Using Neural Networks to Improve the Performance of Radiative Transfer Modeling Used for Geometry Dependent Surface Lambertian-equivalent Reflectivity Calculations

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Introduction

- Surface Lambertian-equivalent reflectivity (LER) is important for trace gas retrievals in the direct calculation of cloud fractions and indirect calculation of the air mass factor.
- Current trace gas retrievals use climatological surface LER’s.
- Surface properties that impact the bidirectional reflectance distribution function (BRDF) as well as varying satellite viewing geometry can be important for retrieval of trace gases.
- Geometry Dependent LER (GLER) captures these effects with its calculation of sun normalized radiances (I/F) and can be used in current LER algorithms (Vasilkov et al. 2016).
- Pixel by pixel radiative transfer calculations are computationally expensive for large datasets.
- Modern satellite missions such as the Tropospheric Monitoring Instrument (TROPMI) produce very large datasets as they take measurements at much higher spatial and spectral resolutions.
- Look up table (LUT) interpolation improves the speed of radiative transfer calculations but complexity increases for non-linear functions.
- Neural networks perform fast calculations and can accurately predict both non-linear and linear functions with little effort.

Methods

- I/F was calculated using the vector linearized discrete ordinate radiative transfer model (VLIDORT) for Ozone Mapping Instrument (OMI) viewing geometry.
- LUT interpolation was performed using linear interpolation across several dimensions.
- Neural networks were trained on the same dimensions as LUT Interpolation.

Analysis & Conclusion

Ocean I/F

<table>
<thead>
<tr>
<th></th>
<th>Neural Network</th>
<th>LUT Interpolation</th>
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</thead>
<tbody>
<tr>
<td>Mean Absolute Error</td>
<td>1.30 * 10^-5</td>
<td>7.36 * 10^-5</td>
</tr>
<tr>
<td>Root Mean Squared Error</td>
<td>2.72 * 10^-3</td>
<td>4.29 * 10^-5</td>
</tr>
<tr>
<td>Daily Processing Time</td>
<td>10.4 seconds</td>
<td>79.0 seconds</td>
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</table>

Land I/F

<table>
<thead>
<tr>
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<th>Neural Network</th>
<th>LUT Interpolation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Absolute Error</td>
<td>1.79 * 10^-3</td>
<td>4.43 * 10^-3</td>
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<tr>
<td>Root Mean Squared Error</td>
<td>3.76 * 10^-3</td>
<td>6.10 * 10^-3</td>
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<td>Daily Processing Time</td>
<td>11.2 seconds</td>
<td>61.7 seconds</td>
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Table 1: Statistical error calculating sun normalized radiances (I/F) for neural network & LUT interpolations with VLIDORT I/F as a reference and approximate computational time to calculate a full day of orbits.

- The neural network showed a mean absolute error and root mean squared error smaller than LUT interpolation over the oceans and land (Table 1).
- Computational time was significantly improved using a neural network instead of LUT interpolation (Table 1).
- Over oceans and land the LUT interpolation showed a systematic high bias at low TOA Rad while the neural network shows no systematic biases (Figure 2).
- The neural network produced more noise at extreme node values, especially over land (Figure 2).

Future Work

- Improve accuracy at extreme input node values by incorporating smart sampling, which determines most ideal training data based on histograms of real data (Loyola et al. 2016).
- Exercise the current neural network model with computationally intensive datasets such as TROPMI.

References