IROS Diffusion Imaging for the LEM-X Observatory

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ML4ASTRO 3

About the Talk...

Topic

Application of generative **diffusion models** to coded-mask imagers

Goal

Improve instrumental **source modelling** and **sky imaging**

Performance benchmark with respect to analytical techniques

Computational effort analysis

Development

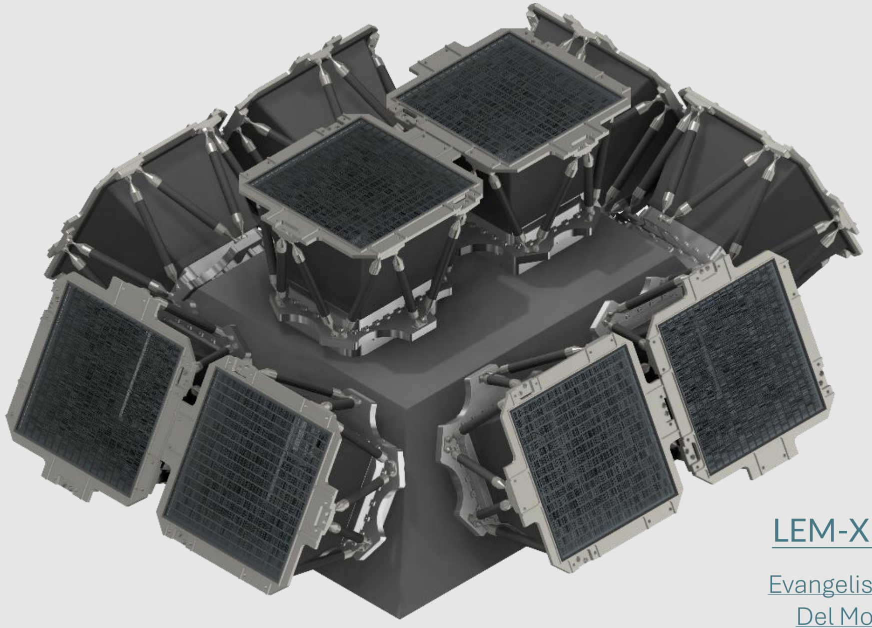
Custom framework implementation and sky imaging tests

Integration into broader imaging pipeline

LEM-X: Observatory Layout

Lunar Electromagnetic Monitor in X-Rays

- Proposed mission by INAF and ASI in the context of the Italian PNRR project Earth-Moon-Mars
- All-sky monitor for **transient** events and **long-term** observations in an **extended energy range** (2-50 keV) and **wide FoV** (half of the sky, **simultaneously**)
- Will support the increase in data collection for **Time-domain** and **Multi-Messenger Astrophysics**

