Krittika Summer Projects 2024

Gamma Ray Bursts Signal Analysis

Rahul E

Contents

Abstract

Gamma-ray bursts (GRBs) are highly energetic cosmic events that provide valuable insights into astrophysical phenomena. Accurate detection and classification of GRBs are crucial for understanding their origins and associated phenomena. In this project, we focused on developing techniques for detrending GRB light curves and evaluating their signal-to-noise ratios (SNR). The detrending methods, including mean of moving averages, median of moving averages, and Savgol filter, effectively removed background noise, enabling precise analysis of GRB signals. We employed various SNR evaluation techniques, such as Gaussian noise fit, Poisson noise fit, and SNR based on mean and variations in noise, to classify genuine GRBs from non-GRB events. Our research included preprocessing the data obtained from the AstroSat CZTI instrument and applying detrending methods to eliminate background noise. By evaluating the SNR, we improved the reliability of GRB detection and classification. Future work involves testing the techniques on fainter GRBs and developing a general framework for distinguishing different types of GRBs from non-GRB signals.

1 Introduction

Gamma-ray bursts (GRBs) are powerful and highly energetic cosmic events that have been a subject of intense research due to their profound implications in astrophysics. Accurate detection and classification of GRBs play a pivotal role in understanding their origins and associated astrophysical phenomena. In this mid-project report, we present our research on determining the signal-to-noise ratio (SNR) as a quantifiable metric for classifying GRBs using data obtained from the AstroSat CZTI (Cadmium Zinc Telluride Imager) instrument.

The primary objective of this project is to develop an effective technique for quantifying the SNR of GRB signals observed by the CZTI instrument. By accurately estimating the SNR, we aim to distinguish genuine GRBs from spurious signals, thereby improving the reliability of GRB detection and classification.

The AstroSat CZTI instrument, equipped with an array of Cadmium Zinc Telluride detectors, provides an excellent opportunity for precise gamma-ray observations. Leveraging the CZTI data, we seek to explore the characteristics of GRB signals and identify the optimal SNR thresholds for distinguishing real GRBs from noise or other non-GRB events.

2 Background

Gamma-ray bursts (GRBs) are transient astrophysical events characterized by highly energetic emissions across the electromagnetic spectrum. They originate from various phenomena, such as the collapse of massive stars or the merger of compact objects like neutron stars or black holes. the detection and classification of GRBs pose significant challenges due to Factors such as instrumental noise, cosmic-ray backgrounds, and the presence of other astrophysical sources emitting similar high-energy signals contribute to the difficulty in distinguishing genuine GRBs from spurious or non-GRB events.

One of the fundamental metrics used in astrophysics to quantify the strength of a signal relative to the background noise is the signal-to-noise ratio (SNR). By establishing an accurate SNR threshold, it becomes possible to differentiate genuine GRBs from noise or other non-GRB signals. Our initial approaches include Gaussian noise fit SNR calculation, Poisson noise fit SNR calculation, and SNR determination based on the mean and variations in the noise. The objective of our research is to compare and rank the different techniques based on their performance in GRB classification and aim to identify the best possible method for determining the SNR and effectively discriminating between real GRBs and spurious signals.

3 Methodology

3.1 Data Collection

The data required for this project was obtained from the AstroSat CZTI instrument. The CZTI data provides crucial information about the energy and arrival time of detected gamma-ray photons. To access the data, we downloaded the necessary files from the AstroSat Data Archive, which is available at AstroBrowse.

The data obtained from the AstroSat CZTI instrument forms the foundation for our analysis and enables us to investigate the characteristics of GRB signals.

3.2 Pre-processing and Calibration

After obtaining the CZTI data from the AstroSat Data Archive, the downloaded data underwent a series of preprocessing and calibration steps to ensure accurate analysis. The following pipelines were employed to clean and prepare the data for further analysis.

3.2.1 Cztgtigen

Generate GTI (Good Time Intervals) based on the current GTI, mkf (attitude) data, and user input. This step helps to identify the time intervals during which the instrument was functioning optimally and the data is reliable.

3.2.2 Cztdatasel

Select events based on the GTI obtained in the previous step. This process involves extracting only the events that fall within the designated good time intervals, discarding data from periods affected by instrumental artifacts or unreliable measurements.

3.2.3 Cztpixclean

Identify and remove noisy pixels and detectors by analyzing the data. This step helps in removing events that are affected by instrumental noise, cosmic-ray contamination, or other anomalies associated with specific pixels or detectors.

3.2.4 Cztflagbadpix

Combine bad pixel lists from multiple sources, if required. This step involves incorporating information about known bad pixels from various sources to ensure accurate identification and removal of problematic pixels during subsequent analysis.

3.2.5 Cztbindata

Generate light curves and spectra from the cleaned and calibrated data. This step involves binning the data to obtain light curves or grouping events to create energy spectra, which can provide valuable insights into the temporal and spectral properties of GRBs.

By following these preprocessing and calibration steps, we aimed to obtain clean and reliable data, free from instrumental artifacts and background contamination, ready for subsequent SNR calculation and GRB analysis.

