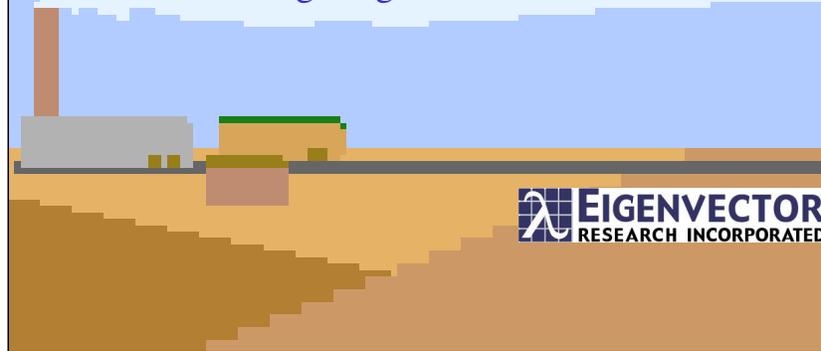


Estimation of trace vapor concentration-pathlength in plumes for remote sensing applications from hyperspectral images

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Objective and Outline

- Objective
 - Show that end members extracted from the off-plume can be used as a basis for the quantification of plume analytes
 - Allows non-negativity constraints to be employed
 - Show how mismatch between the plume temperature and estimator spectra affect the quantification error
- Remote sensing problem
- IR-SAGE (Synthetic Scene Generator)
- Quantification Algorithm
- End-Member Extraction
- Results
- Conclusions

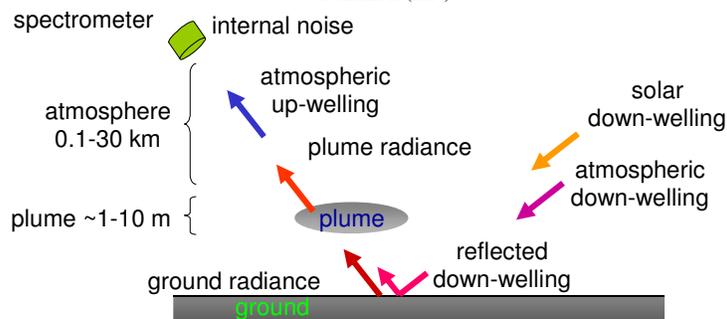
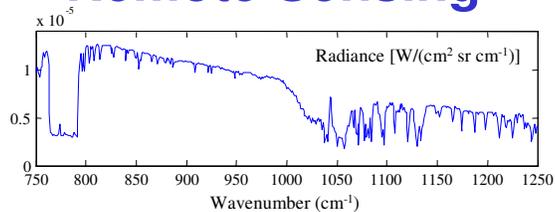


Remote Sensing Problem

- Remote sensing for chemical analytes can be split into 3 tasks:
 - Detection (*where* is the plume?),
 - Classification (*what* is in the plume?), and
 - Quantification (*how much* is in the plume?).
- Interest is in quantification
 - quantification is limited to concentration-pathlength since the actual pathlength is usually unknown



Remote Sensing



Problem with Measured Data

- Hyperspectral images are rarely well-characterized
- There are a large number of factors influencing the measured radiance
 - plume location, contents, quantities, temperature,
 - atmosphere down- and up-welling radiance, and transmittance,
 - ground emissivity and temperature ...
- are *unknown*
- so how to judge performance of algorithms?



Synthetic Data

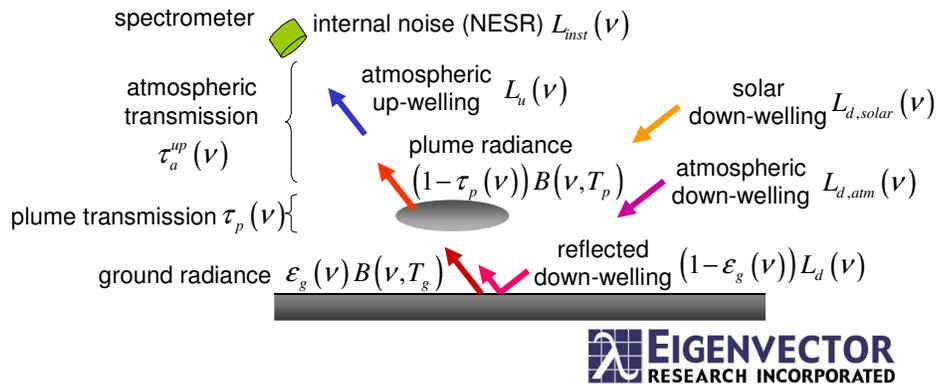
- IR-SAGE: InfraRed - Systems Analysis in General Environments
 - flexible synthetic scene generator (in MATLAB)
 - combines physical models and measured spectra
 - *everything is known*
 - can be used to test detection, classification, and quantification algorithms



