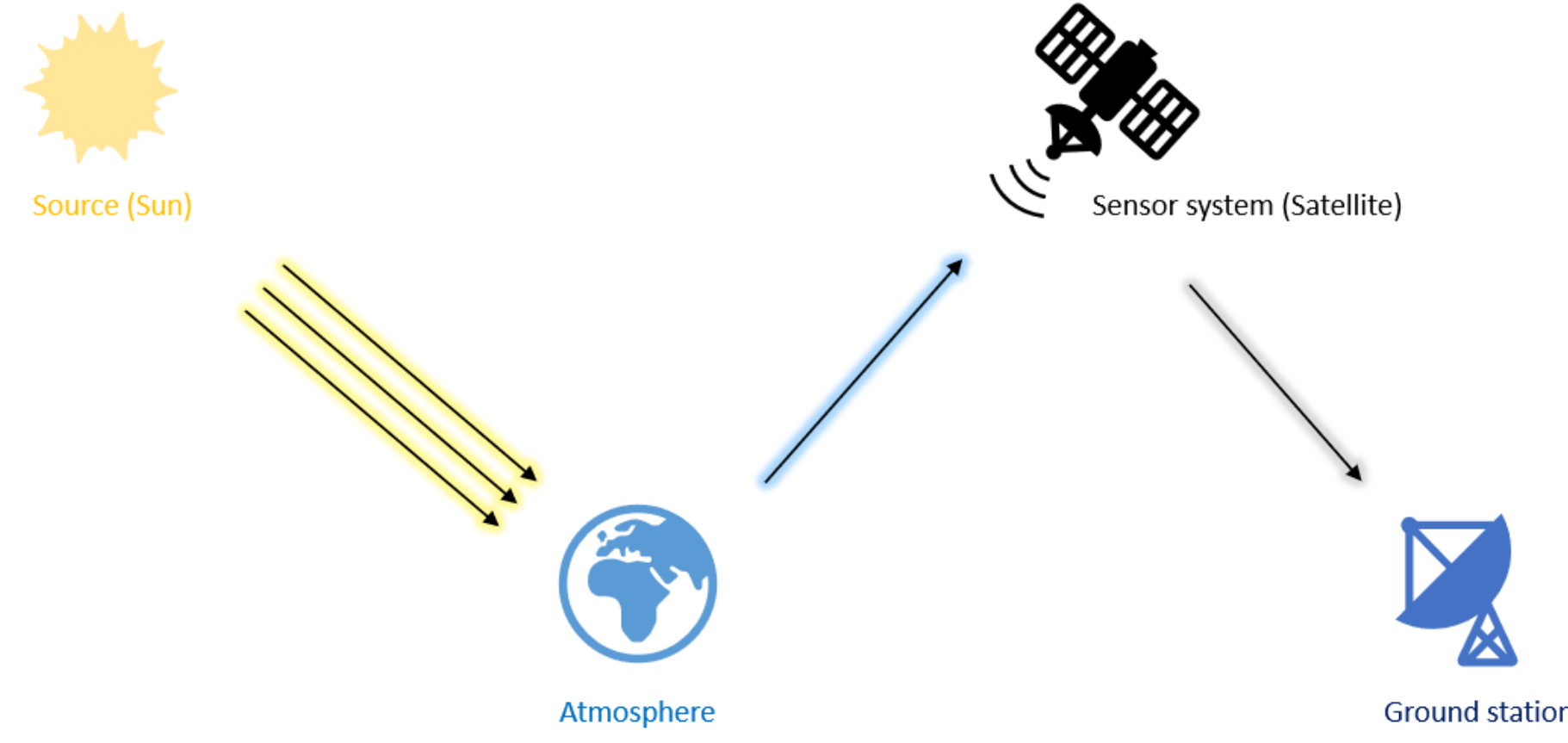


Introduction

Context



- Determination of the concentration of different gases in an atmosphere column
- Use of high-resolution spectrometers

Objectives

- Characterize the instrument model
- Estimate as accurately as possible the Instrument Spectral Response Functions (ISRFs)

ISRF estimation

Observation model

$$S_{\text{meas}}(\lambda_l) = (S_{\text{th}} * I_l)(\lambda_l) \approx \sum_{n=1}^N S_{\text{th}}(\lambda_n^*) I_l(\lambda_l - \lambda_n^*) \quad (1)$$

where $I_l(\lambda_l)$, $S_{\text{meas}}(\lambda_l)$ and $S_{\text{th}}(\lambda_n^*)$ are the ISRF associated with the l -th pixel, the measured spectrum at the wavelength λ_l and the theoretical spectrum defined at the wavelengths λ_n^* .