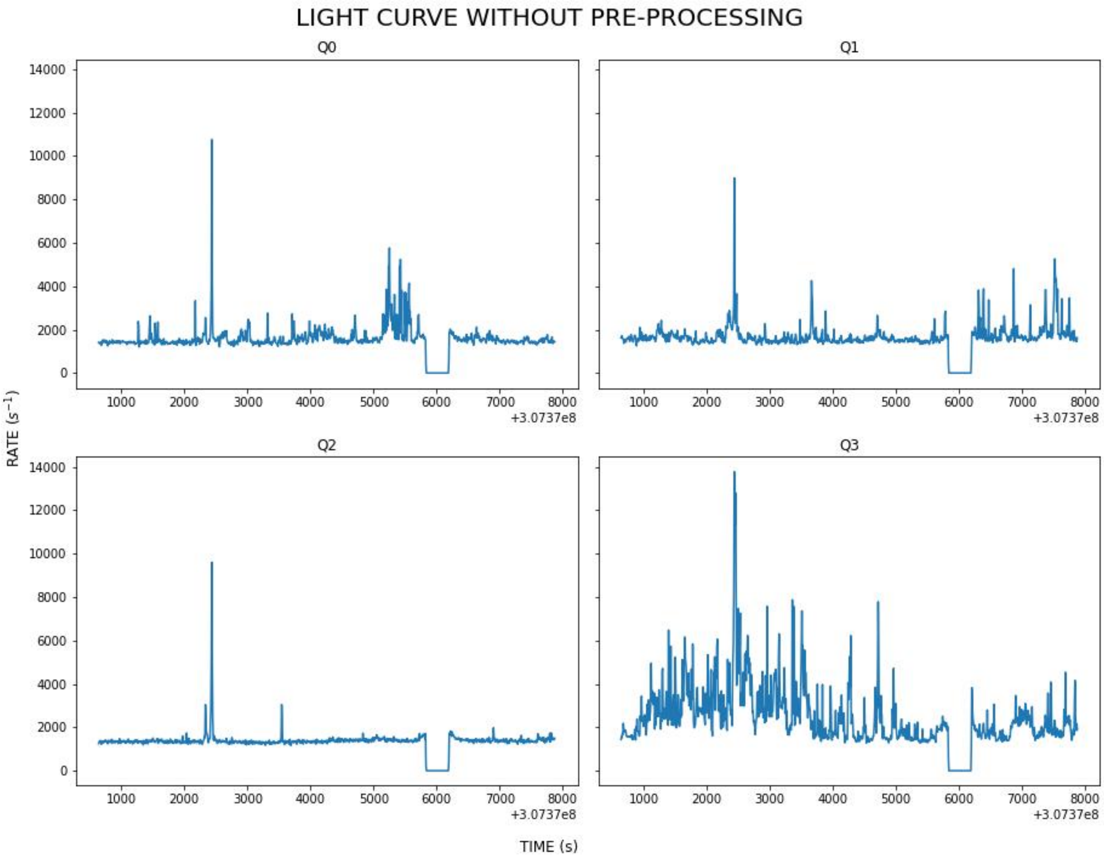

Figure 1: GRB190928A: Light curve with the unprocessed data

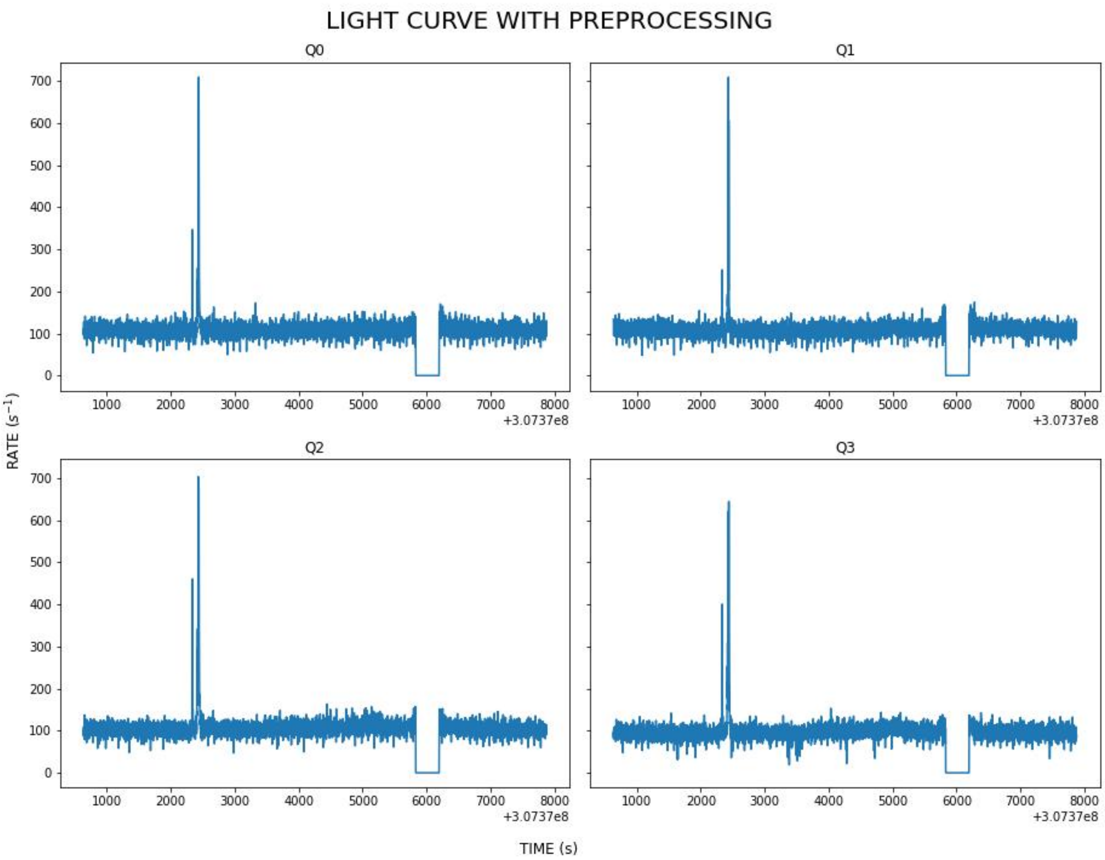

Figure 2: GRB190928A: Light curve with the processed data

3.3 Detrending

Detrending is a data processing technique used to remove long-term trends and systematic variations from a time series or signal, revealing the underlying short-term variations of interest. In the context of GRB light curves, detrending is crucial to eliminate the effects of constant background noise and other unwanted components, enabling a clearer analysis of the burst's intrinsic variability.

There are several detrending methods that can be employed in the analysis of GRB light curves. In your project, three detrending techniques were utilized: the mean of moving averages, the median of moving averages, and the Savgol filter.

3.3.1 Mean of Moving Window

The mean of moving averages method involves calculating the moving average over a specified window size and then taking the mean of these averages to obtain the trend line. This trend line represents the long-term variations or systematic components present in the GRB light curve. To remove this trend from the original light curve, you subtracted the trend line from the light curve.

By subtracting the trend line, you effectively eliminated the long-term variations associated with the constant background noise count and other systematic components. This process helped to isolate the intrinsic variability of the GRB signal, allowing for a more focused analysis and accurate estimation of the signal-to-noise ratio (SNR)