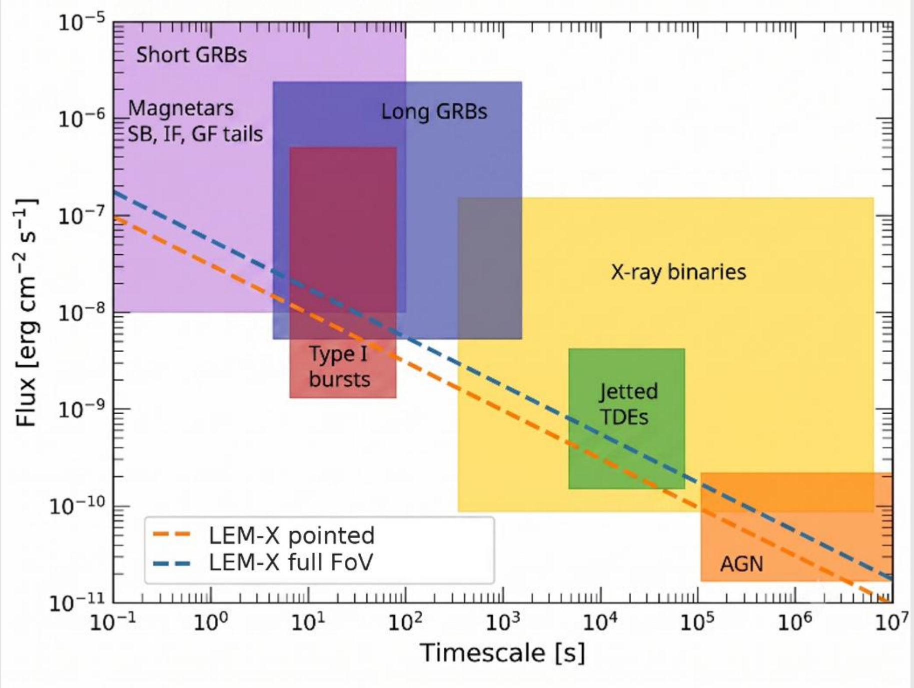


LEM-X project

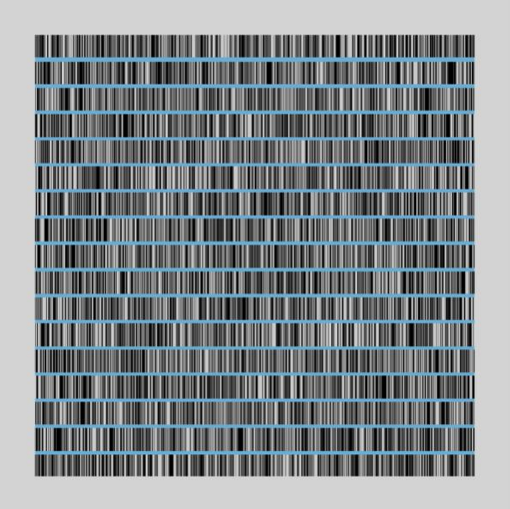
Evangelista+ 2026b
Del Monte+ 2024

Observatory Requirements

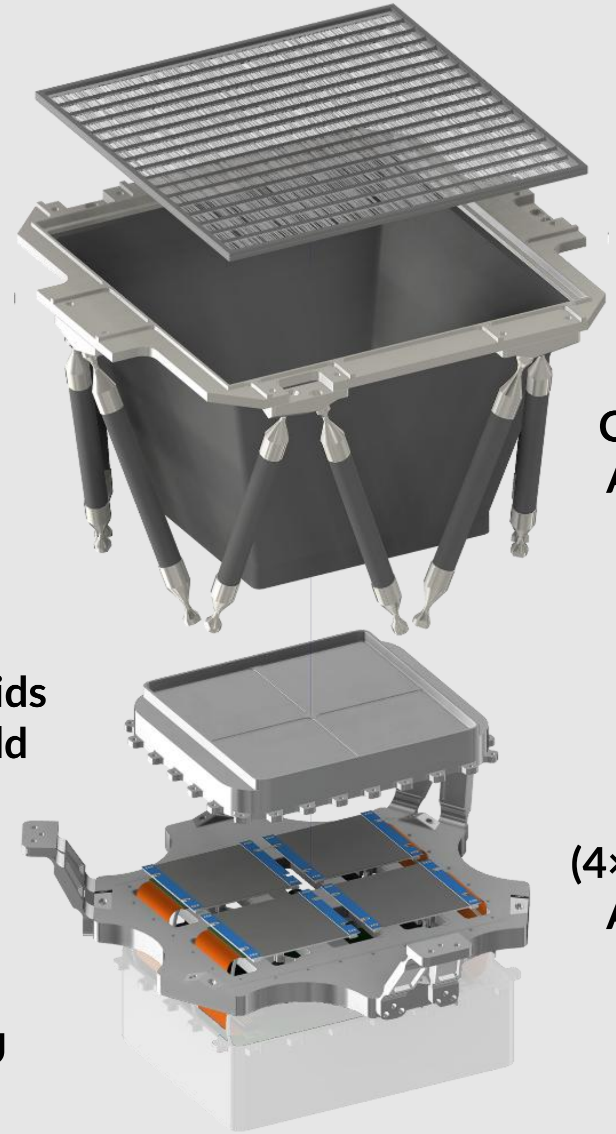
PARAMETER	VALUE	NOTES
Field of View	≥ 5 sr	
Energy Band	2-50 keV	
Energy Res.	≤ 350 eV	FWHM at 6 keV, BOL
Time Res.	10 μs	
Peak Eff. area	≥ 120 cm^2	at 8 keV
Sensitivity	≤ 1000 mCrab, ≤ 5 mCrab	5σ in 1 s, 5σ in 1 ks
Angular Res.	≤ 5‘ × 5’	FWHM
PSLA	≤ 1’ × 1’	FWHM, 90% c.f.
Deadtime	< 30%	at 100 Crab flux



LEM-X: Coded-Mask Cameras



Coded Mask Plate

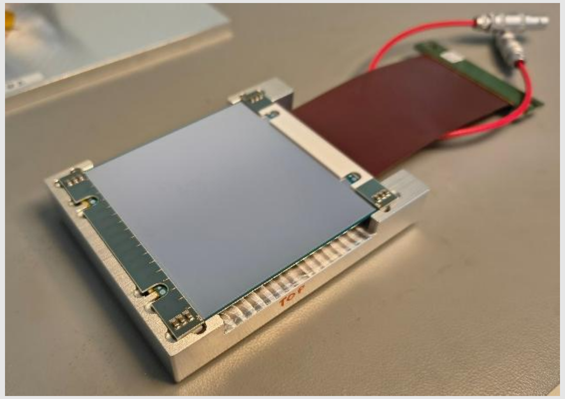


Collimator Assembly

Micro-meteoroids & Optical Shield

(4×) Detector Assembly

BEE and PSU



Detector Assembly: sensor side (top), ASIC side (bottom)

Evangelista+ 2026a
Ceraudo+ 2024a, 2026

LEM-X: Coded-Mask Cameras

The **LEM-X camera** design is built upon the technological and scientific heritage of the **eXTP** and **LOFT** mission studies

The cameras use the **large-area**, linear **Silicon Drift Detectors** (SDDs) combined with **ultra low-noise CMOS** read-out electronics to provide **photon-by-photon** information

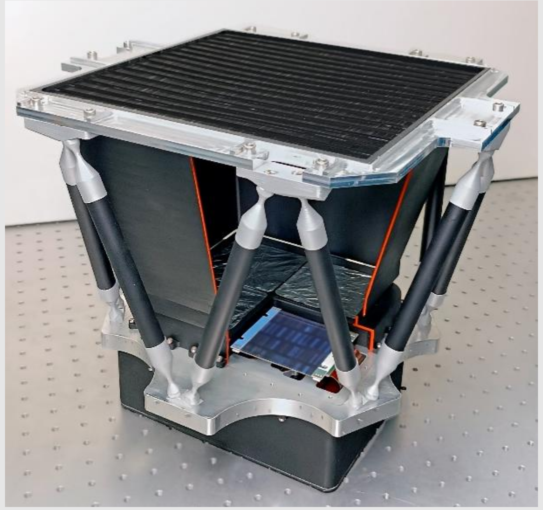
Camera Requirements

PARAMETER	VALUE	NOTES
Field of View	90° × 90° ≥ 40° × 40°	FWZR At 50% eff. area
Peak Eff. area	≥ 65 cm^2	at 8 keV
Spatial Res.	≤ 125 μm × 8mm FWHM	Fine × Coarse
Angular Res.	≤ 5'× 5° FWHM	Fine × Coarse
PSLA	≤ 1' × 1°	FWHM, 90% c.f.
Deadtime	≤ 85 μs	
Time Res.	10 μs	
Energy Band	2-50 keV	
Energy Res.	≤ 350 eV	FWHM at 6 keV, BOL

New ASI-INAF Agreement for "LEM-X camera TRL enhancement"

- Design consolidation, manufacturing and test of main critical technologies
- Support to industrial activities for the LEM-X camera development

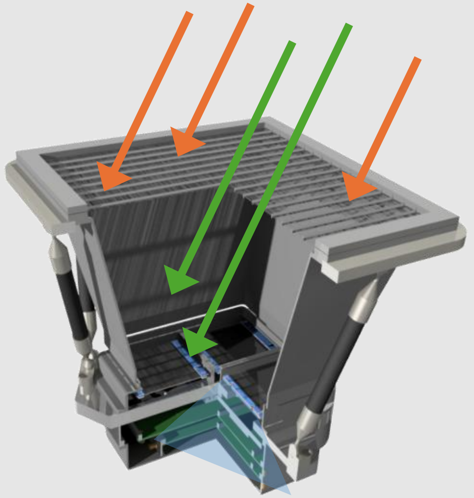
LEM-X Camera Pathfinder ready for first flight opportunity

