td>-0.354</td>
<td>-6.312</td>
</tr>
<tr>
<td>VIL + TMP</td>
<td>52.520</td>
<td>1248.81</td>
<td>-5.005</td>
<td>-7.650</td>
</tr>
<tr>
<td>TMP + V Wind</td>
<td>49.578</td>
<td>1128.25</td>
<td>0.877</td>
<td>2.743</td>
</tr>
</tbody>
</table>

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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

<table>
<thead>
<tr>
<th>Parameter Description</th>
<th>Parameter Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Convolution Kernel Sizes</td>
<td>[6x6, 3x3, 1x1]</td>
</tr>
<tr>
<td>Convolution Stride Lengths</td>
<td>[2, 2, 1]</td>
</tr>
<tr>
<td>Convolution Filter Sizes</td>
<td>[1, 2, 4]</td>
</tr>
<tr>
<td>Attention Output Dimensions</td>
<td>[128, 36, 36]</td>
</tr>
<tr>
<td>Dense Layer Sizes</td>
<td>LSTM, GRU: [16, 3] IndRNN: [16, 97]</td>
</tr>
<tr>
<td>Recurrent Input Size</td>
<td>6</td>
</tr>
<tr>
<td>Recurrent Hidden Layers</td>
<td>100 Cells</td>
</tr>
<tr>
<td>Recurrent Depth</td>
<td>GRU, LSTM: 1 or 2 Layers IndRNN: 2 or 3 Layers</td>
</tr>
<tr>
<td>Optimizer Learning Rate</td>
<td>2x10^-4</td>
</tr>
<tr>
<td>Training Duration</td>
<td>500 Epochs</td>
</tr>
</tbody>
</table>

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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

• Going Forward
  • Model generalization
  • Optimizer and architecture tuning

<table>
<thead>
<tr>
<th>Model</th>
<th>Horizontal Error (μ/σ in nmi)</th>
<th>Vertical Error (μ/σ in ft)</th>
<th>Improvement over Flight Plan (μ_{nmi}/μ_{ft} as percent)</th>
<th>Improvement over CNN-LSTM1lay (μ_{nmi}/μ_{ft} as percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNN-LSTM1lay</td>
<td>63.558</td>
<td>1160.27</td>
<td>39.592</td>
<td>0</td>
</tr>
<tr>
<td>CNN-LSTM2lay</td>
<td>60.995</td>
<td>1167.39</td>
<td>42.024</td>
<td>63.7919</td>
</tr>
<tr>
<td>CNN-GRU1lay</td>
<td>59.895</td>
<td>1120.04</td>
<td>43.074</td>
<td>65.261</td>
</tr>
<tr>
<td>CNN-GRU2lay</td>
<td>47.2278</td>
<td>1156.16</td>
<td>55.1131</td>
<td>64.1404</td>
</tr>
<tr>
<td>CNN-IndRNN3lay</td>
<td>122.8245</td>
<td>1219.86</td>
<td>-16.546</td>
<td>62.1645</td>
</tr>
<tr>
<td>CNN+SA-LSTM1lay</td>
<td>59.325</td>
<td>1178.57</td>
<td>43.615</td>
<td>63.445</td>
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<tr>
<td>SA-LSTM1lay</td>
<td>40.945</td>
<td>864.73</td>
<td>61.084</td>
<td>75.041</td>
</tr>
</tbody>
</table>
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!