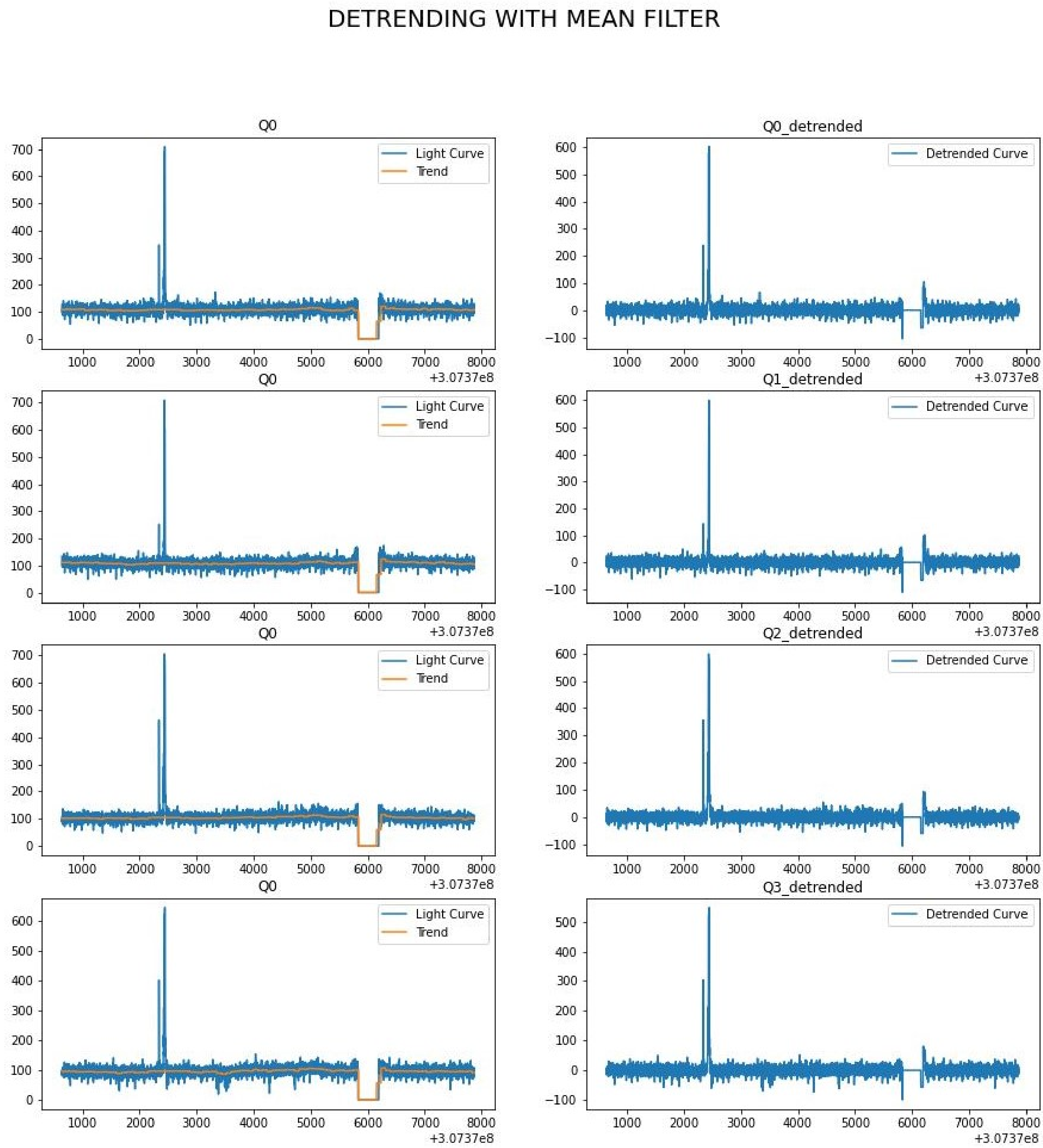

Figure 3: GRB190928A: De-Trending with mean of moving averages on all the four quadrants of CZTI

3.3.2 Median of Moving Window

This is similar to the previous method, but instaed of taking the mean of the moving window, we took the median of the moving window.

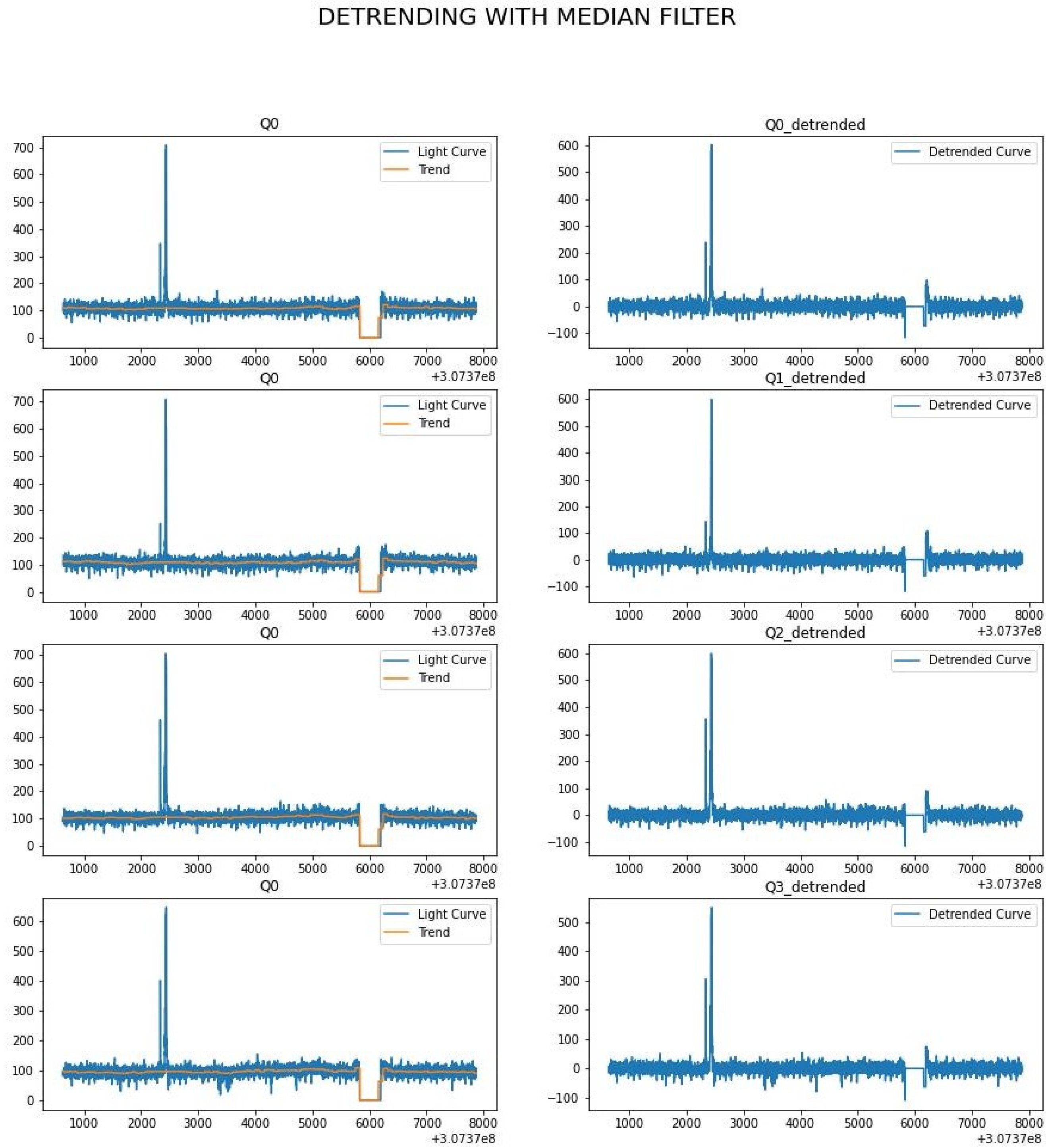

Figure 4: GRB190928A: De-Trending with median of moving averages on all the four quadrants of CZTI

3.3.3 Savgol Filter

The Savgol filter, also known as the Savitzky-Golay filter, is a commonly used signal processing technique for noise reduction and trend removal. It applies a polynomial fit to local segments of the light curve and produces a smoothed representation by minimizing the least squares difference between the polynomial fit and the original data points. By applying the Savgol filter, both the constant background noise count and any other systematic variations, such as the SA window, can be effectively eliminated, revealing the burst's intrinsic variability.