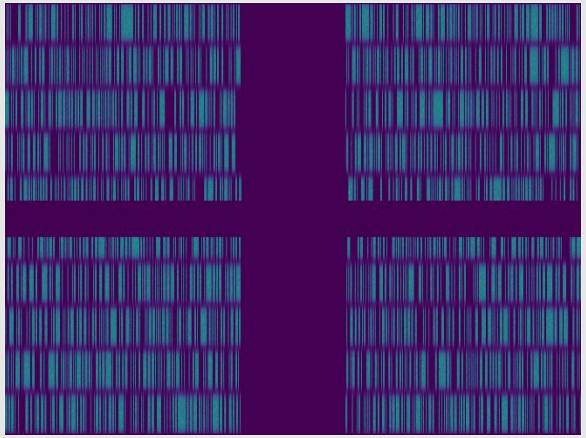


Camera mock-up, exposed @ INAF-stand | SPIE26

CAI: Working Principle

Instruments based on **Coded-Aperture Imaging (CAI)** are **indirect** imaging systems



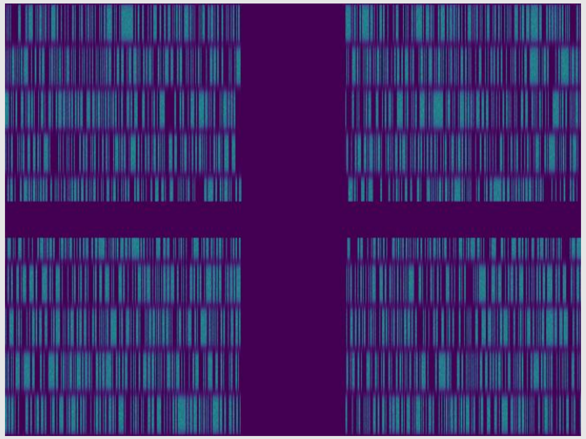


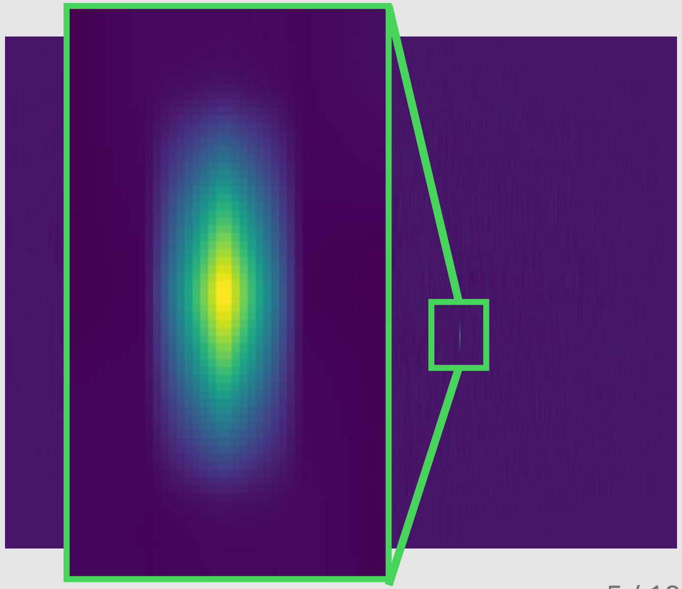
Encoding

- The incident photons collected by a camera **project** the mask pattern on the detector plane, generating a **detector image**
- The detector image encoded by a point-like source is called **shadowgram**

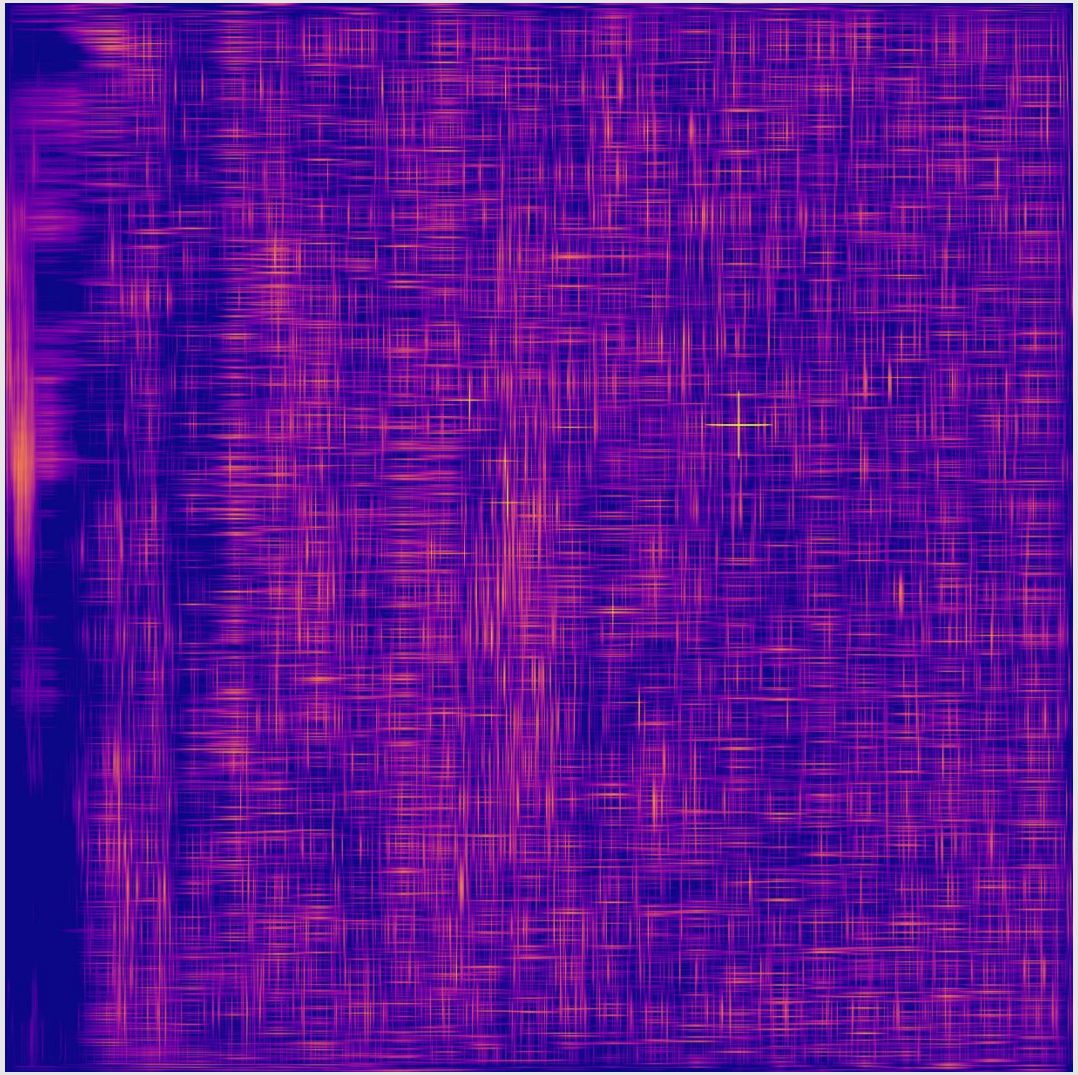
Decoding

- The observed sky-field map, or **sky image**, is obtained by **cross-correlating** the detector image with a **reconstruction array**
- The reconstruction array is built starting from the known coded-mask pattern





