Using regression models to enhance signals from a scattered radiation field: Reducing stray light contamination in the limb profiles of the Ozone Mapper Profiler Suite (OMPS)

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Synopsis

As the technology of remote sensing using radiometric observations advances and we are confronted with weaker and weaker signals, stray light corruption will become an increasingly important challenge. Stray light is particularly damaging for imagers that sample a large dynamic range such as the OMPS limb profiler. In that case, even a very small fraction of photons straying from the high-intensity region of the image can dominate measurements in the low intensity region. For the OMPS limb profiler, stray light represents a small linear perturbation to the overall observed energy, even though it dominates observations for some wavelengths and viewing angles. By exploiting this characteristic, we have found that both iterative techniques based on a Taylor expansion of the inverse stray light operator and linear regression models can effectively reduce stray light contamination from OMPS measurements provided there is sufficient sampling of the radiant energy field and a sufficiently good characterization of the instrument.

Regression models can benefit operational retrievals because the bulk of their cost is incurred during offline training. However, they can perform no better than the data used to train them and work best for systems whose dynamical operators are largely linear. Regression models can be problematic in an operational setting if the instrument undergoes changes (e.g., pixel failure in the detector); with the instrument in orbit, retraining can be difficult. Thus, it is important to both characterize stray light with instrument tests before it is launched and to find stray light removal techniques that are flexible and can be altered to accommodate instrument changes. We examine three variations of an ozone retrieval algorithm that utilize regression models to characterize internal scattering and other instrument effects. These three methods are compared in terms of their general sensitivity to noise, sensitivity to model error, and their ability to handle complications such as pixel saturation and pixel failure.

Our results suggest that regression models can be used to reduce stray light contamination in limb profiles from OMPS. Furthermore, the most effective use of a regression model is to simulate the instrument in the forward model of the optimal estimation (Rodgers 2000) procedure used to retrieve ozone. That is, rather than using radiance for the data vector and a radiative transfer model as the forward model in Rodgers' procedure (as is commonly done), the data vector is comprised of raw observations and the forward model includes a full instrument model – in the form of a regression. With this method, a reasonable amount of pixel saturation and pixel failure can be tolerated without additional correction or re-tuning of the regression model. Errors in the instrument model used to train the regression models can be problematic.

Preliminaries

Conceptual Framework

Satellite-based observations have two important components

The radiative transfer operator $\mathcal{R}(\chi)$ obtains radiance from the viewing state vector χ
The instrument operator $\mathcal{I}$ obtains measurements $\mathcal{M}$ from radiance

$$\mathcal{M}(\chi) = \mathcal{I} \circ \mathcal{R}(\chi)$$

Our understanding is limited to a simplified version of this process

Which is represented by discrete matrix operators

$$\mathbf{M}(\chi) = \mathbf{JR}(\chi) \approx \mathbf{DAR}(\chi)$$

D represents scattering within the instrument
A represents attenuation within the instrument

Retrievals are broken down into two components

A data processing step

$$\mathbf{y} = \mathbf{Q}(\mathbf{M})$$

And the retrieval step (using the notation of Rodgers 2000)

$$\hat{\mathbf{x}} = \mathbf{x}_a + \mathbf{G}\left(\mathbf{y} - \mathbf{F}(\hat{\mathbf{x}}) + \mathbf{K}(\hat{\mathbf{x}} - \mathbf{x}_a)\right)$$

$$\mathbf{y} = \mathbf{F}(\mathbf{x})$$

$$\mathbf{G} = \left(\mathbf{S}_a^{-1} + \mathbf{K}^T\mathbf{S}_\varepsilon^{-1}\mathbf{K}\right)^{-1}\mathbf{K}^T\mathbf{S}_\varepsilon^{-1}$$

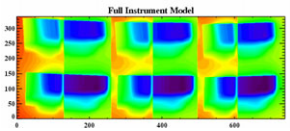
x is the state vector
y is the data vector
F is the forward model
K is the tangent linear model for **F**
G is a generalized inverse for **K**

Philosophical framework

Use a 'perfect model' framework
- Simulate 'measurements'
  - Numerical radiative transfer model
  - Numerical instrument model
- Allows controlled experiments ('truth' is known)
- Allows detailed error analysis
  - Source of error can be perfectly determined
- Allows good statistics
  - Amount of data only constrained by computer time
- Relation to actual measurements is uncertain
- Logic is circular
  - Only known sources of error are accounted for
  - Can lead to over-optimistic results
- Relies on reliable simulators and our ability to validate them

Utilize a detailed (if not accurate) instrument model that has features of the actual instrument
- More efficient to run than a highly accurate simulator
- Can more easily distinguish sources of error
- Can relate simulations to reality if simulation errors are small
- Even the best simulator has inaccuracies