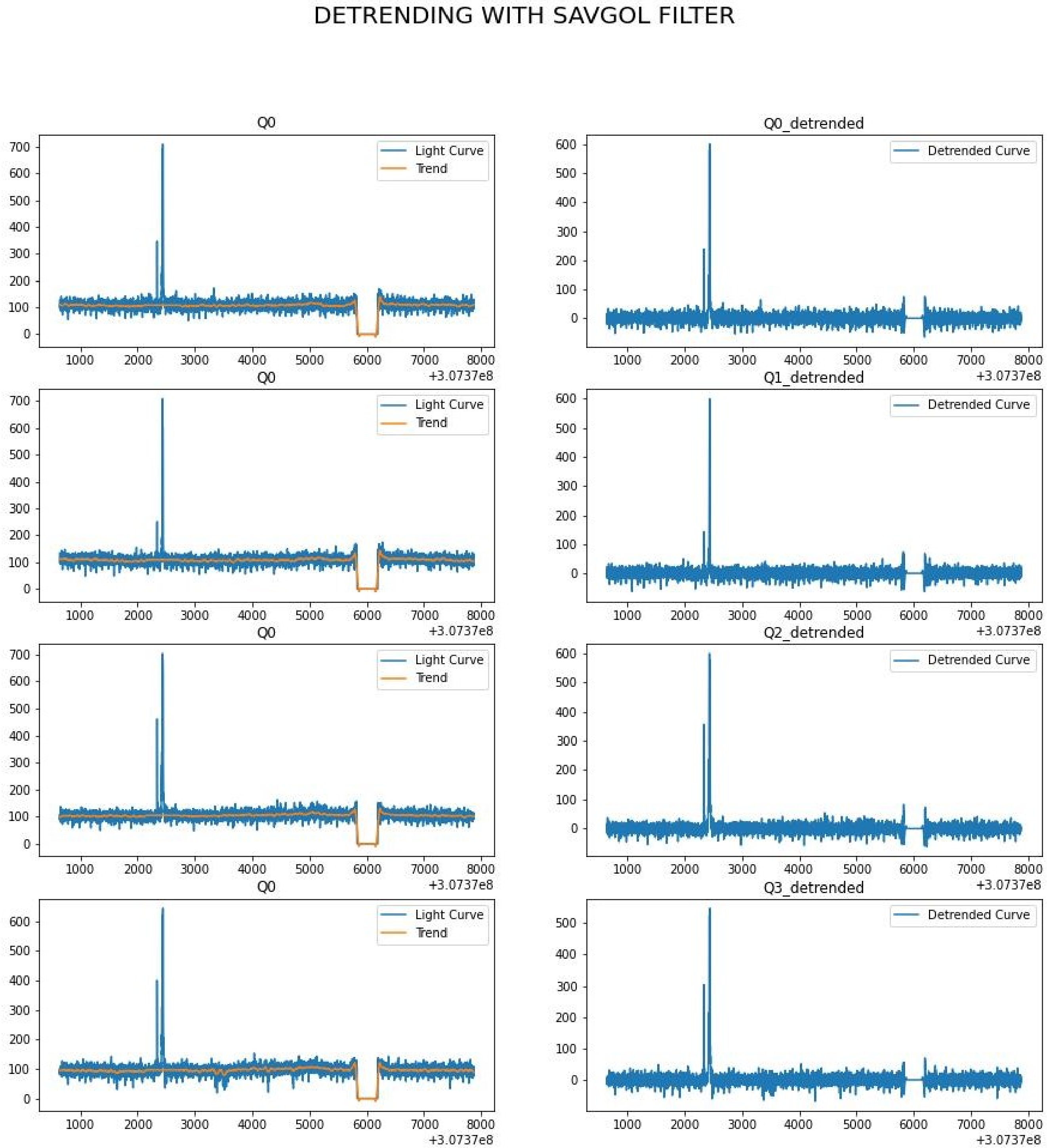

Figure 5: GRB190928A: De-Trending with SAVGOL filter on all the four quadrants of CZTI

Each detrending method has its advantages and considerations. The mean of moving averages and the median of moving averages are relatively simple and straightforward approaches that provide good results in many cases. They are particularly useful when the data contain consistent trends that need to be removed. On the other hand, the Savgol filter offers more flexibility and adaptability, allowing for the adjustment of window size and polynomial order to optimize the detrending performance based on the specific characteristics of the light curve.