Galactic Centre decoding, featuring high noise levels from Sco X-1



Basic decoding techniques do not always provide high reconstruction quality, e.g. in crowded sky-fields and/or very bright sources in the FoV

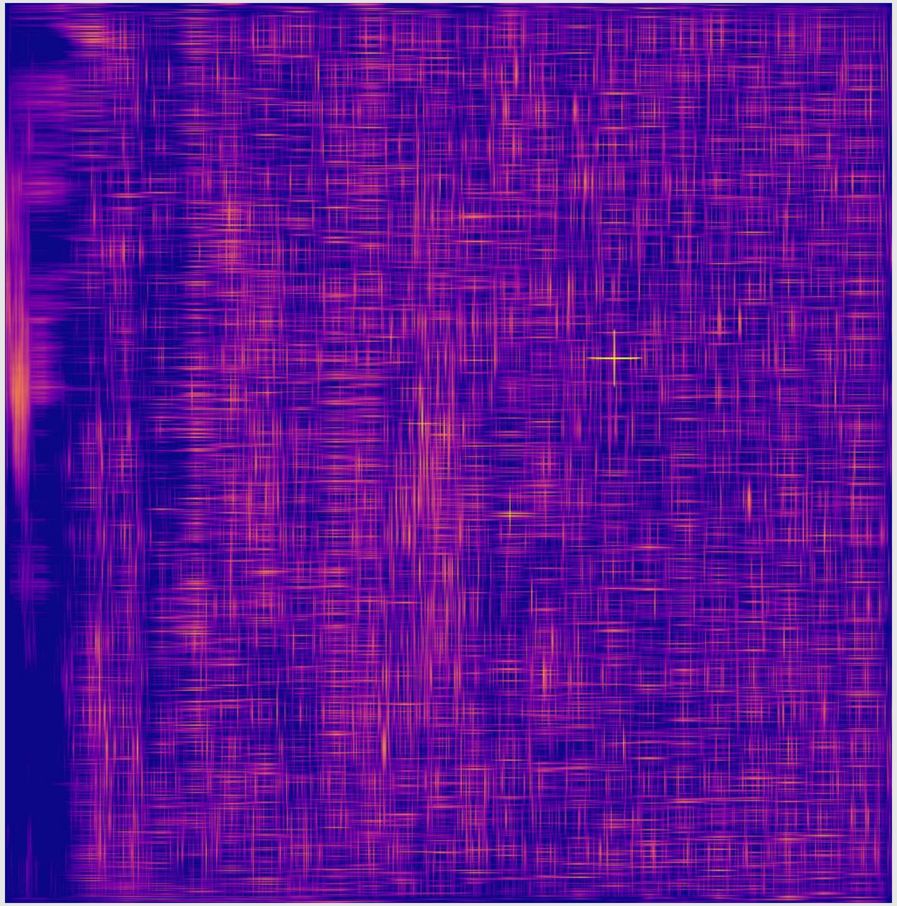
The encoding process produces **coding noise**, which increases with the source intensity

Need for more **effective sky reconstruction** algorithms, balancing **detection efficiency** and **computational cost**

Iterative Removal of Sources* (**IROS**)

*Hammersley+ 1992

CAI: Sky Decoding with IROS

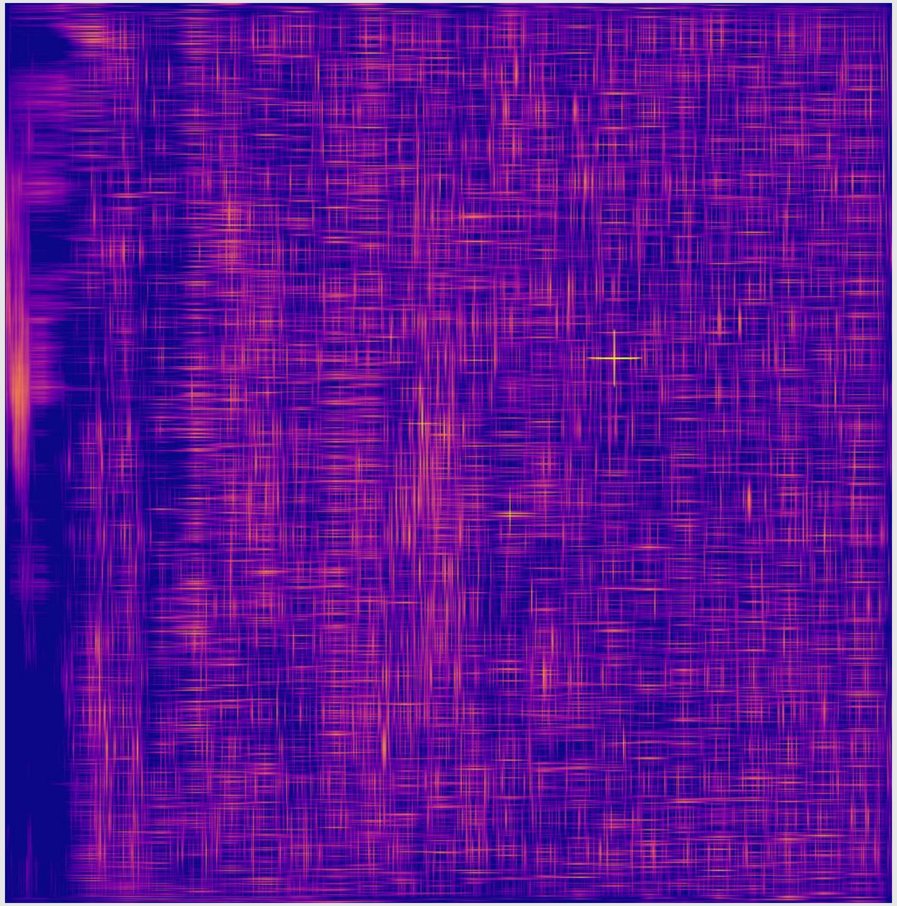


Pre-IROS

IROS **identifies** and **subtracts** sources from encoded **detector image**, allowing **fainter** objects to **emerge** from background; robust tool for sources **detection** and **localisation** with acceptable **computational cost**

