

Imaging MeV Gamma-ray Lines with Advanced Image Reconstruction Framework for COSI

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The Compton Spectrometer and Imager (COSI), scheduled for launch in 2027, will improve sensitivity for MeV gamma-ray line observations by an order of magnitude, opening new windows to study cosmic nucleosynthesis. Primary targets include the 511 keV emission from positron annihilation, ^{26}Al from stellar nucleosynthesis, and ^{44}Ti from supernova remnants. However, image reconstruction in this energy band presents unique challenges: Compton telescopes constrain gamma-ray directions to circles rather than points, necessitating statistical approaches for source recovery. Additionally, complex background environments require careful treatment for reliable source detection.

We present an advanced image reconstruction framework implemented within the COSIpy data analysis library. Our approach extends COSIpy's capabilities by introducing a modified Richardson-Lucy algorithm with Bayesian priors optimized for MeV gamma-ray observations. The framework flexibly incorporates prior distributions for sparseness and smoothness while simultaneously optimizing background components. The modular design enables multi-dataset handling, multi-energy reconstruction, and unbinned likelihood analysis, providing a comprehensive tool for Compton telescope data analysis.

We evaluate the method using three months of simulated COSI observations of key nuclear lines (^{44}Ti at 1.157 MeV, ^{26}Al at 1.809 MeV, and positron annihilation at 0.511 MeV). Our results demonstrate successful suppression of artifacts in point source reconstructions while preserving extended emission features. For the complex 511 keV morphology, our method achieves total flux accuracy within 10% of the true value, while conventional approaches overestimate by $\sim 60\%$ due to artifact amplification. This work establishes a robust foundation for MeV gamma-ray image analysis with COSI and represents an important step toward advancing our understanding of nucleosynthesis, positron annihilation, and other high-energy phenomena in future missions.

1. Introduction

The Compton Spectrometer and Imager (COSI) is an upcoming NASA Small Explorer satellite mission scheduled for launch in 2027 [1]. It utilizes a Compton telescope consisting of 16 high-purity germanium detectors with excellent energy resolution (6.0 keV at 0.511 MeV) and wide field-of-view coverage ($> 25\%$ of the sky instantaneously). With these features, COSI will survey the entire sky in the 0.2–5 MeV energy range with unprecedented sensitivity. The primary science goals of COSI include mapping the spatial distribution of positron annihilation gamma rays and observing nuclear gamma rays from radioactive nuclei.

One of the challenges to achieving the above goals is reconstructing images from Compton scattering events. Image reconstruction for Compton telescopes presents fundamental challenges compared to focusing instruments because Compton imaging is an indirect imaging method. After event reconstruction, each detected gamma ray is characterized by a scattering angle and scattered photon direction, constraining the incoming direction to a circle in the sky rather than a unique point. This ill-posed inverse problem necessitates statistical methods to reconstruct images.

Traditionally, the Richardson-Lucy (RL) algorithm [2, 3] has been adopted for image reconstruction, which iteratively maximizes the Poisson log-likelihood. However, conventional RL methods suffer from well-known limitations: they amplify statistical fluctuations, creating artifacts around bright sources, and struggle with the complex background environments typical of MeV observations, where instrumental backgrounds often dominate celestial signals.

2. COSIpy Framework

2.1 COSIpy Data Analysis Framework Overview

COSIpy represents a comprehensive Python-based data analysis framework developed for COSI observations, potentially with broader applicability to other Compton telescope missions [4]. The framework is capable of performing all the high-level tasks expected for COSI: imaging, spectral, timing analysis, and polarimetry. COSIpy follows a modern likelihood-based approach as an open-source software and is based on the Multi-Mission Maximum Likelihood framework (3ML), which allows for joint spectral fitting across different missions in multi-wavelengths. Currently, it is under development by the COSI team, and an image deconvolution module is also being developed as part of the COSIpy library.

