Localization and Confidence Region Estimation of Short GRBs with the COSI BGO Shield Using a HEALPix-Based Deep Learning Approach

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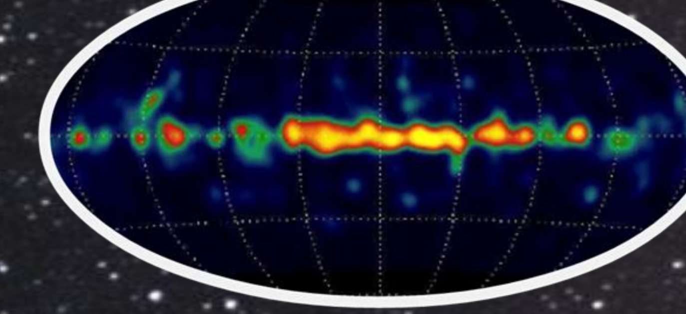

Summary

- The Compton Spectrometer and Imager (COSI)[1] is a NASA satellite mission under development that will survey the entire sky in the 0.2–5 MeV range with a wide-field gamma-ray telescope. Its main instrument consists of a germanium detector array, surrounded on the sides and bottom by bismuth germanate (BGO) scintillator active shields (the Anticoincidence Subsystem, ACS).
- The ACS both suppresses and monitors background events and enables the detection of transient sources. COSI will include an onboard triggering algorithm capable of identifying Gamma-Ray Bursts (GRBs) in the ACS and transmitting data to the ground for further analysis. The GRBs will be localized by an automated pipeline, with the localizations promptly sent to the community via GCN.
- In this work, we present two short GRB localization methods based on ACS data using Deep Learning (DL) techniques. Different network architectures were evaluated to estimate localization uncertainties at the 90% confidence level, including cases where the confidence region is split into multiple areas.

Introduction

The ACS is composed of 22 BGO crystals, ten in the bottom side and three on each lateral side (Figure 1). Each crystal is coupled to a 3×3 array of 6 mm Silicon Photomultipliers (SiPM), each with two gain channels: a high-gain "gamma" channel (≈80 keV – 2 MeV) and a low-gain "proton" channel (>2 MeV). Both channels are read out by an Application-Specific Integrated Circuit (ASIC), with one ASIC serving four crystals to reduce readout time and power use. Count rates are recorded every 50 ms for GRB detection, and localization is achieved by combining data from lateral and bottom modules. The analyses in this work use only the "gamma" channel. The Light Curves of the ACS segments are obtained by grouping a lateral wall per ASIC with two further ASICs reading out the bottom wall. The final two bottom BGO modules are combined with two lateral walls as illustrated in Figure 2. The red boxes indicate the aggregation of bottom modules into lateral walls to use available ASIC channels while minimizing the effect on localization.

In previous works, we compared the localization performance of our deep learning (DL) model with the χ^2 fit and the bc-tools localization methods. However, that comparison was limited to the angular distance error between the simulated GRB positions and the localized positions, since the first DL model could not estimate the 90% confidence error regions. In this work, we present a new DL model capable of estimating the 90% confidence error areas, allowing for a direct comparison with traditional localization methods.

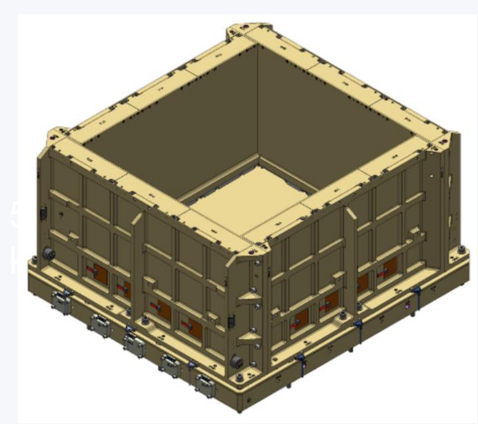

Figure 1: COSI ACS Design

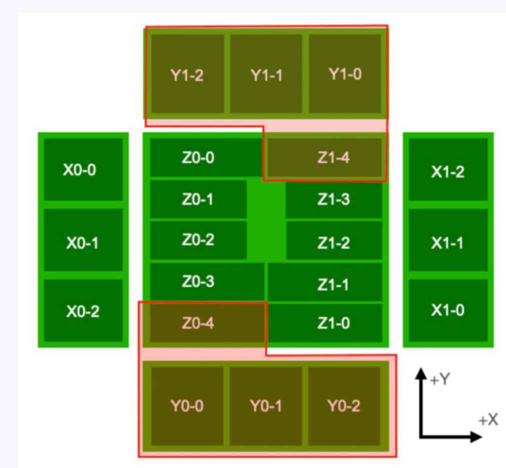

Figure 2: BGO Crystals Scheme

Methods

Dataset Simulation

We simulated two GRB datasets using MEGAlib[2] for training and testing purposes. The testing dataset contains 49,152 GRBs following the HEALPix coordinate system (nside=64), while the training dataset contains 100,000 GRBs randomly sampled from the HEALPix positions with nside=128. The GRBs are simulated with a flux ranging between 1 and 30 ph/cm^2/s in the energy range 10 keV – 10 MeV, a duration of one second and three possible spectral models. We used alpha = -1.9, beta = -3.7, and E_{break}= 230 keV for soft Band spectrum and alpha = -1, beta = -2.3, and E_{break}=699.9 keV for medium Band spectrum. The hard spectrum is defined with a Comptoinzed function having alpha = -0.5 and E_{cutoff}=1500 keV.