Radiance Model

$$L_{off}(\nu) = \left\{ \underline{\varepsilon_g(\nu)B(\nu, T_g)} + \underline{(1 - \varepsilon_g(\nu))L_d(\nu)} \right\} \underline{\tau_a^{up}(\nu)} + \underline{L_u(\nu)}$$

$$L_{on}(\nu) = \left[\underline{\varepsilon_g(\nu)B(\nu, T_g)} + \underline{(1 - \varepsilon_g(\nu))L_d(\nu)} \right] \underline{\tau_p(\nu)} + \underline{(1 - \tau_p(\nu))B(\nu, T_p)} \underline{\tau_a^{up}(\nu)} + \underline{L_u(\nu)}$$



How to Quantify?

- Lot's of parameters, so ...
 - split the problem into parts, and assume some parameters are known
 - (future work)
 - assume plume location is known (detection)
 - assume plume analytes are known (classification)
- Assume that on-plume pixel “looks like” an off-plume pixel if there were no plume
 - on-plume “background” lies in subspace spanning off-plume pixels

Rearrange Radiance Model for τ_p

as $\tau_p \rightarrow 1$ (no plume), $L_{on}(v) \rightarrow L_{off}(v) \equiv L_{bkg}(v)$

$$\tau_p = e^{-cS^T} = \frac{L_{on}(v) - L_u(v) - \bar{\tau}_a^{up} B(v, T_p)}{L_{bkg}(v) - L_u(v) - \bar{\tau}_a^{up} B(v, T_p)}$$



Assumptions

- Assumed we know: $\bar{L}_{u,off}$, $\bar{\tau}_{a,off}^{up}$, T_p
- Don't require knowledge of: T_g and ϵ_g
- Taylor Series, substitute known parameters

$$cS^T(v) = \frac{L_{on}}{d(v)} - \frac{L_{bkg}}{d(v)} \quad d(v) = \bar{L}_u + \bar{\tau}_a^{up} B(T_p) - \bar{L}_{bkg}$$

$$c\tilde{S}^T(v) = L_{on} - L_{bkg}$$



Quantification: ELS

- Extended mixture model (extended least squares) which can be solved for $[\mathbf{c} \ \mathbf{t}]$ using least squares

$$\mathbf{l}_{on} = [\mathbf{c} \ \mathbf{t}] [\tilde{\mathbf{S}} \ \mathbf{P}_{bkg}]^T$$

- End-member extraction for background basis

$$\mathbf{l}_{on} = [\mathbf{c} \ \mathbf{c}_{bkg}] [\tilde{\mathbf{S}} \ \mathbf{S}_{bkg}]^T$$