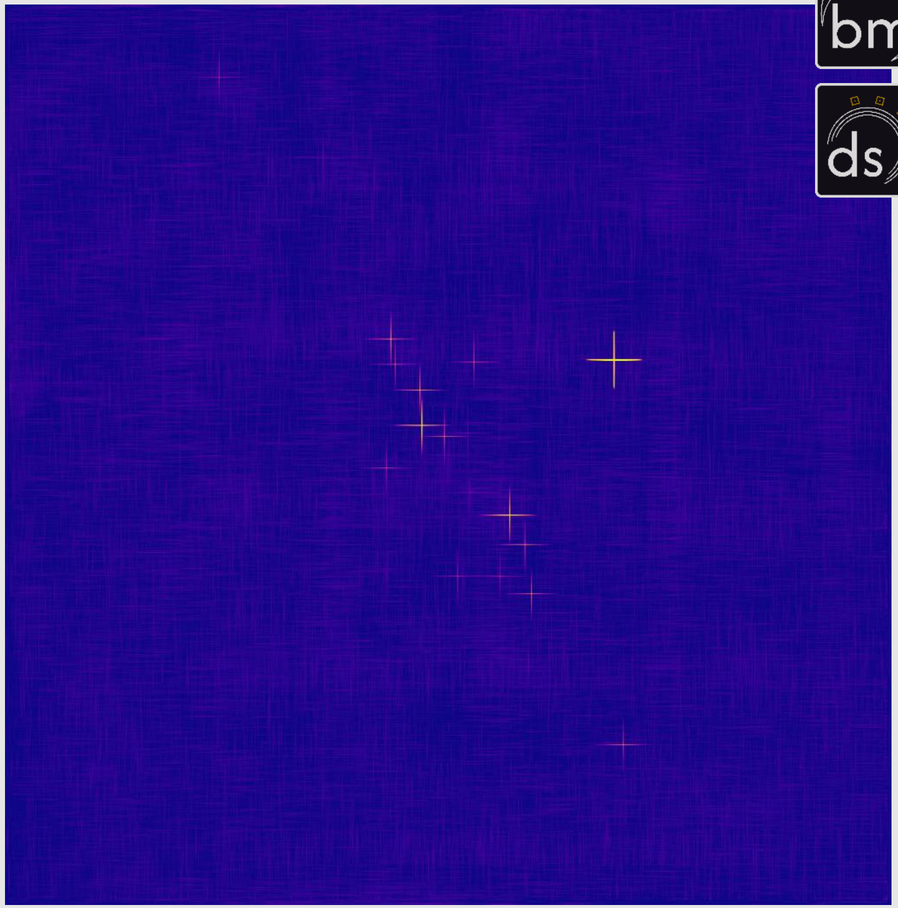
@github/peppedilillo/bloodmoon

@github/EdoardoGiancarli/darksun



Pre-IROS

Galactic Centre reconstruction with the **IROS** pipeline (1 ks, 2-50 keV)