Hypothesis: I_l is assumed to be constant on a sliding window, i.e., for L measurements associated with the wavelengths $\lambda_{l-\frac{L}{2}}, \dots, \lambda_{l+\frac{L}{2}}$.

Parametric modeling [1]

Gaussian parameterization

$$I_l(\lambda, \beta_G) = A_G \exp\left(-\frac{(\lambda - \lambda_l - \mu_G)^2}{2\sigma^2}\right), \text{ where the vector } \beta_G = (A_G, \mu_G, \sigma^2)^T \text{ is estimated.} \quad (2)$$

Super-Gaussian parameterization

$$I_l(\lambda, \beta_{SG}) = A_{SG} \exp\left(-\left|\frac{\lambda - \lambda_l - \mu_{SG}}{w}\right|^k\right), \text{ where the vector } \beta_{SG} = (A_{SG}, \mu_{SG}, w, k)^T \text{ is estimated.} \quad (3)$$

Minimization of the residuals using the Least Square method

$$R_l(\beta) = \sum_{l'=l-\frac{L}{2}}^{l+\frac{L}{2}} \left[S_{\text{meas}}(\lambda_{l'}) - \sum_{n=1}^N S_{\text{th}}(\lambda_n^*) I_l(\lambda_{l'} - \lambda_n^*; \beta) \right]^2 \quad (4)$$

Sparse representation

Sparse approximation

- Dictionary $\Phi \in \mathbb{R}^{N \times N_D}$ created using an SVD
- I_l modeled using K atoms from the dictionary Φ

$$I_l \approx I_l^K = \sum_{k=1}^K \alpha_k \Phi_{\gamma_k} \quad (5)$$

- Sparse approximation problem [2]

$$\arg \min_{\alpha} L(\alpha, \mu) = \arg \min_{\alpha} \left\{ \|I_l - \Phi \alpha\|_2^2 + \mu \|\alpha\|_0 \right\} \quad (6)$$

- Use of the Orthogonal Matching Pursuit algorithm

Solving the inverse problem

$$S_{\text{meas}}(\lambda_l) \approx \sum_{n=1}^N S_{\text{th}}(\lambda_n^*) \sum_{k=1}^K \alpha_k \Phi_{\gamma_k}(\lambda_l - \lambda_n^*) = \sum_{k=1}^K \alpha_k \Psi_{\gamma_k}(\lambda_l) \quad (7)$$

Key results

Dataset and simulation scenarios

CNES simulations for the MicroCarb mission

- Theoretical spectra obtained with the 4A/OP radiative transfer software
- Measured spectra computed by convolution