2.2 Image Deconvolution Module

The image deconvolution module within COSIpy adopts an instrument-agnostic approach through standardized interfaces between three components: the model, data interface, and deconvolution algorithm parts (see Figure 1). The model part defines a model space to be reconstructed, such as a pixelized all-sky map in Galactic coordinates or a three-dimensional gamma-ray intensity map. The data interface handles observed data, background models, and calculates expected counts from the input model using the detector response function. Finally, the deconvolution algorithm part implements image deconvolution algorithms. This modular design enables flexible image deconvolution, for instance, testing different algorithms using the same data and model configurations.

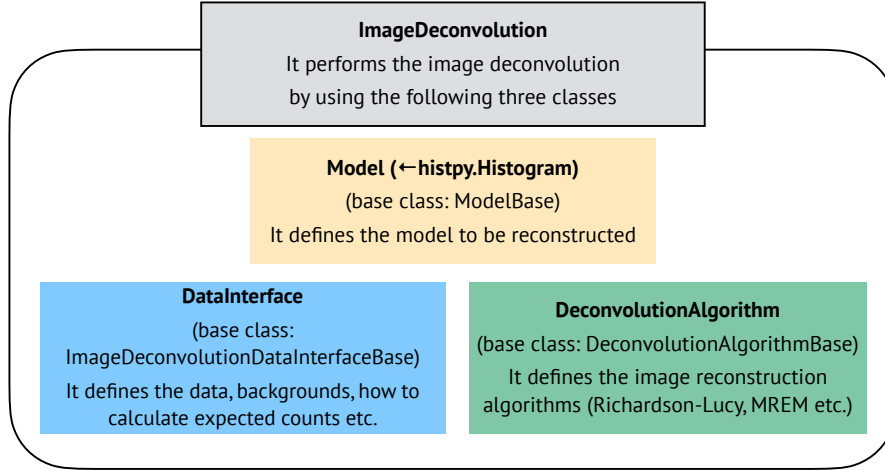


Figure 1: COSIpy image deconvolution framework architecture showing the modular design with configurable algorithms, data interfaces, and model components.

For example, Figure 2 shows reconstructed images over multiple energy bands using simulated data of the Crab pulsar and nebula and orbital background for three months of COSI observations. The framework demonstrates spatial-spectral reconstruction by utilizing all-sky detector response functions, including energy dispersion effects over the energy bins. Additionally, the framework will support unbinned likelihood analysis, which operates directly on photon event lists rather than pre-binned histograms. This capability is expected to be particularly effective for transient event analysis, in which rapid source localization is crucial.

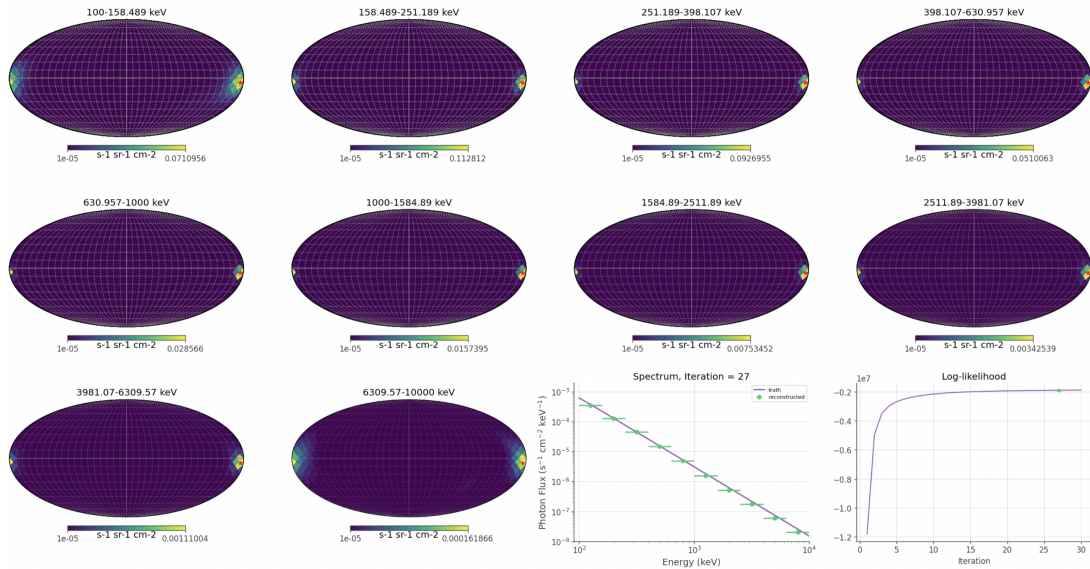


Figure 2: Spatial-spectral reconstruction of the Crab pulsar and nebula using three months of simulated COSI observations. The two bottom right panels show the reconstructed spectrum and likelihood evolution.