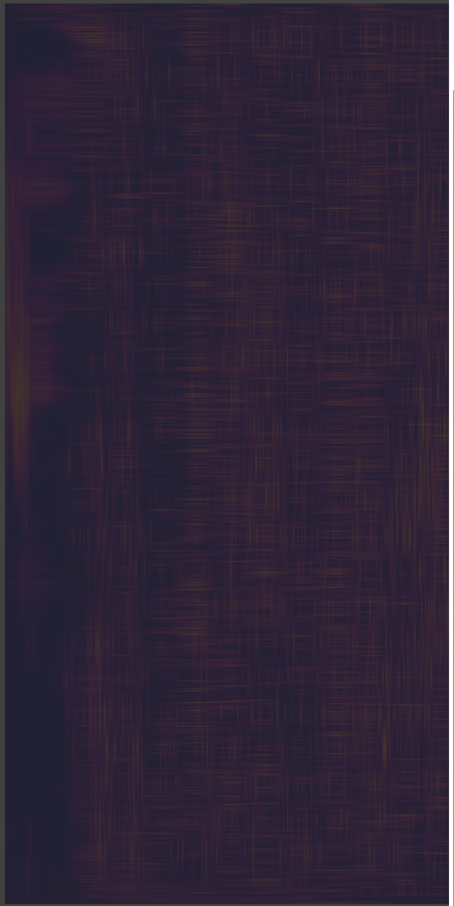


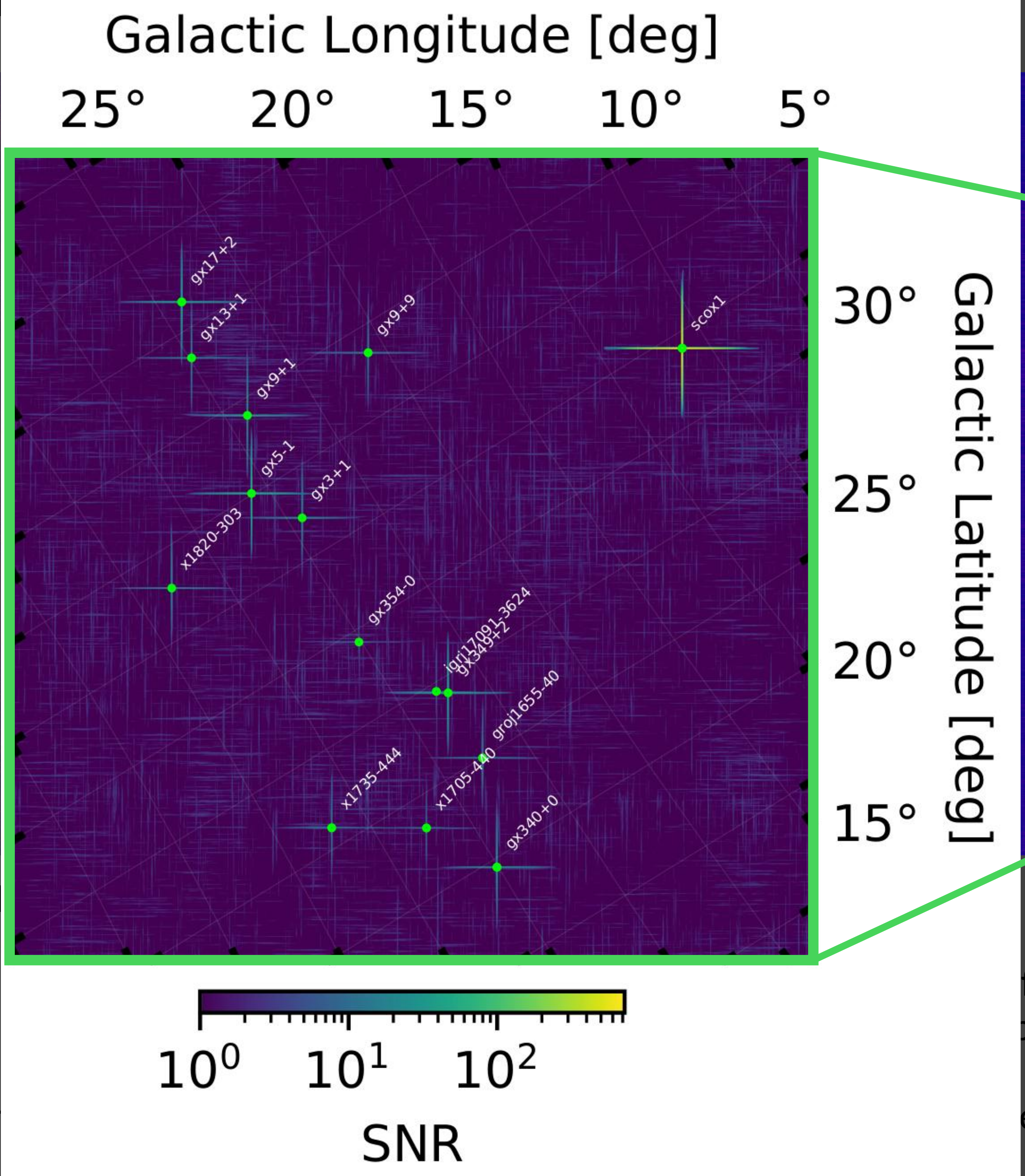
Post-IROS

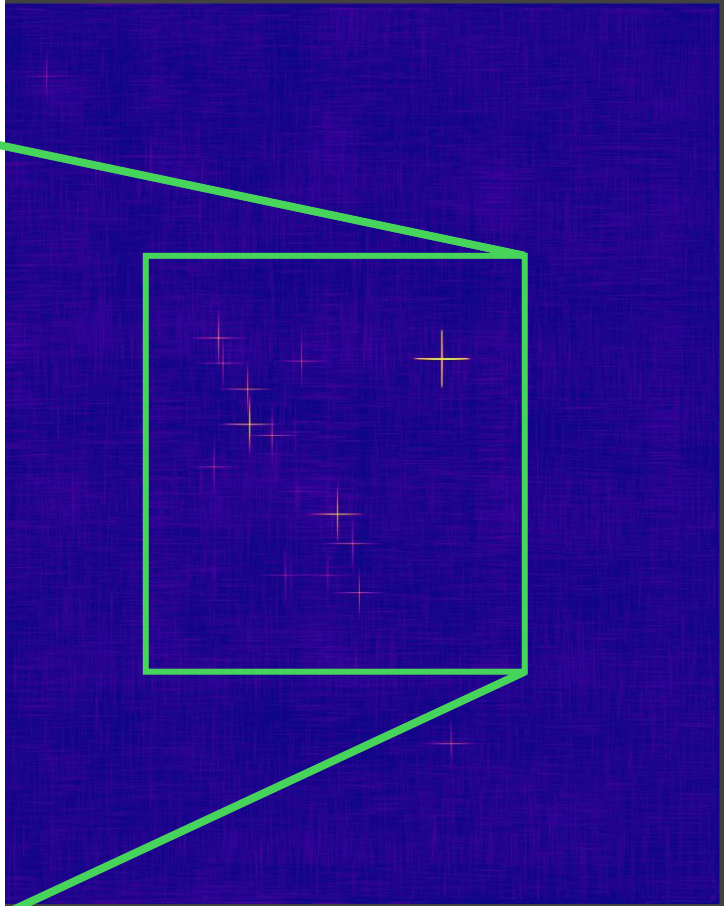
Giancarli+ 2026, in prep.

IROS **identifies** and **subtracts** sources from encoded **detector image**, allowing **fainter** objects to **emerge** from background; robust tool for sources **detection** and **localisation** with acceptable **computational cost**

Generative deep learning methods can be integrated into the pipeline to **enhance** imaging







Pre-I

Post-IROS

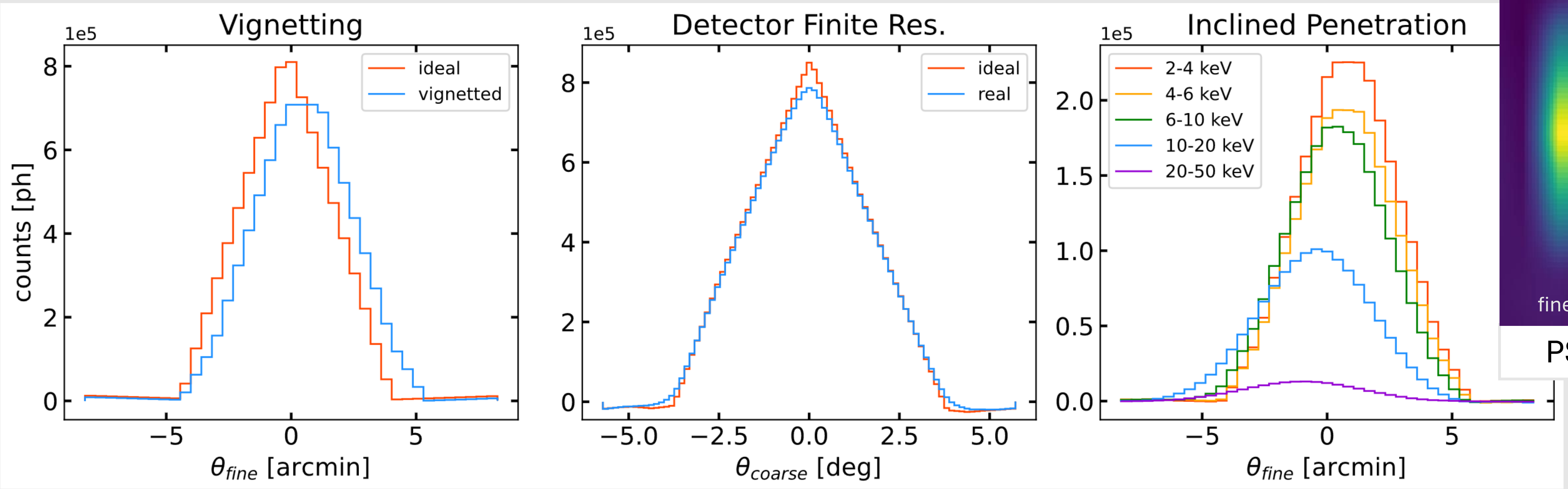
Giancarli+ 2026,
in prep.