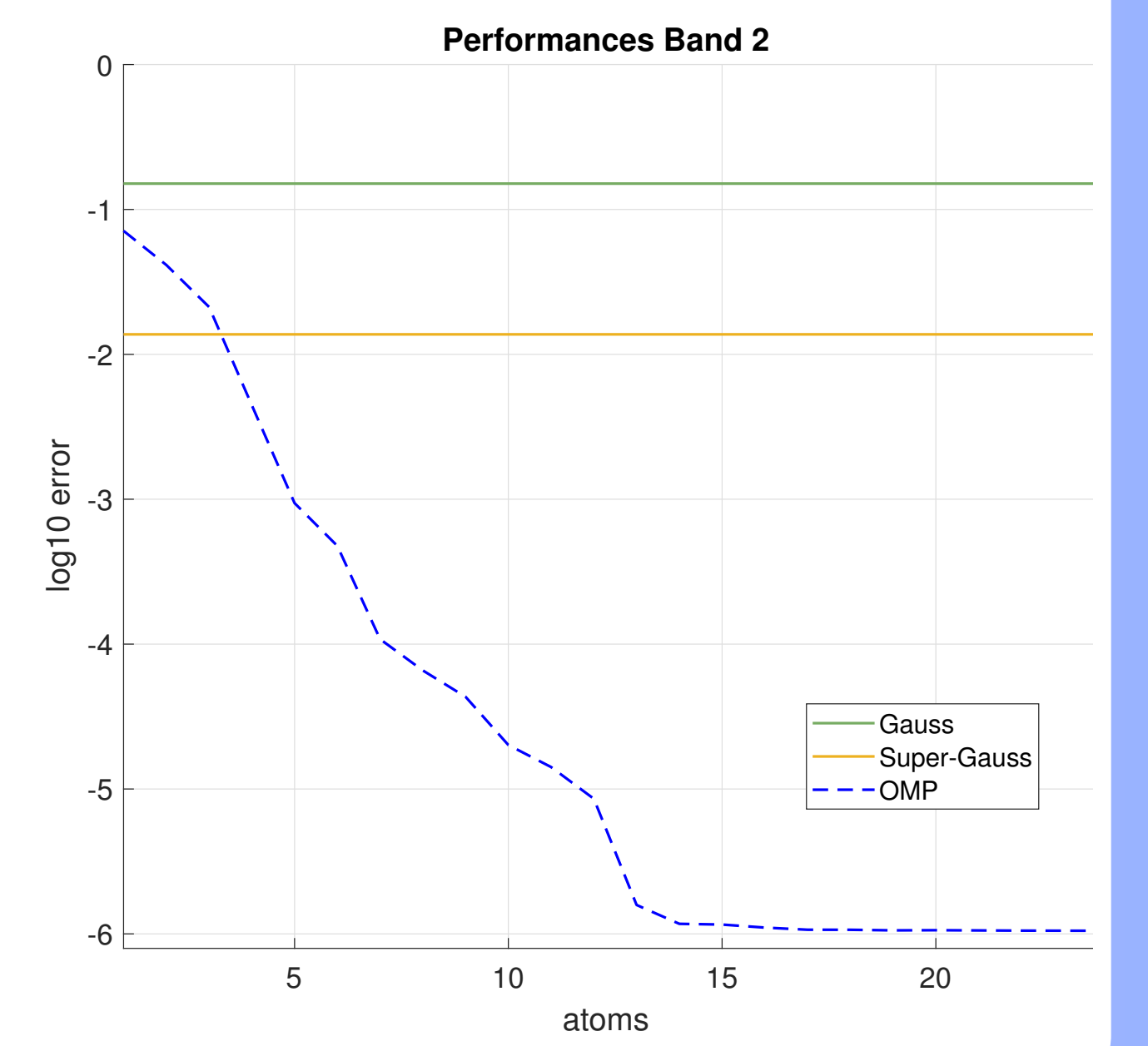
