

LST-1: Ensuring a correct pointing & Improving our GRB detection ability

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CTAO – Quick presentation

Bending Model

What is it? Why do we need it? How can we improve it?

Gamma Ray Burst Analysis

What are GRBs? Why are they so important? Can we improve the detection ability?

CTAO: array of imaging atmospheric Cherenkov telescopes

- \rightarrow 2 sites in each hemisphere
- \rightarrow 3 types of telescopes to cover from 20 GeV to 100 TeV

Illustration of the future CTAO South site, Credit : Gabriel Pérez Diaz (IAC)/Marc-André Besel (CTAO)/ESO/ N. Risinger (skysurvey.org)

CTAO: array of imaging atmospheric Cherenkov telescopes

 \rightarrow LST-1: first telescope of the array

LST-1 picture, at twilight

LST-1 moving

CTAO: array of imaging atmospheric Cherenkov telescopes

 \rightarrow Detection principle

Working principle of LST-1 (don't judge please, I did this gif myself)

y ray $20 10$ 100 m

 $0.3 TeV$

Scheme of the electromagnetic shower Credit: J.A. Hinton and W. Hofmann

1 TeV

proton

km

Bending Model: Ensuring a correct pointing

Working principle, Optimization, Improvements

Goal

developed at LAPP by a former phd student, Mathieu de Bony

 \rightarrow taking into account the deformation of the structure

=> correcting the systematic errors of the pointing (**< 1 arc-minute**)

Goal

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	- => correcting the systematic errors of the pointing (**< 1 arc-minute**)

Pictures of the CDM, at the center of the dish

Goal

- \rightarrow taking into account the deformation of the structure
	- => correcting the systematic errors of the pointing

Sketch of the CDM field of view

 \rightarrow derive a mechanical model from star misspointing

Example of an observation

 \rightarrow derive a mechanical model from star misspointing

Example of an observation

LST-1 picture, with LEDs switched on

LEDs picture

 \rightarrow derive a mechanical model from star misspointing

Example of an observation

LST-1 picture, with LEDs switched on

LEDs picture

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Example of an observation

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Distributions of (a) pointed stars between over a certain period and (b) corresponding misspointing, in polar representation

 \rightarrow derive a mechanical model from star misspointing

Compute the misspointing for each point, with mechanical model

Distribution of miss-pointing compared with the predicted miss-pointing evaluated with mechanical model, in polar representation

→ 9h/Moon cycle, *time is precious !*

Questions:

▪ how many stars do we need to ensure a robust mechanical model ?

▪ how can we gain time on data taking ?

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100 points in the sky grid seems to be a good approximation

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Bending model data taking can be done in **Moon condition** (not causing parasite light)

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Bending model data taking can be done in **Moon condition** (not causing parasite light)

Optimize **observation sequence**

 \rightarrow add scheduler process in the bending model code

Sequence

 \rightarrow \rightarrow select a star Star selected Go position star done 50 LEDs data acquisition done Star data acquisition done ▪ go to star position Go position dark done Dark data acquisition done 40 Transfer data done ▪ data acquisition LEDs 30 Frequency **-** data acquisition star 20 **·** go position dark **- data acquisition dark** 10 $•$ transfer data Ω Ω 100 200 300 400 500 Time relative to the sequence (in seconds)

> *Distribution of the end event times, relatively to the start of the observation*

 \rightarrow add scheduler process in the bending model code

Sequence

New sequence

- \rightarrow \rightarrow select a star
	- go to star position
	- data acquisition LEDs
	- **· data acquisition star**
	- **·** go position dark
	- **data acquisition dark**
	- \blacksquare transfer data
- select a star **(only first observation)**
- \rightarrow \bullet go to star position
	- data acquisition LEDs
	- **data acquisition star**
	- **·** go position dark
	- data acquisition dark + **select next star**
- $•$ transfer data

 \rightarrow add scheduler process in the bending model code

How much time can be gained for each observation ?

 \rightarrow add scheduler process in the bending model code

How much time can be gained for each observation ?

June 2023

Distribution of dark patch data taking duration, since June 2023

 \rightarrow add scheduler process in the bending model code

First results

Tests have been done the 23rd and the 29th of October

 \rightarrow over 2 observations, 36 seconds are gained

New mechanical model will be performed in December

 \rightarrow wait & see...