The image deconvolution module supports analysis with multiple datasets, which is crucial for handling temporal variations in detector response and background models during long-duration astronomical missions. By dividing data into appropriate periods, the framework can adequately account for detector degradation, satellite orbit changes, and increasing gamma-ray flux from accumulated radioactive events. This multi-dataset capability also enables joint image analysis using different missions, such as combined COSI and INTEGRAL/SPI observations, expanding scientific reach through cross-mission studies.

3. Modified Richardson-Lucy Implementation

3.1 Richardson-Lucy algorithm based on Maximum A Posteriori

As an extension to COSIpy's capabilities, we have proposed and implemented a modified Richardson-Lucy algorithm based on Maximum A Posteriori (MAP) estimation within a Bayesian framework [5]. By incorporating prior distributions $P_s(\lambda)$ for source images and $P_b(\mathbf{b})$ for background normalization parameters, this approach addresses the MeV gamma-ray specific challenges, i.e., artifacts in reconstructed images and background treatment. We note that the bold letters represent the set of parameters, such as the image values $\lambda = \{\lambda_1, \lambda_2, \dots\}$ and the background normalizations $\mathbf{b} = \{b_1, b_2, \dots\}$. The optimal solution maximizes the log-posterior probability:

$$\log Q(\lambda, \mathbf{b}) = \log L(\lambda, \mathbf{b}) + \log P_s(\lambda) + \log P_b(\mathbf{b}), \quad (1)$$

where $\log L(\lambda, \mathbf{b})$ is the standard Poisson log-likelihood. Using the Expectation-Maximization algorithm, the M-step is modified to solve:

$$\frac{\lambda_j^{\text{old}}}{\lambda_j^{\text{new}}} \sum_i \frac{D_i}{\epsilon_i} R_{ij} - \sum_i R_{ij} + \frac{\partial \log P_s(\lambda_j^{\text{new}})}{\partial \lambda_j} = 0, \quad (2)$$

where D_i and ϵ_i are observed and expected counts at the bin index i in a data space; R_{ij} is a response matrix. The index j is for the model space. We solve this equation approximately using a perturbation approach, enabling efficient computation. Details are provided in Yoneda et al. 2025 [5].

Background optimization employs gamma distribution priors that naturally incorporate preliminary background estimations and uncertainties:

$$P_b(b) = \prod_k \frac{b_k^{\alpha_{b,k}-1} \exp(-b_k/\beta_{b,k})}{\Gamma(\alpha_{b,k}) \beta_{b,k}^{\alpha_{b,k}}}. \quad (3)$$

Since the gamma distribution is the conjugate prior to the Poisson distribution, the M-step for the background normalizations can be solved explicitly as

$$b_k^{\text{new}} = \frac{\alpha_{b,k} - 1 + b_k^{\text{old}} \sum_i \frac{D_i}{\epsilon_i} B_{ik}}{\sum_i B_{ik} + \frac{1}{\beta_{b,k}}}, \quad (4)$$

where B_{ik} , which we refer to as the background template matrix, describes the event distribution pattern in a data space for a certain background component.

4. Applications & Results

4.1 Testing Sparsity and Smoothness Priors

We evaluate the framework using three months of simulated COSI observations spanning diverse source morphologies and different prior distributions. For sparsity regularization, we implement the approach of Ikeda et al. 2014 [6], which recognizes that traditional L1 norm regularization becomes ineffective because the sum of probability is conserved in gamma-ray flux reconstruction:

$$\log P_s(\lambda) = - \sum_j c_j^{\text{SP}} \log \lambda_j. \quad (5)$$

With a ^{44}Ti point source (Cas A) simulation, we apply the sparsity prior to suppress artifacts arising from background fluctuations. Figure 3 demonstrates the effectiveness of different sparsity coefficients, showing how increasing c^{SP} eliminates artifacts while preserving the true point source structure.