By applying these detrending methods to the GRB light curves in your project, you were able to effectively remove the constant background noise count and the SA window, resulting in detrended light curves that emphasized the burst's genuine variability. These detrended light curves served as the basis for subsequent SNR calculations and classification analyses, enabling a more accurate characterization and classification of GRB signals.

3.4 Particle Events

A particle event refers to the detection of high-energy particles, such as cosmic rays or energetic charged particles, in a detector or observational instrument. These particles can originate from various sources, including the Sun, other stars, supernovae, or even distant astrophysical objects. When these high-energy particles interact with the Earth's atmosphere or the detector material, they produce secondary particles, and the resulting shower of particles can be detected and recorded.

In light curve analysis, a particle event would typically result in a sudden increase in the detected particle flux, followed by a gradual decrease as the shower of secondary particles subsides. The light curve of a particle event might appear as a sharp peak or spike in the data, depending on the energy and intensity of the detected particles.

Particle events can resemble GRB (Gamma-Ray Burst) signals in a light curve due to their sudden increase in count rate and energy deposition patterns, resembling the initial intense phase of a GRB. The issue can lead to false astrophysical interpretations and misrepresentation of the true phenomena in the universe. Accurate identification of GRBs is crucial for understanding high-energy processes in distant astrophysical sources, and the presence of particle events in the data can significantly impact the reliability and validity of scientific findings.

3.4.1 Elimination of Particle Event

Particle events, caused by high-energy particles like cosmic rays, typically exhibit a continuous and broad energy spectrum (5-100 KeV) without distinct spectral features. They are usually of short duration, ranging from milliseconds to seconds, and often show a sudden increase in count rate followed by a rapid decline. Properly analyzing the energy distribution and duration in the light curve, along with considering the instrument's response and background, are crucial in identifying and distinguishing particle events from other astrophysical signals, ensuring accurate interpretations and data analysis in high-energy astrophysics.

Steps taken to eliminate Particle Event

1. Splitting the Energy bands - The total energy of the GRB is 5-261 KeV. Particle events are mostly present in 5-100 Kev, therefore we split the light curve into three energy bands.

- 5-50 KeV
- 50-100 KeV
- 100-200 KeV

SNR analysis is done on each energy range separately and the weightage for the three energy band is assigned appropriately

2. Checking all the Quadrants - If GRB signal is detected it would reflect on all the four Quadrants (if not four, at least three). But for particle event, the sudden burst will present only in one or two of the quadrants.

With help of these two techniques it is possible to eliminate the false detection of particle event as an GRB signal and ensuring accurate interpretations and data analysis in SNR calculation.

3.5 SNR Calculation Techniques

To determine the signal-to-noise ratio (SNR) of GRB signals, we explored multiple calculation techniques. These techniques included

3.5.1 Gaussian Noise Fit SNR Calculation

This method involves fitting a Gaussian distribution to the background noise to obtain the mean background noise. To calculate the SNR of the GRB, the maximum value of the count in the GRB window is divided by the mean background noise calculated.

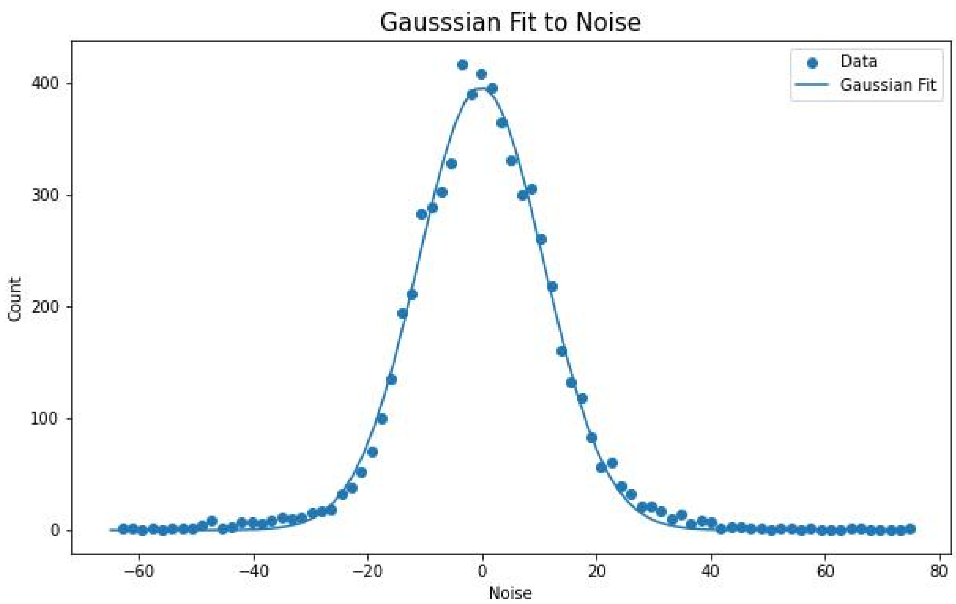

Figure 6: GRB190928A: Gaussian Fit for noise in Quadrant 0

3.5.2 Poisson Noise Fit SNR Calculation

This method involves fitting a Poisson distribution to the background noise to obtain the mean background noise. For poisson fit, an offset must be added to detrended data to get a proper fit. To calculate the SNR of the GRB, the maximum value of the count in the GRB window is divided by the mean background noise calculated.