Gamma Ray Burst: Improving our detection ability Analysis methods & first results

Context

with Mathieu de Bony and Edna Ruiz Velasco

- \rightarrow Gamma Ray Burst (GRB)
	- transient events
	- extragalactic sources (*isotropic distribution*) cyan: WT settling - blue: WT - red: PC 10 Count Rate (0.3-10 keV) (s⁻¹) $F(t) \infty t^{-\alpha}$ 0.1 0.01 100 1000 $10⁴$ Time since BAT trigger (s) *GRB220306B light curve, fitted with a power law (Swift/XRT data)*

GRB artist impression

Context

with Mathieu de Bony and Edna Ruiz Velasco

- \rightarrow Gamma Ray Burst (GRB)
	- transient events

Methods

 \rightarrow observation of two regions

 N_{ON} counts during T_{ON}

 N_{OFF} counts during T_{OFF}

Methods

 \rightarrow observation of two regions

 N_{ON} counts during T_{ON}

ON Definition of background and signal

$$
\frac{}{\overline{s}+\overline{b}} = \frac{\langle N_{ON} \rangle}{T_{ON}}
$$

$$
\bar{b}\!=\!\frac{\langle N_{\it OFF}\rangle}{T_{\it OFF}}
$$

background NOFF counts during TOFF

PP

Gamma Ray Burst analysis

Gamma Ray Burst analysis

 \rightarrow Li&Ma time dependent:

Gamma Ray Burst analysis

 \rightarrow Compute significance of the source:

$$
o = \sqrt{TS}
$$

 \Rightarrow σ > 5: detection !

- \rightarrow generate simulated bursts with parameters:
	- delay
	- **temporal index α**
	- spectral index Γ
	- $-$ normalization $φ₀$
	- redshift z

Assuming:

. power law spectral model

$$
\phi(E)\mathord{=}\phi_0\big(\frac{E}{E_0}\big)^{-\Gamma}
$$

. power law temporal model

$$
F(t) = \left(\frac{t - t_{ref}}{t_0}\right)^{-\alpha}
$$

- \rightarrow generate simulated bursts with parameters:
	- delay
	- **temporal index α**
	- spectral index Γ
	- $-$ normalization $φ₀$
	- redshift z
- \rightarrow compute:
	- **· Significance**
	- Time dependent significance

Assuming:

. power law spectral model

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. power law temporal model

$$
F(t) = \left(\frac{t - t_{ref}}{t_0}\right)^{-\alpha}
$$

 \rightarrow results with 50,000 simulations

Plot of the significance computed with tdep depending on the classic Li&Ma significance

Plot of the significance computed with tdep depending on the classic Li&Ma significance

Plot of the significance computed with tdep depending on the classic Li&Ma significance (zoom around 5σ)

Gamma Ray Burst analysis

First results

Plot of the significance computed with tdep depending on the classic Li&Ma significance

with both methods

Gamma Ray Burst analysis

First results

Plot of the significance computed with tdep depending on the classic Li&Ma significance

with both methods

 \rightarrow results with 50,000 simulations

In which cases does time dependent Li&Ma performs better ?

 \rightarrow results with 50,000 simulations

In which cases does time dependent Li&Ma performs better ?

Li&Ma time dependent performs better for GRBs with very **sharply temporal evolution** (i.e. high α)

Temporal evolution: $F(t) {\propto} t^{-\alpha}$

Coming soon...

 \rightarrow new method, developed by Mathieu de Bony

Plot of the significance computed with STF method depending on the classic tdep Li&Ma significance

Coming soon...

\rightarrow new method, developed by Mathieu de Bony

Plot of the significance computed with STF method depending on the classic tdep Li&Ma significance

Spectral temporal fit

- \rightarrow appears to be performing better
- \rightarrow still ~10% of the fit are failing

Conclusion

Bending Model

- new bending model for the next LSTs
- calibration of new CDMs

Picture of the CTAO North site, with the 4 LSTs (September 2024)

Bending Model

- **. new bending model for the next LSTs**
- **Example 2** calibration of new CDMs

Gamma Ray Burst

- article on analysis methods
- article on GRB catalog

Thanks for your attention

Back up - Part I Bending Model

Working principle: fit the center of the camera with the LEDs

Sky grid: impact of a biased dataset

 \rightarrow dataset used as a reference

Conditions : - correct repartition of the observations in the grid

- rather short period
- no OARL problems

Choice : from 1^{st} of April to 1^{st} of June

Observations grid for the selected period

Sky grid: impact of a biased dataset

 \rightarrow impact of a biased dataset on the mechanical model parameters

Grid for dataset with azimuth selection

Dispersion of the AzEncoderShift parameter values for both datasets

Time optimization: impact of the number of observations

- \rightarrow fit of the model parameters
	- \rightarrow how many observations are needed ?

Distribution of the parameter values, fitted for different number of stars, for 200 random selection

Time optimization: impact of the number of observations

- \rightarrow fit of the model parameters
	- \rightarrow how many observations are needed ?

100 points in the sky grid seems to be a good approximation, for the fit of the parameters

Distribution of the parameter values, fitted for different number of stars, for 200 random selection

Time optimization: impact of the Moon

Some observations: failing

→ **does the Moon have an impact on the success of BM data taking ?**

Picture taken by the CDM, presenting strange effect due to parasite light

Time optimization: impact of the Moon

 \rightarrow change of reference, with the example of BM observation 970

Back up - BM

Time optimization: impact of the Moon

Change of reference for the study

Telescope reference → Dish reference

Back up - BM

Observation

Moon, for correct observations Moon, for rejected observations due to valid analysis criteria

 0°

Time optimization: impact of the Moon

Moon, for rejected observations 315 due to fit SNR criteria 270 135°

Pointing reference, useful for the stacking of relative Moon position

Spatial distribution of the Moon position (for correct and rejected observations), in the dish reference

180

Bending model data taking can be done in Moon condition

CTA

 90°

Time optimization: scheduler process

 \rightarrow 2 processes communicating via a pipe

Time optimization: scheduler process

- \rightarrow objective : recent full-sky view
- \rightarrow how does scheduler works ?

