Neural Network Estimation of Atmospheric Profiles Using AIRS/IASI/AMSU Data in the Presence of Clouds

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Why Another Retrieval Algorithm??

The SCC/NN retrieval algorithm I’ll discuss today should complement current physical / 1DVAR algorithms AND data assimilation routines by offering the following advantages:

• Excellent retrieval accuracy and yield
  – Comparable to state-of-the-art methods (results presented today)
  – Especially accurate in areas of heavy clouds and over land where modeling is difficult
  – Highly-accurate “first-guess” could help initialize physical / 1DVAR algorithms and/or backfill when these algorithms don’t converge

• Error/cloud characterization:
  – Averaging kernels and full error-covariance matrix
  – Quality control variables
  – Cloud parameters

• SPEED!!
  – Approximately 1000 retrievals per second using IASI (all channels) and AMSU with desktop PC
  – Very appealing for data assimilation and direct broadcast applications
Outline

• Brief algorithm overview
  – Stochastic cloud clearing (SCC)
  – Projected Principal Components compression
  – Multilayer feedforward neural networks (NN)

• SCC performance with Quality Control (QC)

• SCC+NN performance comparisons with AIRS L2 Version 5 algorithm

• Infrared Atmospheric Sounding Interferometer (IASI) Information Content Analysis

• IASI versus AIRS: SCC/NN temperature retrieval performance

• Future Work / Summary
Algorithm Block Diagram

Cloudy radiances
Multi-FOV

\[ R \]

Cloud-cleared radiances
FOR

\[ \tilde{R} \]

Projected
Principal Components
Transform

PPC’s
FOR

\[ \tilde{P} \]

Temperature/Moisture Profile
FOR

\[ \hat{T} \]

Stochastic
Cloud
Clearing

FOR

Input
layer

First
hidden
layer

Second
hidden
layer

Output
layer
Stochastic Cloud Clearing

• SCC estimates cloud contamination solely based on statistics.
  - Hyperspectral IR and microwave observations are collocated to ground truth (ECMWF, radiosondes, etc.)

• Key concept: Principal component analyses of $\Delta R$, not $R$.
  - Principal components of cloudy radiances can distribute cloud signal to non-cloud-impacted channels, etc.
  - Also mitigates crosstalk from surface emissivity variability

• Nonlinearity is accommodated using stratification (sea/land, latitude, day/night), multiplicative scan angle correction, etc.

• Advantages
  - Simple: SCC does not need physical models (retrieval or radiative transfer).
  - Fast: Based on matrix addition and multiplication
Block Diagram of SCC Algorithm

Stochastic Cloud Clearing with AIRS/AMSU: Comparisons with Sea Surface Temperature

- Angle-corrected TB images at window channels

AIRS 2390.1cm\(^{-1}\): near Hawaii  
AIRS 2399.9cm\(^{-1}\): near SW Indian Ocean

- Clearing works well even if there is no hole (clear FOV)
Projected PCT (Canonical Correlations)

\[ c(\cdot) = E[(\hat{R}_r - R)^T (\hat{R}_r - R)] \]

- It is sometimes useful to remove the PCA constraint of uncorrelated components:

\[ \hat{R}_r \triangleq L_r \tilde{R} \]

\[ L_r = E_r E_r^T C_{RR}(C_{RR} + C_{\psi\psi})^{-1} \]

\[ E_r = [E_1 \mid E_2 \mid \cdots \mid E_r] \]

are the \( r \) most significant eigenvectors of

\[ C_{RR}(C_{RR} + C_{\psi\psi})^{-1} C_{RR} \]

- The Wiener-filtered radiances are projected onto the \( r \)-dimensional subspace spanned by \( E_r \). It is this projection that motivates the name “projected principal components.”

- An orthonormal basis for this \( r \)-dimensional subspace of the original \( m \)-dimensional radiance vector space \( \mathcal{R} \) is given by the \( r \) most-significant right eigenvectors, \( V_r \), of the reduced-rank linear regression matrix, \( L_r \).

\[ \tilde{P} = V_r^T \tilde{R} \]
Another useful application of the PPC transform is the compression of spectral radiance information that is correlated with a geophysical parameter, such as the temperature profile.