- can apply non-negativity constraints



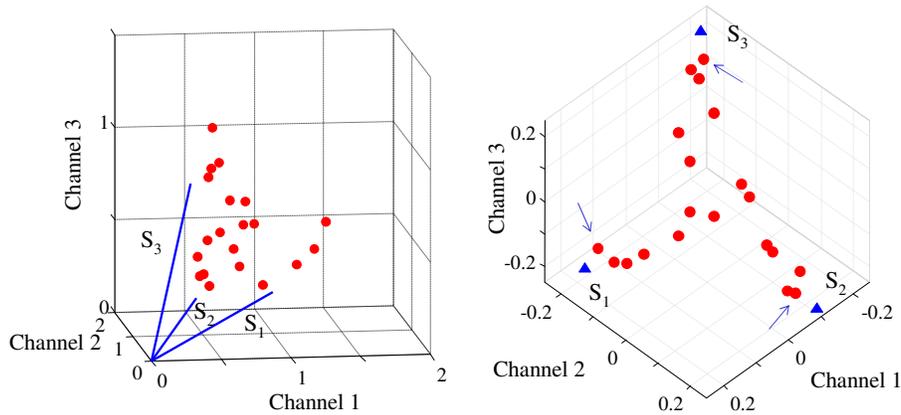
End-Member Extraction

- Initial solution: extremes of mean centered 1-norm
- ALS with non-negativity constraints
- Sequential for “smaller” factors
 - extracted 14 to 53 factors
- Provides a basis on which non-negativity constraints can be used in quantification

$$\mathbf{L}_{off} = \mathbf{c}_{bkg} \mathbf{S}_{bkg}^T + \mathbf{E}$$



End-Member Extraction



Quantification: GLSI

- ELSI predictions were good for narrow-featured spectra but not as good for broad-featured spectra

$$\mathbf{c}\tilde{\mathbf{S}}_i^T(\nu) = [L_{on}(\nu) - \bar{L}_{off}(\nu)] - [L_{off}(\nu) - \bar{L}_{off}(\nu)]$$

$$\mathbf{W} = [\mathbf{L}_{off} - \bar{\mathbf{L}}_{off}]$$

$$\hat{\mathbf{c}} = (\mathbf{1}_{on} - \bar{\mathbf{L}}_{off}) \mathbf{W}^{-1} [\tilde{\mathbf{S}} \ \mathbf{s}_{bkg}] \left([\tilde{\mathbf{S}} \ \mathbf{s}_{bkg}]^T \mathbf{W}^{-1} [\tilde{\mathbf{S}} \ \mathbf{s}_{bkg}] \right)^{-1}$$

- GLS, after the last ELSI iteration, resulted in better estimates for broad-featured

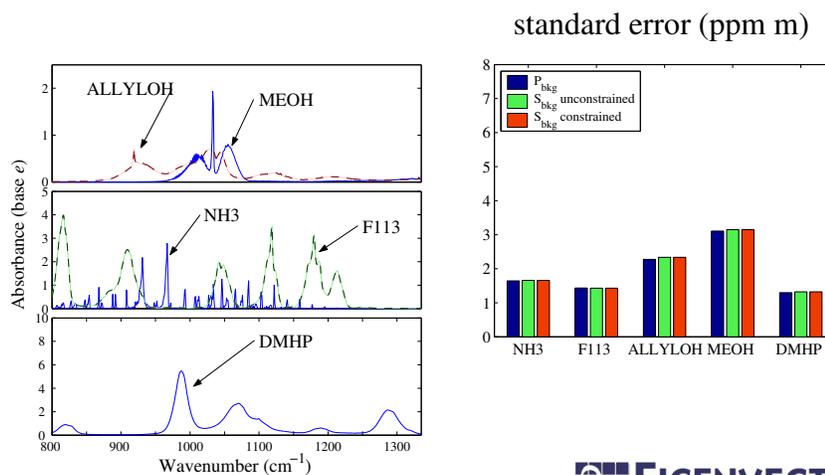


Algorithm Testing

- Image 128x128 x 536 (800 to 1335 cm^{-1})
 - 1, 2, 4, 8, 128 different background materials ϵ_g
 - temperature variability, $T_p - T_g$ (12 to 32 K)
 - plume 16x128 pixels
 - plume spectra at 298 K, estimator at 298 K: matched
 - plume spectra at T_p , estimator at 298 K: unmatched
 - 5 analytes in the plume, 9 to 26 ppm·m
 - atmospheric variability
 - 0.112 cm^{-1} res, 0.06 cm^{-1} spacing, convoluted to 1 cm^{-1}