Example 2 associate each point with a priority (depending on the date of the last acquisition)

- **Example 16 Index** is a valid star for each point
- select the star for each star region around the point:
	- \rightarrow altitude in observable range
	- \rightarrow distance with the Moon
	- \rightarrow no other star that could be detected
	- \rightarrow dark patch at 2°

▪ compute observation time for each star (depending on star magnitude and position)

Back up - Part II GRB analysis

$$
L = \left(\prod_{t_i = (\Delta t, \ldots, N\Delta t)} \frac{(\Delta t (b+s(t_i)))^{[0,1]}}{[0,1]!} e^{-\Delta t (b+s(t_i))})} \left(\frac{(b T_{OFF})^{N_{OFF}}}{N_{OFF}!} e^{-b T_{OFF}}\right)
$$

\n
$$
\rightarrow \text{Definition of the signal: } s(t) = \theta f(t)
$$

 \rightarrow Only 1 free parameter: amplitude of the signal θ

because b is defined with the identity: *b* ∂ log *L* ∂ *b* (*θ*)+*θ* ∂ log *L* ∂*θ* (*θ*)=0

 \rightarrow Maximize the likelihood by finding the root of the partial derivative:

$$
\frac{\partial \log L}{\partial b}(\theta) = \frac{N_{OFF}}{b} + \sum_{t_i \in t_{ON}} \frac{1}{b + \theta f(t_i)} - (T_{ON} + T_{OFF})
$$

 \rightarrow Evaluating the likelihood:

$$
L = (\prod_{t_i = (\Delta t, \ldots, N \Delta t)} \frac{(\Delta t (b + s(t_i)))^{[0,1]}}{[0,1]!} e^{-\Delta t (b + s(t_i))}) (\frac{(b T_{OFF})^{N_{OFF}}}{N_{OFF}!} e^{-b T_{OFF}})
$$

 \rightarrow Simplification of the likelihood:

$$
\lim_{N \to +\infty} L = \left(\Delta t^{N_{ON}} \prod_{t_i \in \{t_{ON}\}} \left(b + s(t_i)\right)\right) \frac{\left(b T_{OFF}\right)^{N_{OFF}}}{N_{OFF}!} e^{-b(T_{OFF} + T_{ON}) - \int_{0}^{T_{ON}} dt \, s(t)}
$$

 \rightarrow With the identity:

$$
\lim_{N \to +\infty} L = (\Delta t^{N_{ON}} \prod_{t_i \in \{t_{ON}\}} (b + s(t_i))) \frac{(b \, T_{OFF})^{N_{OFF}}}{N_{OFF}!} e^{-(N_{OFF} + N_{ON})}
$$

$$
\rightarrow \text{ Evaluating the significance:} \quad TS = -2 \log \left(\frac{L_0}{L} \right) \qquad \quad \sigma = \sqrt{TS}
$$

with
$$
L_0 = \frac{e^{-\bar{b}_0 T_{ON}} (\bar{b}_0 T_{ON})^{N_{ON}}}{N_{ON}!} \frac{e^{-\bar{b}_0 T_{OFF}} (\bar{b}_0 T_{OFF})^{N_{OFF}}}{N_{OFF}!}
$$

$$
L = (\Delta t^{N_{ON}} \prod_{t_i \in \{t_{ON}\}} (b + s(t_i))) \frac{(b T_{OFF})^{N_{OFF}}}{N_{OFF}!} e^{-(N_{OFF} + N_{ON})}
$$

and
$$
b_0 = \frac{N_{ON} + N_{OFF}}{T_{ON} + T_{OFF}}
$$
 $b = \frac{N_{ON} + N_{OFF} - \theta \int_0^{T_{ON}} dt f(t)}{T_{ON} + T_{OFF}}$ $s(t) = \theta f(t)$ $f(t) = t^{-1}$

 \rightarrow optimization issue

=> Need, in some cases, a negative amplitude

\rightarrow optimization issue

Plot of the partial derivative of the likelihood, depending on the amplitude of the signal, in the case of divergence with negative amplitude

In some cases, divergence for negative amplitude values

 \rightarrow choose carefully the range

 \rightarrow no root for ~0.7% of the analysis

Both partial derivative of log likelihood at b and θ, in the case where the identity is not respected

Spectral Temporal Fit: method (developed by Mathieu)

- \rightarrow spectral temporal fit
	- **·** fit data with base model (no emission)
	- **.** fit data with spectral model
	- **.** fit data with temporal model
	- fit data with complete model (spectral + temporal)
	- evaluate significance of the complete model vs base model