Probabilistic Regressor Implementation

We developed a custom Keras DL model to predict the GRB's incoming direction as θ and φ angles. Detector panel signals serve as inputs and are processed through multiple dense layers (256, 128 and 64 neurons respectively) with LeakyReLU activations and dropout regularization. The network outputs both a mean direction vector, (sin θ, cos θ, sin φ, cos φ), and a lower-triangular covariance matrix, representing the prediction as a multivariate normal distribution. This probabilistic formulation enables the model to provide not only directional estimates but also associated uncertainties.

Neural Network Classifier Implementation

This second model maps the ACS panel counts to a probability distribution over sky positions represented in HEALPix format. The architecture consists of fully connected layers with 256, 128, and 64 neurons, each followed by LeakyReLU activations and dropout regularization to prevent overfitting. The final layer uses a softmax activation to produce a normalized probability distribution over all HEALPix pixels. The targets are one-hot encoded HEALPix maps representing the true source position. To improve training stability, the true positions are smoothed to avoid collapsing onto a single pixel.

Results

The results show that the probabilistic regression model outputs a multivariate normal distribution and describes GRB localization uncertainties as elliptical error regions. This approach suits cases where the error distribution is unimodal and Gaussian-like. However, it cannot capture complex or multimodal error structures caused by detector geometry. In contrast, the HEALPix-based probabilistic model, predicting a probability distribution over the sky map, enables estimation of multimodal error regions covering multiple possible sky areas as shown in Figure 3. The HEALPix probability maps reveal richer spatial structures, capturing several peaks in the predicted localization probability.

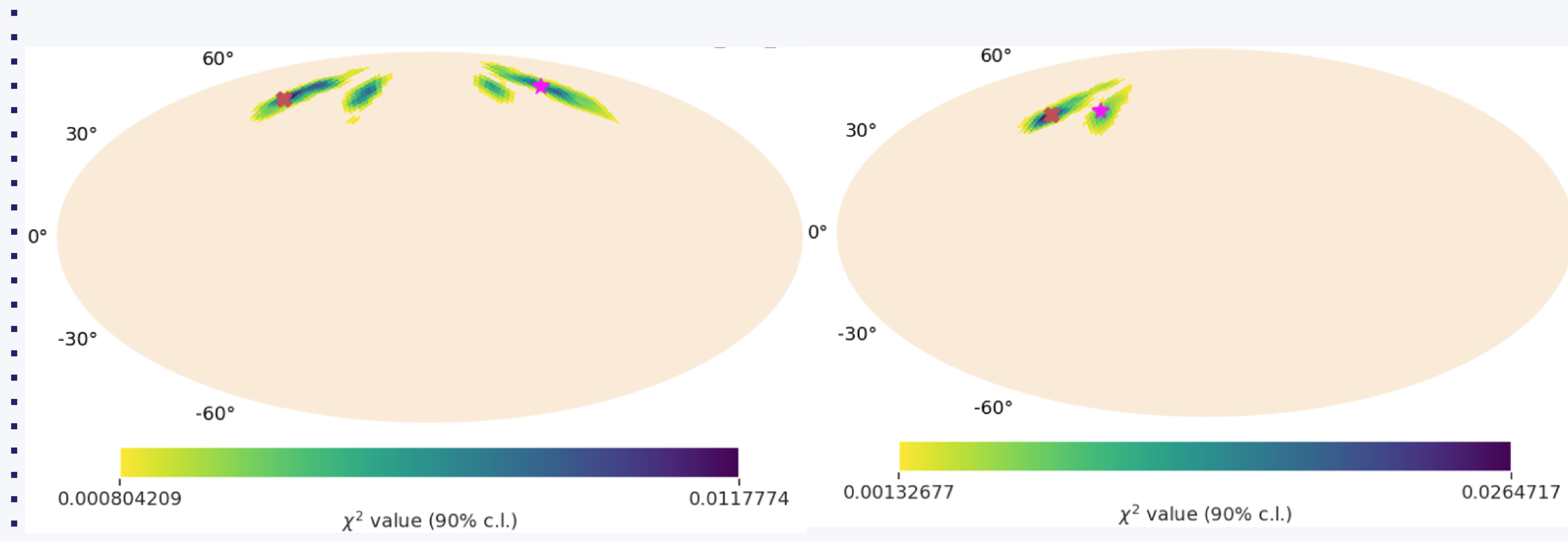

Figure 3: Examples of 90% C.L. error regions with multi-modal behaviour. Purple star markers indicate the simulated GRB positions, while red X markers indicate the GRB localizations.

Conclusions

The results of this work demonstrate that the HEALPix-based classification model can successfully estimate GRB localization error regions from COSI-ACS data, even when the probability distributions are multi-modal, up to four distinct regions. This approach extends the model's applicability beyond simple Gaussian assumptions, providing a more realistic representation of localization uncertainty. Ongoing analyses aim to further characterize these error regions and compare them with those obtained using traditional methods, such as MLE and χ^2 fitting.

[1] Tomsick, J., Boggs, S., Zoglauer, A., et al. 2024, in 38th International Cosmic Ray Conference, 745,1028 doi: 10.48550/arXiv.2308.12362
[2] MEGAlib: https://megalibtoolkit.com/home.html

cosi.ssl.berkeley.edu

Acknowledgements
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