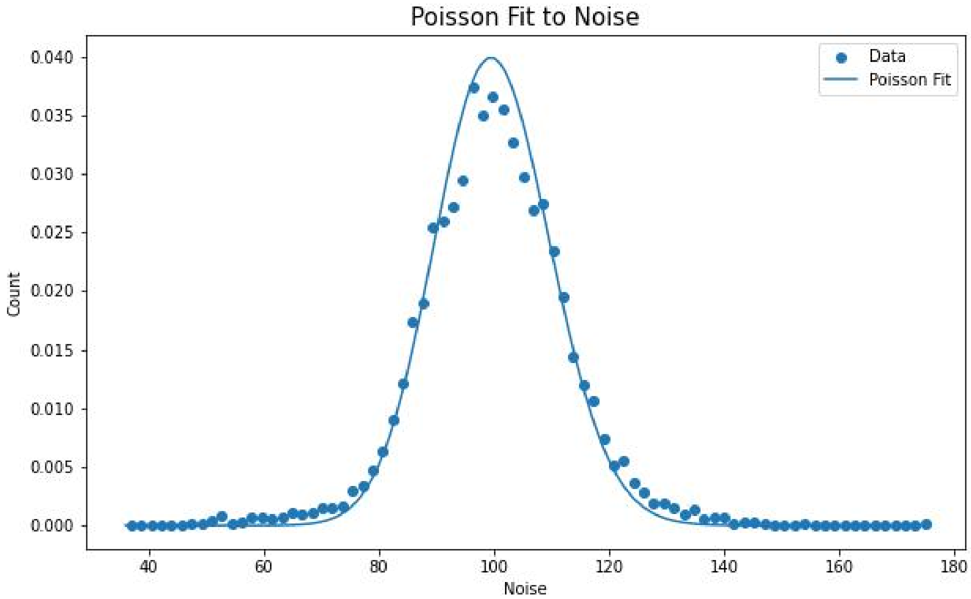

Figure 7: GRB190928A: Poisson Fit for noise in Quadrant 0

3.5.3 SNR using Mean and Variations in Noise

This approach involves calculating the mean and variations in the background noise and utilizing these statistical parameters to estimate the SNR.

The SNR calculated using the Mean and variance after detrending the data appears to be the best method to calculate the SNR, after analyzing the different parameters such as RMSE, Kurtosis, Skewness, Variance.

4 Software Tools and Platforms

We conducted our research using data obtained from the AstroSat CZTI instrument. The data cleaning and preprocessing steps were performed using various software tools and platforms, including the following components.

1. Operating System: The data cleaning pipelines were executed on the Ubuntu operating system, providing a reliable and stable environment for running the required software tools.

2. Data Cleaning Pipelines: The data cleaning pipelines, including cztgtigen, cztdatasel, cztpixclean, cztevtclean, and cztflagbadpix, were executed within the Ubuntu environment. These pipelines were specifically designed for cleaning, filtering, and removing instrumental artifacts from the CZTI data.

3. Jupyter Notebook: Python codes for implementing different SNR techniques were programmed using Jupyter Notebook. Jupyter Notebook provided an interactive and versatile platform for developing and executing the code. The notebook format allowed for easy documentation and visualization of the analysis process

4. Python Libraries: Several Python libraries were utilized within the Jupyter Notebook environment. These libraries included
   - NumPy: Used for numerical computations and array operations.
   - Pandas: Utilized for data manipulation and analysis.
   - Matplotlib: Employed for data visualization and generating plots.
   - Scipy: Used for scientific computing and statistical analysis.
   - Astropy: Employed for astronomical data analysis and manipulation.
   - Random: Utilized for generating random numbers and implementing randomization techniques

5 Results

We present the results obtained from the analysis of the three faint GRBs- GRB210519A, GRB210709A, GRB210516A data. The data underwent preprocessing using the CZTI pipeline to ensure accurate and reliable analysis. After preprocessing, detrending techniques were applied to remove the background noise and systematic components from the GRB light curve. Subsequently, signal-to-noise ratio (SNR) calculation techniques were done to quantify the strength of the GRB signals.

The SNR values will be further analyzed and compared to determine the optimal method for accurately quantifying the SNR and distinguishing real GRBs from noise or non-GRB events. These findings will contribute to the development of an effective classification algorithm for GRBs based on their SNR characteristics.