The r-rank linear operator that captures the most radiance information which is correlated to the temperature profile is

$$L_r = E_r E_r^T C_{TR} (C_{RR} + C_{\psi \psi})^{-1}$$

$$E_r = [E_1 | E_2 | \cdots | E_r]$$

are the r most significant eigenvectors of

$$C_{TR} (C_{RR} + C_{\psi \psi})^{-1} C_{RT}$$
Performance Comparison of Principal Components Transforms

“Radiance Reconstruction Error”

“Temperature Profile Estimation”

Multilayer Feedforward Neural Networks

- Parameterized, nonlinear function

- Parameters ("weights" and "biases") are found by numerically minimizing some cost function (usually SSE)

- Sophisticated methods for finding optimal weights exist ("back-propagation" of errors)
Perceptron weights and biases are iteratively adjusted by “back propagation” of errors. Differentiable activation functions typically used to facilitate gradient searches.

Perceptron

\[ \sum x_i w_i + \beta_i \]

\[ F(y_i) \]

“Activation Function”

\[ F(y) \]

\[ y \]

\[ z_i \]
Retrieval Performance Validation with AIRS/AMSU

Case 1: ECMWF atmospheric fields

- >1,000,000 co-located AIRS/AMSU/ECMWF observations from ~100 days:
  - Every fourth day from December 1, 2004 through January 31, 2006
  - Used for training

- ~250,000 profiles set aside for validation and testing sets

Case 2: Radiosonde data

- ~50,000 quality-controlled radiosondes from NOAA FSL global database co-located with AIRS/AMSU observations
  - Used for validation

Global: Cloudy, Land & Ocean, Day & Night
Descending, Land, Edge-of-Scan, Spring05
Cloudy Conditions, 910 Global Radiosondes

~1km vertical layers
AIRS+AMSU

Latitudes within ±60°

Excellent SCC/NN performance in lower troposphere!

910 radiosondes are “truth”
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T(h) RMS Error Versus Cloud Fraction
Common Ensemble

SCC/NN is much less sensitive to cloud amount!
Typical NN Retrieval Error Covariance
Typical NN Retrieval Averaging Kernels

Very high vertical resolution in lower troposphere!
IASI Temperature Retrievals Over Ocean

~1km vertical layers
IASI+AMSU

Near-nadir scan angles, ±60° Latitude

ECMWF is “truth”

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NN temperature retrieval is vastly superior to linear regression!
(Effect is even more pronounced over land.)
AIRS versus IASI: Ocean, Night

~1km vertical layers
IASI+AMSU

Near-nadir scan angles, ±60° Latitude

ECMWF is “truth”

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Future Work

- Additional and more extensive performance assessments
  - Match-ups with radiosonde data
  - Integration with latest AIRS Level 2 algorithm (V6)

- Algorithm optimizations, especially for IASI and CrIMSS
  - Improved handling of land, including elevated surface terrain and surface emissivity
  - Retrieval extensions to include ozone, trace gases, and cloud microphysical properties

- Experiments with data assimilation and direct broadcast applications
  - We’re looking for collaborators – please contact me if interested
Summary and Conclusions

• SCC/NN RMS retrieval accuracies and yield substantially exceed those of the AIRS L2 algorithm (V5) in cloudy conditions over land. Moisture retrievals show similar characteristics.

• SCC/NN algorithm is characterized by full error covariance matrix, quality control, and averaging kernels, facilitating its use with other retrieval and assimilation methodologies.

• High computational efficiency (1000 retrievals/sec) makes SCC/NN particularly attractive for near-real-time data assimilation and direct broadcast applications.

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Backup Slides
Philosophical Musings

• Physical / 1DVAR retrievals are only as good as the models

• Empirical statistical retrievals (i.e., using real observations, not simulated observations) are only as good as the ground truth

• Cloud and surface emissivity models, while progressing rapidly, are still inadequate to provide retrievals with highest possible fidelity in “problem areas” (Cloudy/Land)

• Sophisticated statistical/stochastic methods can be very helpful here:
  – Cloud/SE modeling error greatly exceeds profile ground truth error
  – There is hope: INFORMATION CONTENT IS IN THE RADIANCES

• My contention (to be supported by evidence in today’s talk): Presently, the best statistical retrievals, which are essentially 4-D interpolators of the ground truth, exceed the accuracies of the best physical retrievals IN CLOUDS OVER LAND
Stochastic Cloud Clearing
Quality Control

Ocean, All latitudes
Algorithm Overview (Part I)