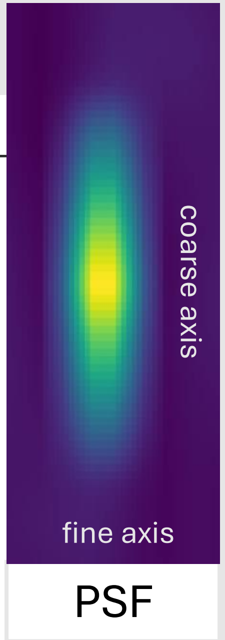
IROS **identifies** … **fainter** objects to **emerge** from
backgroun … ptable **computational cost**

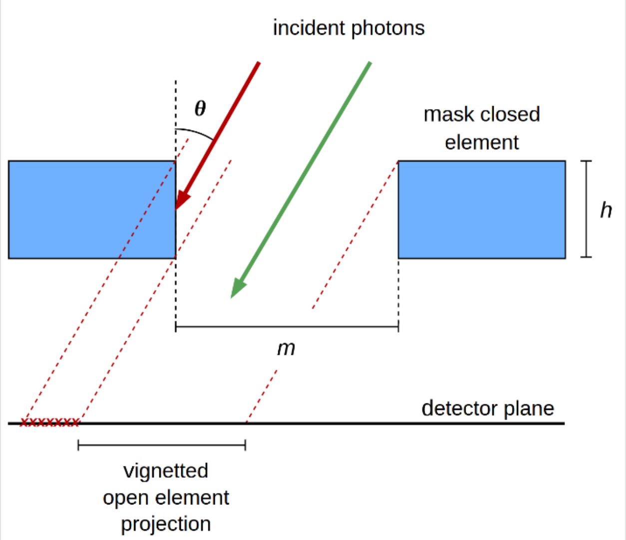
Gener … e to **enhance** imaging

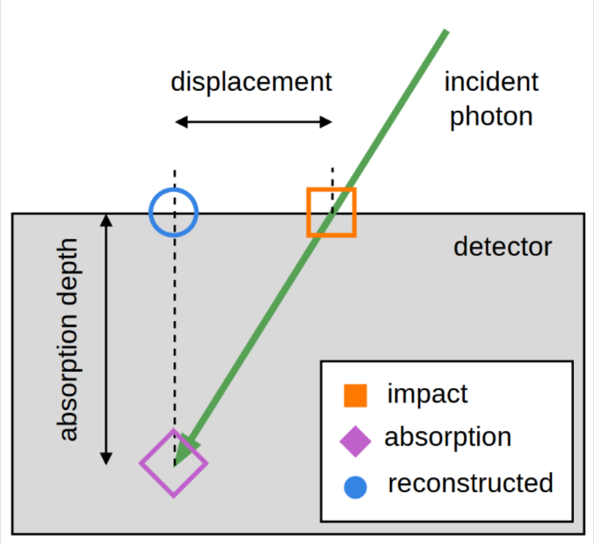
CAI: Camera Instrumental Effects on Source PSF Profile

Giancarli+ 2026,
in prep.









IROS: Analytic Approach Challenges

Current Limitations

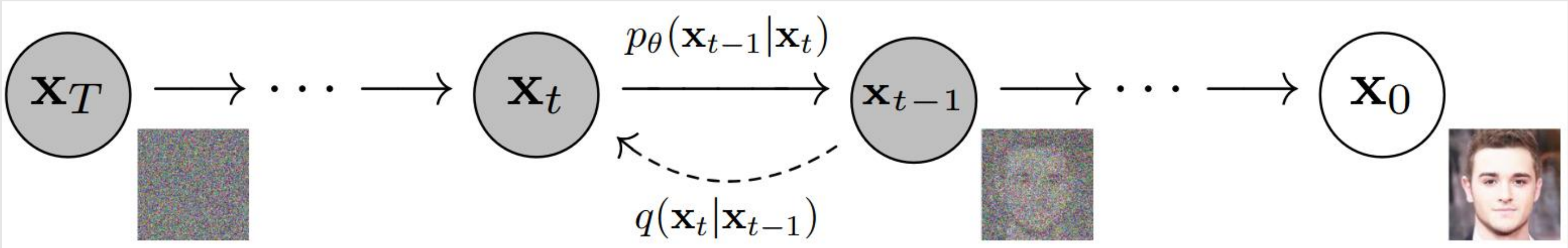
- **Source modelling** is a major step in IROS, as it directly influences the **subtraction** efficiency and the **parameter estimation** accuracy
- Shadowgrams generation must account for **instrumental effects** and internal **misalignments** / thermo-elastic **deformations**
- Analytic modelling is limited to the known instrumental aspects that can be reproduced and relative computational cost

Diffusion Approach

- **IDEA:** a generative **data-driven** approach should account for complex effects embedded in the observed signal
- Direct application to source modelling and parameters estimation, using **information** extracted from **decoded sky-map** images
- **Reduced** computational cost at inference, **speeding up** IROS sky reconstruction (use of advanced sampling techniques)