Table 1: GRB210519A SNR values.

	band 20-50		
	at GRB	at Particle event	at Random Position
Q0	-0.789	0.274	0.819
Q1	6.402	-2.44	5.535
Q2	-0.898	-3.793	0.041
Q3	11.212	-0.486	-5.587
Combined	2.448	-3.257	3.383

	band 50-100		
	at GRB	at Particle event	at Random Position
Q0	10.741	0.834	0.015
Q1	14.982	-2.541	2.416
Q2	10.05	-7.978	-4.136
Q3	1.941	1.188	-14.057
Combined	19.468	-5.12	-0.839

	band 100-200		
	at GRB	at Particle event	at Random Position
Q0	9.434	-6.479	9.239
Q1	16.814	-5.174	-1.782
Q2	7.341	-0.335	-5.721
Q3	1.147	1.35	-9.851
Combined	18.594	-6.59	0.745

Table 2: GRB210709A SNR Values

	band 20-50		
	at GRB	at Particle event	at Random Position
Q0	0.3	3.39	8.625
Q1	10.505	4.601	-1.352
Q2	1.942	5.131	-2.051
Q3	3.099	-1.123	2.315
Combined	6.783	7.324	3.237

	band 50-100		
	at GRB	at Particle event	at Random Position
Q0	12.347	-0.029	7.51
Q1	8.138	1.465	-8.045
Q2	13.532	-0.692	-3.666
Q3	4.971	3.516	4.741
Combined	19.14	0.53	-2.924

	band 100-200		
	at GRB	at Particle event	at Random Position
Q0	18.668	1.702	0.931
Q1	10.7	6.134	6.146
Q2	2.448	4.454	-3.245
Q3	1.838	-4.397	4.71
Combined	17.431	7.019	2.723

Table 3: GRB210516A SNR Values

	band 20-50		
	at GRB	at Particle event	at Random Position
Q0	0.56	-5.979	5.107
Q1	1.821	4.569	-1.946
Q2	4.326	-3.83	-1.017
Q3	5.963	2.198	3.579
Combined	6.122	-2.158	3.034

	band 50-100		
	at GRB	at Particle event	at Random Position
Q0	4.37	0.834	0.015
Q1	9.387	-2.541	2.416
Q2	4.371	-7.978	-4.136
Q3	0.026	1.188	-14.057
Combined	9.04	-7.117	0.306

	band 100-200		
	at GRB	at Particle event	at Random Position
Q0	10.715	-2.45	-0.345
Q1	6.167	-0.081	2.131
Q2	1.868	5.493	-2.743
Q3	6.696	-0.504	3.891
Combined	12.374	1.205	1.355

5.1 Observation

For these three GRBs the 20-50 band did not give proper SNR values. But the other two bands had significantly large SNR values. The SNR value for particle event and at random position for all the three bands where low even negative for some quadrants (which i have marked in yellow). At GRB the SNR values were high (more than 6), marked in green. For GRB210519A and GRB210709A the quadrant 3 was bad, hence I did not consider them for all quadrant combined SNR value. While for GRB210516A, the Q3 was not that bad so I included it for combined SNR calculation

5.2 Inference

From these three GRB SNR calculation for different bin sizes and different energy band, if the SNR values are more than 6 in at least two quadrants and two energy bands(in my case it was 50-100 and 100-200) we can say that it is GRB signal. If there is a negative SNR value in two quadrants and two energy bands, we can say that it is a particle event or some bogus signal and not an GRB signal. For example, in a particle event the SNR value will be really high in one particular quadrant where particle event occurred but the other unaffected quadrants will have a negative SNR from which we can say that it is a particle event and not a GRB signal.

References

[AAR] Astrosat archive.

[ACD] Astrosat czti dqr.

[Ber14] Edo Berger. Short-duration gamma-ray bursts. *Annual Review of Astronomy and Astrophysics*, 52:43-105, 2014.

[Blo11] Joshua S. Bloom. *What Are Gamma-Ray Bursts?* Princeton Frontiers in Physics. Princeton, 2011.

[CZT18] *LEVEL-2 PIPELINE SOFTWARE FOR ASTROSAT CZTI*. 2018.

[GRBa] Czti grb monitor page.

[GRBb] Gamma-ray burst simulations.

[K17] Bhalerao V ; Bhattacharya D ; Vibhute A ; Pawar P ; Rao A R ; Hingar M K ; Khanna Rakesh ; Kutty A.P K ; Malkar J P ; Patil M H ; Arora Y K ; Sinha S ; Priya P ; Samuel Essy ; Sreekumar S ; Vinod P ; Mithun N P S ; Vadawale S V ; Vagshette N ; Navalgund K H ; Sarma K S ; Pandiyan R ; Seetha S ; Subbarao K. The cadmium zinc telluride imager on astrosat. *Journal of Astrophysics and Astronomy*, Volume 38 Issue 2, 2017.

[S21] Sharma Y; Marathe A; Bhalerao V; Shenoy V; Waratkar G; Nadella D; Page P; Hebbar P; Vibhute A; Bhattacharya D; Rao A R; Vadawale S. The search for fast transients with czti. *Journal of Astrophysics and Astronomy*, Volume 42 Issue 2, 2021.

[Var21] Abraham Sheelu ; Mukund Nikhil ; Vibhute Ajay ; Sharma Vidushi; Iyyani Shabnam ; Bhattacharya Dipankar ; Rao A R; Vadawale Santosh ; Bhalerao Varun;. A machine learning approach for grb detection in astrosat czti data. *Monthly Notices of the Royal Astronomical Society*, Volume 504 Issue 2, 2021.

[Wik] Gamma-ray burst.