Simulated observations



Instrument simulator includes:
- Quantum efficiency
- Optical through put
- Stray light
- Stray light filters
- Noise

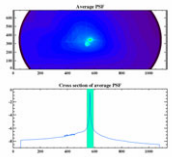
6 images on 1 CCD (3 slits, 2 different gains)

Stray light allows in inter-image interference

The Stray Light Problem:

What makes it a difficult problem and why it is soluble

Typical point spread function

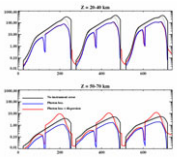


Point spread function includes:

A sharp peak that reduces the resolution

and broad low amplitude wings that allows high intensity regions of the image to corrupt low intensity regions (stray light)

Impacts on instrument error

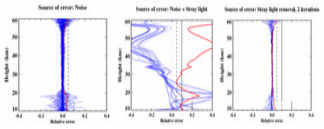


Photon counts from a CCD cross section: **Perfect instrument** (thick black line), and impacts of **attenuation** (thick blue line) and **internal scattering** (stray light; thick red line).

Globally, stray light is a small error, but it can be locally dominant

Impact on ozone retrievals

Since stray light is a small global perturbation, we attempt to remove it via a Taylor expansion of the inverse operator



Uncorrected stray light leads to 20 - 40% retrieval errors

Iterative method based on Taylor expansion is very effective after only 2 iterations

Remaining problems

PSFs are expensive to apply and even more so to invert
- Answer: Use a regression model

Instrument inversion requires an accurate instrument model

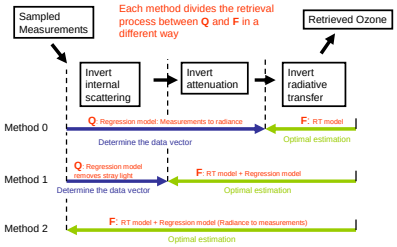
Regression models are efficient – the expense is incurred during offline training - but difficult to test and retrain during operation (instrument is in orbit)

Questions:
- Will regression models withstand rigorous testing?
- How will they handle loss of information due to pixel failure and pixel saturation?
- How do instrument model errors affect the results?

Our solution to stray light contamination

We investigate the viability of three different methods of using regression models to remove stray light

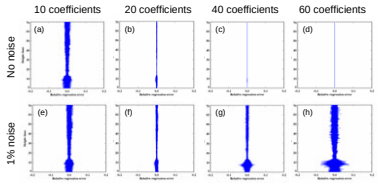
The three methods



Testing procedure

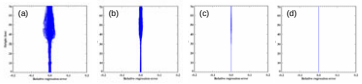
Compare methods in terms of ozone retrieval errors
Run an ensemble of retrievals
Each uses the same ozone a priori
Each has noise added as the only additional source of error
- Gaussian white noise clipped at 2 σ
- Uniform amplitude 1% of signal

Regression errors and noise sensitivity: Method 0



- Without noise, adding coefficients makes the regression better
- But, regressions degrade beyond 20 coefficients with noisy input data
- Method 1 results are nearly identical

Regression error: Method 2



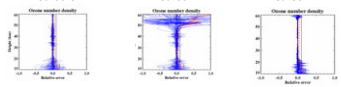
Errors of similar amplitude to Methods 0, 1 but concentrated in the upper atmosphere

Noise sensitivity of method 2 is not relevant

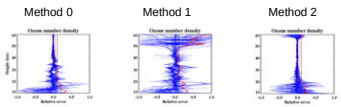
Results and conclusions

Due to noise-amplification immunity of method 2, it performs well in the face of several different types of instrument error

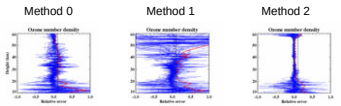
Noise (1% of amplitude at each pixel)



Pixel saturation (10% of pixels)

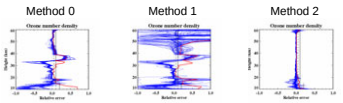


Pixel failure (20% of pixels)



Instrument error: Attenuation

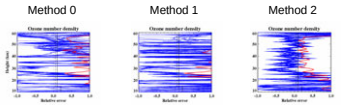
Elements of the Attenuation matrix **A** are increased uniformly by 0.02



Instrument error: Internal scattering (1 σ errors)

Columns of the internal scattering matrix **D** (PSFs) are all set equal to the average PSF (elements of each row are set to the row-average)

In this case, the standard deviation of the error is roughly equivalent to the standard deviation of measured PSFs



Since precise measurement of the PSFs is difficult, we recommend that hardware solutions be exhaustively explored before resorting to a software solution – however, given any hardware solution, our method should be able to reduce stray light contamination further.