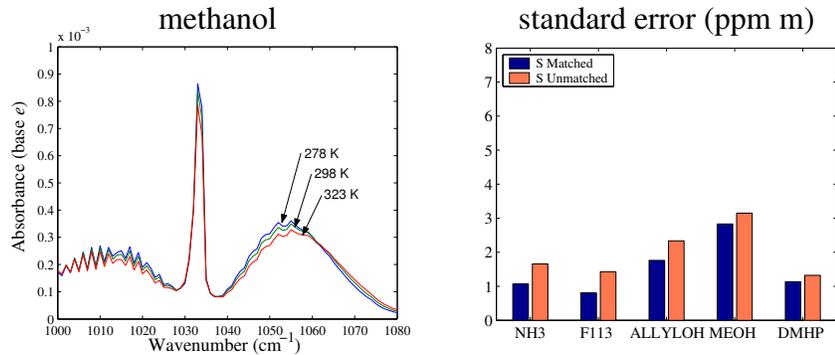


Unconstrained vs. Constrained



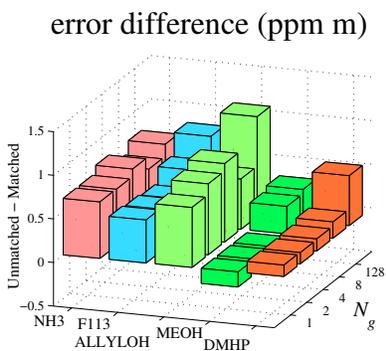
Matched vs. Unmatched

- temperature mismatch \Rightarrow higher estimation error



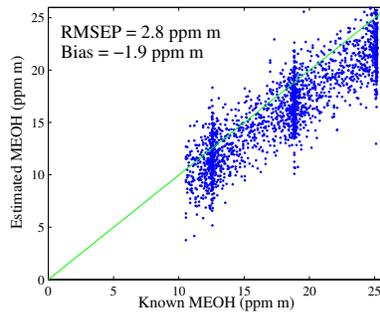
Unmatched - Matched

- Mismatch generally results in higher error



Model Bias

- Estimates of \mathbf{c} tend to have a low bias due to model assumptions
 - Taylor series approx.
- Temperature mismatch can result in a high bias that partially offsets the model bias



Conclusions

- End member extraction can be used to obtain a basis on which non-negativity constraints can be applied
- Temperature mismatch between the plume temperature and the spectrum used for estimation generally results in higher estimation error



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Extra Slides



Summary of Assumptions

- plume location is known*
- plume analytes are known*
- for off-plume \bar{L}_u ,** $\bar{\tau}_a^{up}$,* and \bar{L}_{bkg} * are known
- T_p is known*
- L_{bkg} lies in subspace spanned by off-plume \mathbf{P}_{bkg}

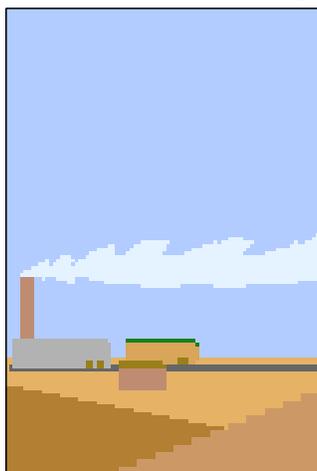
* same assumption as present state-of-the-art