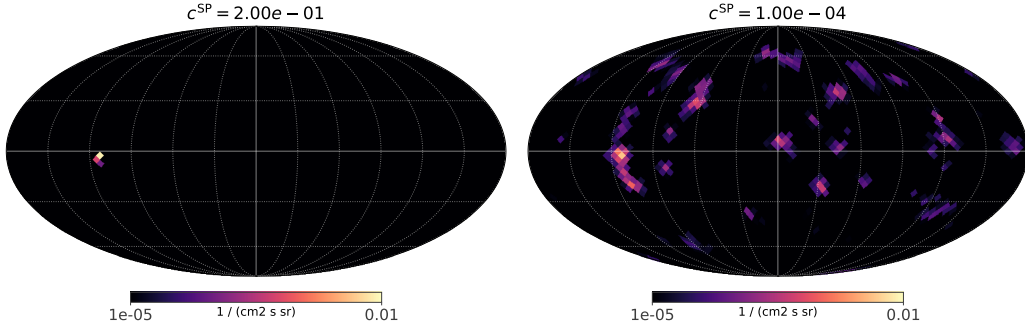


Figure 3: ^{44}Ti point source reconstruction with different sparsity coefficients [5]. Left: $c^{\text{SP}} = 2.0 \times 10^{-1}$ showing sparse reconstruction. Right: $c^{\text{SP}} = 1.0 \times 10^{-4}$ showing artifacts from insufficient regularization.

For smoothness regularization, we implement Total Square Variation (TSV):

$$\log P_s(\lambda) = -c^{\text{TSV}} \sum_j \sum_{j' \in \sigma_j} (\lambda_j - \lambda_{j'})^2, \quad (6)$$

where σ_j represents the set of adjacent pixels of the pixel j . With a ^{26}Al extended source simulation, we apply the TSV smoothness prior to maintain continuous spatial structure. Figure 4 compares our MAP RL approach with conventional RL, clearly showing how the smoothness prior prevents fragmentation of the extended emission into artificial point-like features.

4.2 511 keV Analysis Results & Performance Validation

For 511 keV positron annihilation, we demonstrate the framework's capability to handle complex multi-component morphologies. Here we adopt both sparseness and smoothness priors. Figure 5 shows reconstruction results for the thin disk model, which includes a point source at the Galactic center, two Gaussian bulge components, and extended disk emission. Our Bayesian approach (MAP RL) successfully maintains continuous disk structure while conventional RL fragments the emission into artificial point-like features.

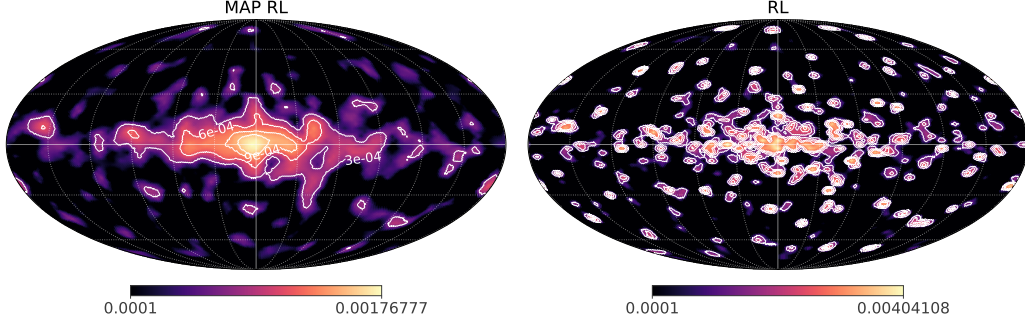


Figure 4: ^{26}Al extended emission reconstruction [5]. The left panel shows the image obtained from our algorithm, and the right panel is from the conventional RL algorithm.

