



ATMS Radiometric Noise Characterization

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ATMS Overview

- Advanced Technology Microwave Sounder
- Primary data products: atmospheric temperature and moisture profiles
- Follow-on to AMSU-1 and MHS
- Operational on Suomi NPP and NOAA-20 (JPSS-1)



Key ATMS Applications Weather forecasting

Noise Spectral

Characteristics

- Two components:
- > White thermal noise, related to receiver noise figure
- \succ 1/f^{α} noise, due to gain fluctuations

Examples from JPSS-1:



Impacts of Low-Frequency Noise

- Contributes to Calibration Noise
- 2-point calibration data collected once per scan
- Weighted data from multiple scans used in calibration algorithm
- Calibration errors due to two sources:
 - Thermal noise of weighted average of calibration samples
 - Decorrelation of gain fluctuations between

Storm tracking Climate prediction models > Precipitation, snow and ice



Channel 2 Surface Imaging, SNPP





calibration samples and scene observations

- Weighting functions selected to minimize total calibration noise
- Resulting calibration noise is therefore proportional to low-frequency noise
- Produces "striping", since calibration noise is an error applied to each scan line
- Contributes to inter-channel correlated noise
 - Front-end RF and IF amplifiers used for multiple channels
 - Gain fluctuations in these amplifiers therefore produce correlated noise for their channels

Alternative Time-Domain Characterization

- Use autocorrelation of warm-calibration noise
- Can be computed from operational-mode data, on-orbit as well as from ground tests
- Allows for updated characterizations throughout mission, without exiting operational mode
- Approach to Derive Autocorrelation Function

Computation of Calibrated Scene Noise

The error in inferred brightness temperature of a scene sample, after calibration, can be expressed as

$\delta T_s = \frac{\delta C_s}{G} - \frac{\delta C_c}{G} \left(\frac{C_w - C_s}{C_w - C_c} \right) - \frac{\delta C_w}{G} \left(\frac{C_s - C_c}{C_w - C_c} \right)$

Expected worst-case condition is for scene temperature = warm-cal temperature,

Data Used in Computations

- Orbits # 1667-1676, March 15, 16, 2018
- Images shown for channel 2, orbits 1668-1673



- Collect warm-cal data for several orbits
- Apply corrections for target physical temperature
- Remove long-term thermal-induced drifts
- Compute correlations at scan intervals (ρ_i), for i up to 10 scans
- > Derive sample-to-sample correlation (ρ_0) from NEDT and Allan variance (σ_w^2)

 $\rho_0 = 1 - \frac{\sigma_w^2}{NEDT^2}$

- Use polynomial regressions to estimate complete autocorrelation function
- Evaluate $\rho(\tau_i)$ where τ_i are intervals between scene nadir and each warm-cal sector



Variance of inferred scene temperature is then the sum of the weighted covariances of scene and warmcal measurements: $VAR = \overline{w}^T \overline{cov} \overline{w}$ is the weighting function where $\overline{w} =$ The elements of the covariance matrix are $\overline{cov}_{ij} = [\bar{\sigma}\bar{\sigma}^T]_{ij}\bar{\rho}_{ij}$ where the standard deviation vector is $\bar{\sigma} = \begin{vmatrix} \sigma_a \\ \vdots \end{vmatrix}$

 σ_s is the standard deviation of the scene measurement (Kelvin) σ_{a} is the standard deviation of averaged warm calibration measurement ρ_{ii} is the correlation coefficient between each pair of measurements



Weighting Functions Employed:





Resulting Correlation Functions



Evaluation of Weighting Functions

Resultant total noise in the inferred scene temperature is plotted below for each of the channels, as a function of selected calibration weighting functions

Conclusions

The Table below shows the total noise for each weighting function that was evaluated. The lowest (optimal) values are highlighted.

		Uniform					Triangle			
	No. Pts:	2	4	6	8	10	4	6	8	10
	1	0.241	0.238	0.237	0.237	0.237	0.237	0.236	0.236	0.236
	2	0.302	0.299	0.298	0.297	0.297	0.298	0.297	0.296	0.296
	3	0.342	0.337	0.336	0.335	0.336	0.336	0.335	0.334	0.334
	4	0.271	0.274	0.276	0.278	0.279	0.271	0.273	0.274	0.275
	5	0.247	0.248	0.249	0.250	0.251	0.246	0.246	0.247	0.248
	6	0.269	0.269	0.270	0.271	0.272	0.268	0.268	0.269	0.269
	7	0.240	0.240	0.241	0.242	0.243	0.238	0.239	0.239	0.240
	8	0.243	0.242	0.242	0.243	0.243	0.240	0.240	0.241	0.241
	9	0.276	0.278	0.279	0.281	0.282	0.275	0.276	0.278	0.278
e	10	0.401	0.404	0.405	0.405	0.406	0.400	0.401	0.402	0.403
Chann	11	0.534	0.530	0.529	0.529	0.529	0.528	0.527	0.527	0.527
	12	0.555	0.555	0.555	0.556	0.556	0.551	0.551	0.552	0.552
	13	0.825	0.826	0.827	0.827	0.828	0.820	0.820	0.821	0.822
	14	1.154	1.144	1.141	1.140	1.139	1.139	1.136	1.135	1.135
	15	1.842	1.832	1.829	1.828	1.828	1.823	1.820	1.820	1.820
	16	0.228	0.236	0.240	0.244	0.246	0.231	0.235	0.238	0.240
	17	0.368	0.369	0.371	0.373	0.374	0.366	0.368	0.369	0.370
	18	0.336	0.331	0.331	0.331	0.332	0.331	0.330	0.330	0.330
	19	0.391	0.393	0.394	0.396	0.397	0.389	0.390	0.392	0.393
	20	0.462	0.461	0.462	0.463	0.463	0.458	0.458	0.459	0.460
	21	0.495	0.502	0.506	0.508	0.510	0.496	0.499	0.502	0.504
	22	0.668	0.667	0.669	0.671	0.672	0.663	0.664	0.665	0.667

for which: $\delta T_s = \frac{\delta C_s}{C} - \frac{\delta C_w}{C}$

Comparison of Rho(1) to low-frequency noise derived from spectra:









- In most cases, the triangle weighting function performs better than the uniform function
- For channels with greatest low-frequency noise content, such as channel 16, the 2-sample uniform function is best
- Compared effectiveness of various weighting functions for noise reduction, but more optimal functions could be constructed
- Other algorithms for striping reduction should be similarly evaluated relative to total noise criterion
- Minimization of inter-channel correlation would require use of only two calibration sectors, weighted by interpolation to the scene observation times. This is a future task, in process.