** present state of the art assumes T_g is known

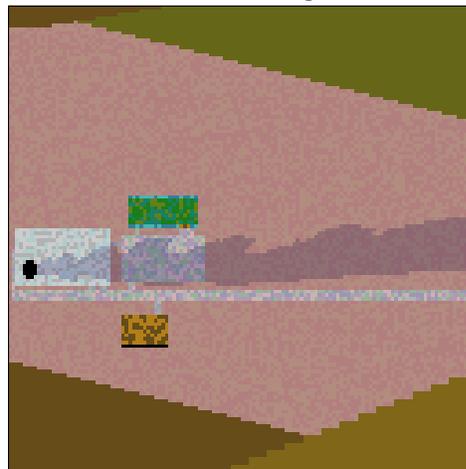


Scenarios

side-looking



down-looking

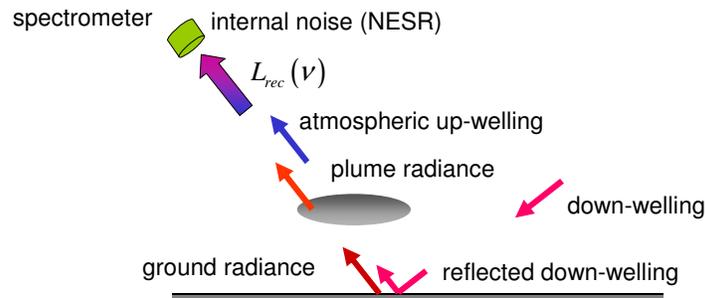


Noise Model

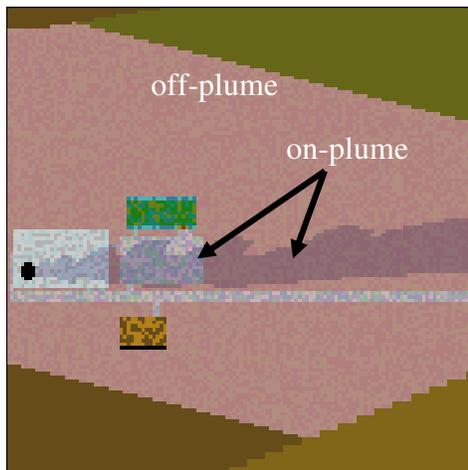
$$NESR(\nu) = L_{rec}(\nu) / SNR(\nu)$$

$$SNR(\nu) = \frac{\text{number of signal photo-electrons}}{(\text{total number of carriers from all sources})^{1/2}}$$

multiple sources:
fore optics, cold shield,
cold filter, spectrometer
body, electronics ...



Quantification



examples for down-welling scenarios
can be used for side-, up-welling scenarios:
need to know **where** the signal is (detection), and
need to know **what** is in the signal (classification)



Not all terms are known...

- Approximate $e^{-\mathbf{cS}^T} \approx 1 - \mathbf{cS}^T$
- isolate \mathbf{cS}^T
- and assume $L_u(v) \approx \bar{L}_{u,off}(v)$
 $\tau_a^{up}(v) \approx \bar{\tau}_{a,off}^{up}(v)$
 T_p known
- yielding

$$\mathbf{cS}^T(v) = \frac{L_{on} - L_{bkg}}{\bar{\tau}_{a,off}^{up} B(T_p) + \bar{L}_{u,off} - L_{bkg}}$$

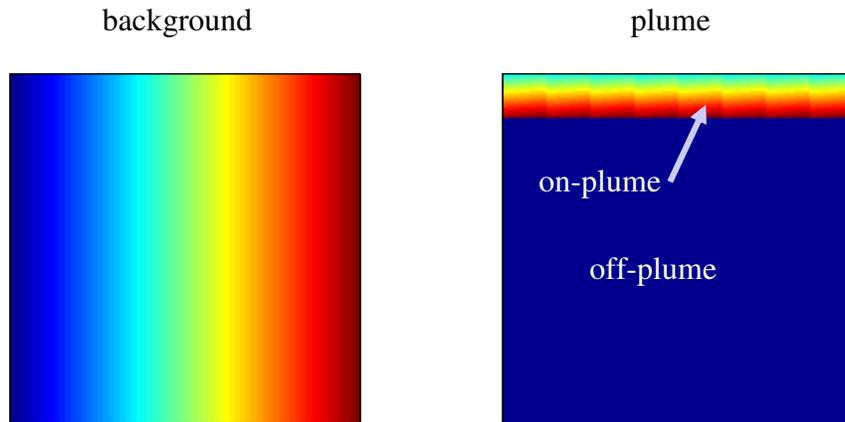


Algorithm Testing

- Image 128x128 x 536 (800 to 1335 cm⁻¹)
 - 1, 2, 4, 8, 128 different background materials ϵ_g
 - T_g (284 to 300 K), $T_p - T_g$ (12 to 32 K)
- Plume 16x128 (9 to 26 ppm·m)
 - 1 to 4 analytes in the plume
- US 76 Standard Atms
 - 101 different FASCODE realizations
 - 1 % T and 3 % C variation w/in each layer
 - H₂O, CO₂, O₃, N₂, CO, CH₄, O₂, and 25 others
- All spectra
 - 0.112 cm⁻¹ res, 0.06 cm⁻¹ spacing
 - convoluted to 1 cm⁻¹