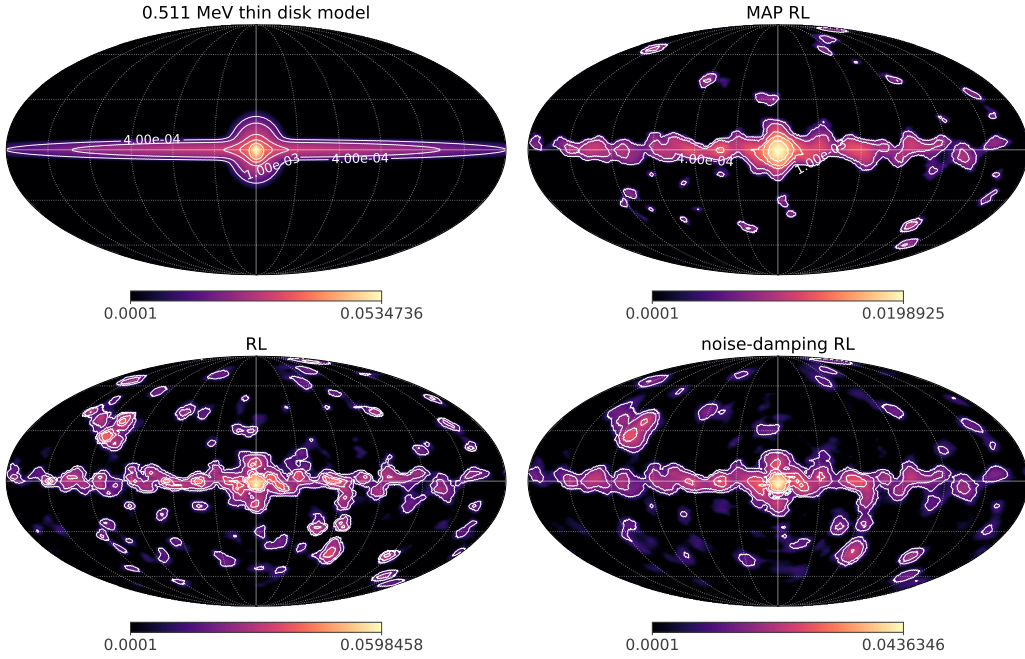


Figure 5: 511 keV thin disk model reconstruction comparison [5]. Top: Input model (left) and MAP RL result (right). Bottom: Conventional RL (left) and noise-damping RL (right) showing significant artifacts.

We also evaluate the performance of the proposed method over conventional methods quantitatively. For the 511 keV analysis, our method achieves total flux accuracy within 10% of the true value, while conventional approaches overestimate by $\sim 60\%$ due to artifact amplification in regions with low exposure. The proposed algorithm also successfully distinguishes between competing thin and thick disk models, demonstrating sensitivity to morphological differences crucial for understanding positron origins.

5. Conclusions

As part of the COSIpy library, we have developed an image reconstruction framework and also proposed an advanced image reconstruction algorithm based on a Bayesian approach as an extension

of the framework. By incorporating optimized priors for Poisson data and enabling simultaneous background optimization, it successfully addresses fundamental challenges in Compton telescope data analysis. With three months of simulated COSI observations, we demonstrated improvements in reconstructed images, including artifact suppression in point source reconstructions, preservation of extended emission structures, under dominant background environments.

The framework adopts an instrument-agnostic design and modular architecture, potentially making it a valuable community tool extending beyond COSI to benefit broader MeV gamma-ray astronomy. Future developments will leverage COSI's unprecedented sensitivity to advance our understanding of nucleosynthesis, positron annihilation, and high-energy astrophysical processes throughout the Galaxy.

Acknowledgements

HY acknowledges support by JSPS KAKENHI Grant Number 23K13136 and the Bundesministerium für Wirtschaft und Klimaschutz via the Deutsches Zentrum für Luft- und Raumfahrt (DLR) under contract number 50 OO 2219. The Compton Spectrometer and Imager is a NASA Explorer project led by the University of California, Berkeley with funding from NASA under contract 80GSFC21C0059. Resources supporting this work were provided by the NASA High-End Computing (HEC) Program through the NASA Advanced Supercomputing (NAS) Division at Ames Research Center.

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