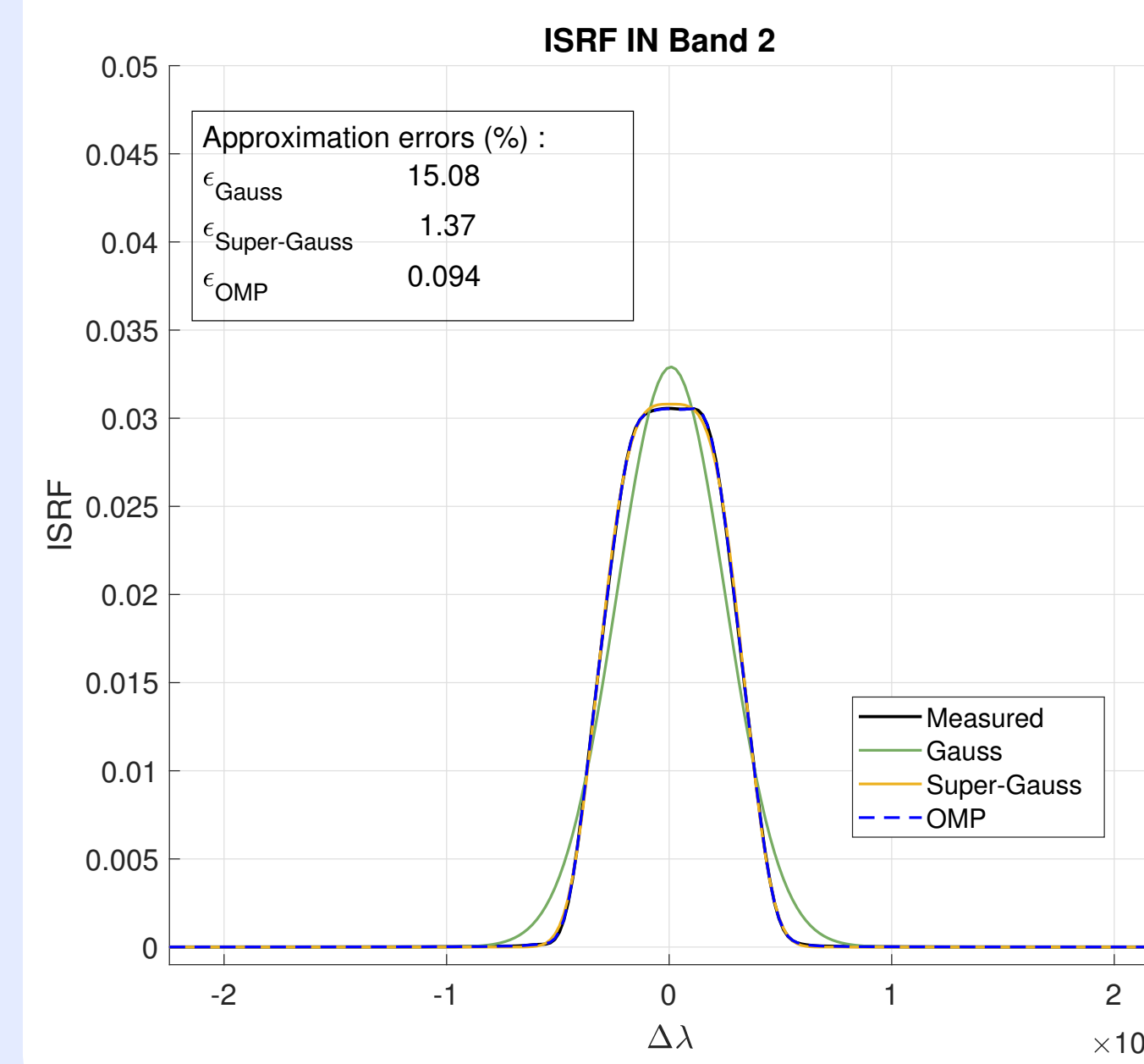