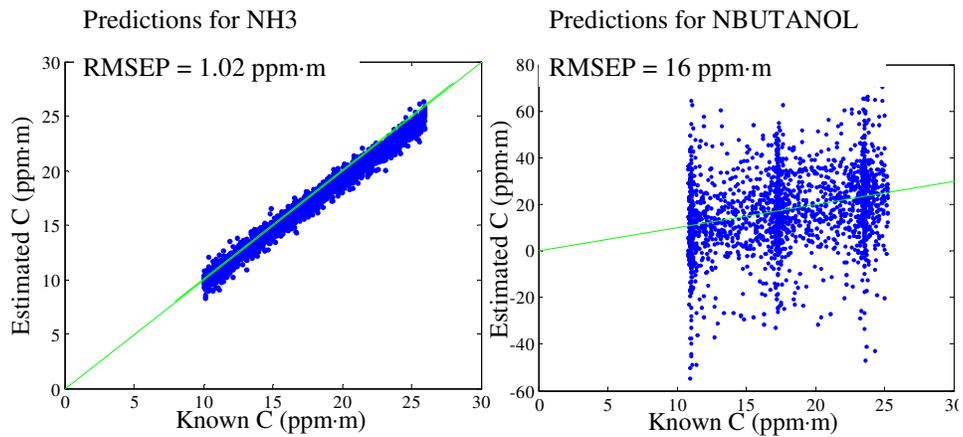
“Mathematical Construct”



Results: 4 Dissimilar Analytes

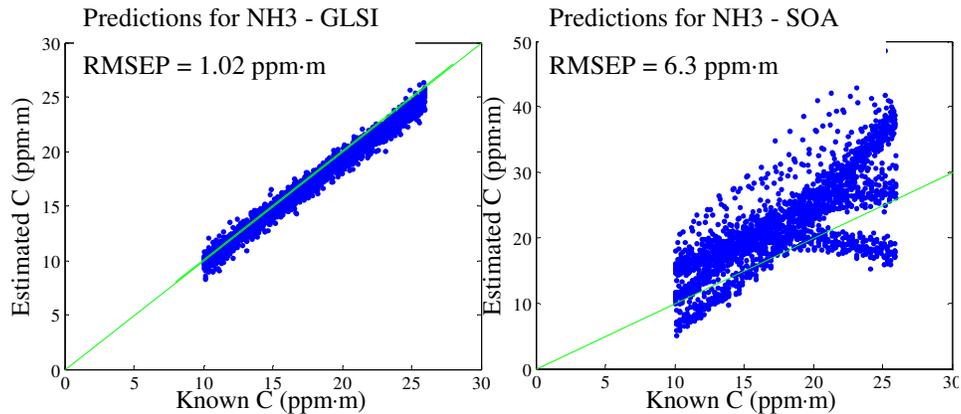
Plume: NH₃, N-Butanol, F113, CH₄

Background: 128 ϵ_g



Results: 4 Dissimilar Analytes

Plume: NH₃, N-Butanol, F113, CH₄



Results: GLSI / SOA

- Compare GLSI to State-of-the-Art (SOA)
- For 4-analyte plume of dissimilar analytes

<u>Analyte</u>	<u>RMSEP (ppm·m)</u>	
	<u>GLSI</u>	<u>SOA</u>
NH ₃	1.0	6.3
NBUTANOL	16	69
CH ₄	39	49
F113	1.0	8.3



Results: Num. of Backgrounds

- Compare GLSI vs number of backgrounds
- For 4-analyte plume of dissimilar analytes

<u>Analyte</u>	<u>Number of Backgrounds</u>				
	<u>128</u>	<u>8</u>	<u>4</u>	<u>2</u>	<u>1</u>
NH3	1.0	0.85	0.85	0.93	0.94
NBUTANOL	16	4.7	3.4	3.9	3.9
CH4	39	32	32	36	38
F113	1.0	0.65	0.63	0.67	0.66



Estimation vs. NAS

- Net Analyte Signal accounts for spectral modification and number of basis vectors in \mathbf{P}_{bkg}