- Temperature and moisture profile retrievals are produced in all cloud conditions
- Cloud-cleared radiance estimates are produced for all 2378 AIRS channels
- Retrieval is global:
  - All latitudes
  - Ocean and land
  - Day and night
- Quality control has been implemented
- IR-only option implemented
- Very fast: Cloud-cleared radiances and retrieved profiles generated for one field of regard in ~1 msec using PC!!
  - Two-three orders of magnitude faster than current operational methods
  - One-two orders of magnitude faster than iterative, pseudochannel methods
Algorithm Overview (Part II)

- Algorithm is composed of linear and non-linear statistical operators
  - Projected principal components transform
  - Neural network estimation

- Coefficients are derived empirically, off-line:
  - Co-location of sensor measurements with “truth” (Radiosondes, NWP, etc.)
  - Model-generated data
  - Data stratification is used for:
    - Sensor scan angle
    - Latitude
    - Solar zenith angle
    - Surface type
    - Surface elevation
Principal Components Transform (PCT)

- Objectives:
  - Remove noise from spectral radiance observations (exploit redundancy)
  - Compress radiance information into fewer components

\[
\hat{R}_r \triangleq G_r \tilde{R} \quad \quad C_{\tilde{R}\tilde{R}} = C_{RR} + C_{\Psi\Psi}
\]

- Cost function: Minimize sum-squared error between estimated noise-free radiances and actual noise-free radiances

\[
c(\cdot) = E[(\hat{R}_r - R)^T(\hat{R}_r - R)]
\]

- Noise-Adjusted Principal Components (NAPC) transform:

\[
G_r = C_{\Psi\Psi}^{1/2} W_r W_r^T C_{\Psi\Psi}^{-1/2}
\]

- Where \( W_r^T \) are the \( r \) most significant eigenvectors of the whitened covariance matrix:

\[
C_{\tilde{W}\tilde{W}} = C_{\Psi\Psi}^{-1/2} (C_{\tilde{R}\tilde{R}}) C_{\Psi\Psi}^{-1/2}
\]
SCC/NN versus AIRS L2 (Version 5)
Descending, Ocean, Edge-of-Scan, Spring

~1km vertical layers
AIRS+AMSU

Latitudes within ±60°

ECMWF is “truth”
SCC/NN versus AIRS L2 (Version 5)
Descending, Land, Edge-of-Scan, Spring

~1 km vertical layers
AIRS + AMSU

RMS Temperature Error (K)

Latitudes within ±60°

ECMWF is “truth”
SCC/NN versus AIRS L2 (Version 5)
Descending, South Pole*, Edge-of-Scan, Spring

~1km vertical layers
AIRS+AMSU

ECMWF is "truth"
Quality is suspect
IASI/ECMWF/SARTA Matchup Database

- Global database spanning May07-Dec07

- Approximately 100,000 fields-of-regard
  - IASI observations (2x2)
  - ECMWF atmospheric fields
  - Radiosondes (available for some FOR’s)
  - IASI clear-air spectra calculated with SARTA v1.05

- Database stratified by surface type, latitude, solar zenith angle, sensor scan angle, surface pressure
RMS IASI Cloudy Obs - Clear Calcs (i.e., Before Cloud Clearing)

Window
15-micron
4-micron
Opaque 4-micron
Water vapor

SCC RMS with AIRS

Ocean
Correlation of “IASI OBS” and “IASI OBS-CALCS” Eigenvectors

Correlation decreases as atmospheric signal is removed.

Eigenvectors almost identical Indicates channels responsive to clouds

Ocean
IASI Eigenanalysis

Predominantly cloud effects

Atmospheric and sensor “noise”

Ocean
IASI “OBS” and “OBS-CALCS” Eigenvectors

(a) Eigenvector set #1

(b) Eigenvector set #2

(c) Eigenvector set #3
Stochastic Cloud Clearing of IASI

473 IASI channels were cleared
Descending orbits within ±60° latitude, ocean

ECMWF is “truth”
Stochastic Cloud Clearing of IASI

473 IASI channels were cleared
Descending orbits within ±60° latitude, land

ECMWF is “truth”
IASI Temperature Retrievals Over Land

~1km vertical layers
IASI+AMSU
Near-nadir scan angles, ±60° Latitude
ECMWF is “truth”

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AIRS versus IASI: Land

AIRS is significantly better near the surface.

~1km vertical layers
IASI+AMSU

Near-nadir scan angles, ±60° Latitude

ECMWF is “truth”
AIRS versus IASI NEdT
AIRS Retrieval Degradation After Adding Noise to Shortwave Channels

~1km vertical layers
IASI+AMSU
Near-nadir scan angles, ±60° Latitude

ECMWF is “truth”