Estimation methods applied to band 2 associated with CO₂

- Minimization of $L(\alpha, \mu)$ using the simplex method (MATLAB function *fminsearch*)
- Dictionary built using the SVD of a matrix of 1024 examples of ISRFs for each spectral band
- Performance evaluated using the normalized absolute error: $\epsilon_l = \frac{\sum_n^N |I(\lambda_l - \lambda_n^*) - \hat{I}(\lambda_l - \lambda_n^*)|}{\sum_n^N I(\lambda_l - \lambda_n^*)}$

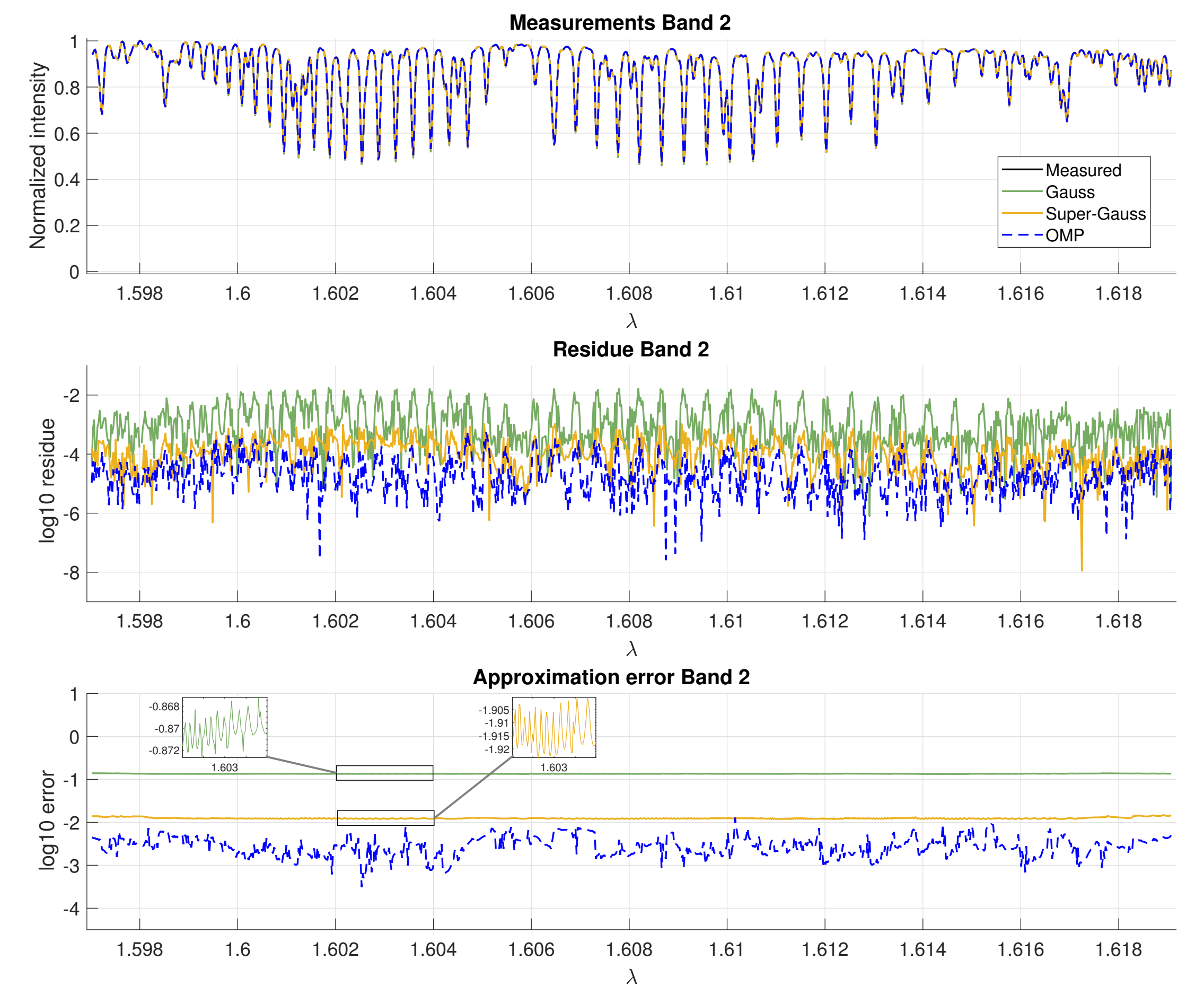
Approximation problem

Approximating ISRFs ($N_D = 25$, $K = 5$ atoms)



Solving the inverse problem

Reconstruction of the measured spectrum ($N_D = 25$, $K = 5$ atoms)



Conclusion & Prospects

- A new method for estimating spectral responses of spectrometers
- Analysis of other dictionary learning methods
- Take into account spectrum errors (scattered or stray light) that can degrade the estimation.
- ISRF denoising problem

References

- [1] S. Beirle et al., "Parameterizing the instrumental spectral response function and its changes by a super-Gaussian and its derivatives," *Atmos. Meas. Tech.*, vol. 10, no. 2, pp. 581-598, 2017.
- [2] Z. Zhang et al., "A Survey of Sparse Representation: Algorithms and Applications," *IEEE Access*, vol. 3, pp. 490-530, 2015.