Denoising Diffusion Probabilistic Models

Gaussian noise — reverse sampling → Image signal



Ho+ 2020

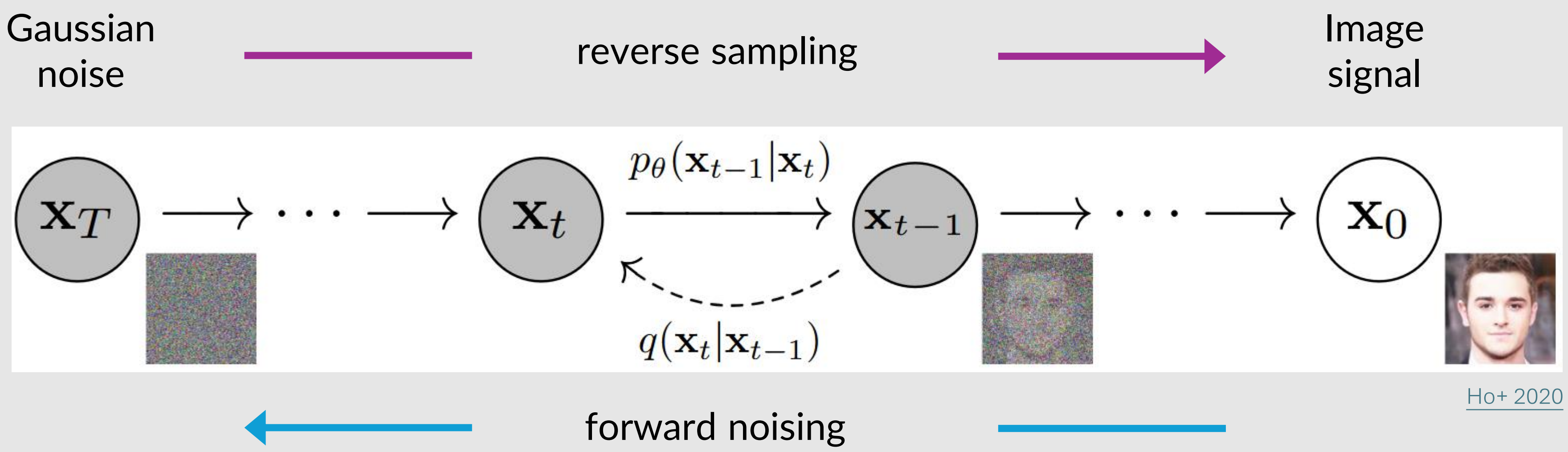
← forward noising —

DDPMs are generative models that synthetise data by learning to **reverse** a gradual noise-addition process

In practice, a model is trained to **predict the noise** added during the forward diffusion process

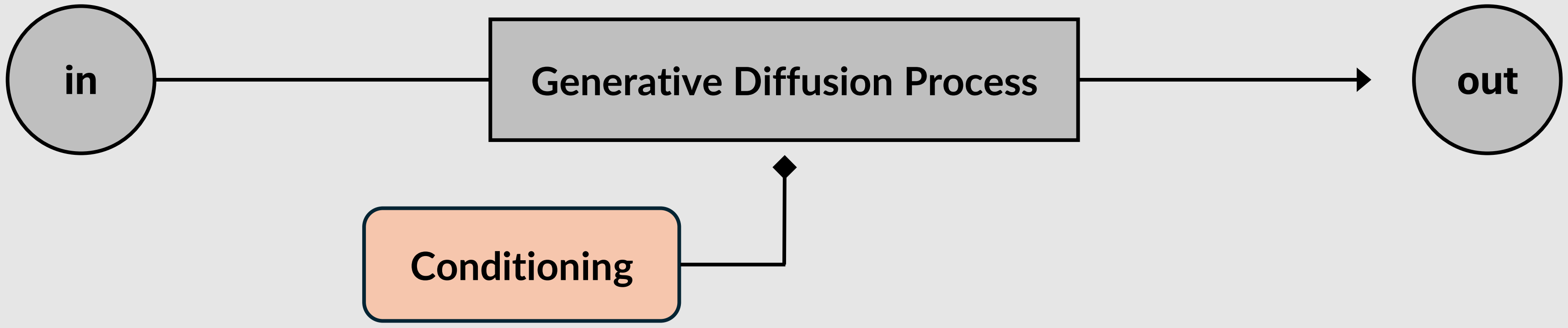
A signal is generated by iteratively subtracting the learned noise from pure Gaussian noise in many **time-steps** t

Denoising Diffusion Probabilistic Models



Ho+ 2020

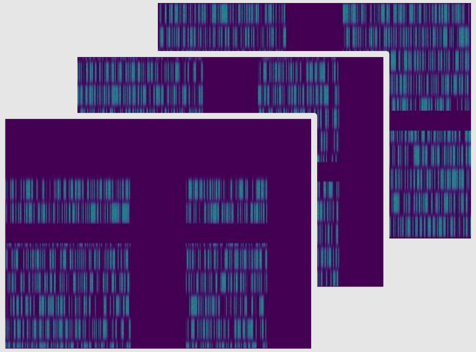
Output signal can be also generated by **guiding** the process with external **conditioning** (e.g., text / images)



IROS Joint-Diffusion: Sources Dataset

Signal

ground-truth source shadowgrams



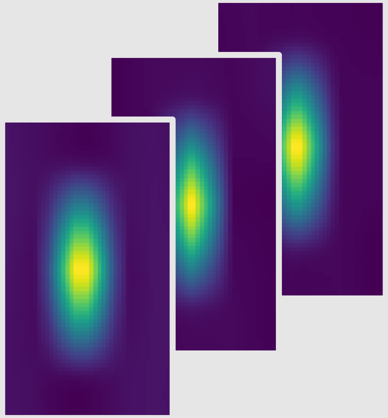
ground-truth source params

camera local-frame coordinates

total collected photon counts

Conditioning

source PSF map



extracted source params

reconstructed counts @ PSF peak

camera local-frame coordinates @ PSF peak

Data Normalisation and Centering

DATA TYPE	TRANSFORM	NOTES
Source Shadowgrams	z-score centering	Centering performed wrt projected elements
Source PSF Map	log-SNR transform + abs unilateral norm	SNR computed with instrumental variance
Local-frame Coordinates	abs bilateral norm	Normalised wrt camera FoV
Photons Counts	log-SNR transform + abs unilateral norm	SNR computed with instrumental variance

IROS Joint-Diffusion: Generative Logic

Input Noise

- src sg noise ~ N(0, I)
- params noise ~ N(0, 1)

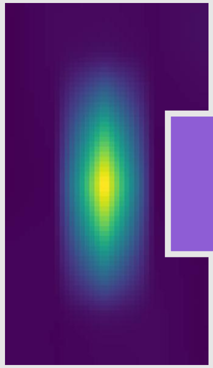
Generative Diffusion Process

Output Data

- src shadowgram
- src optimised params

PSF maps info is analysed through **cross-attention**, parameters info is introduced through **positional embeddings + AdaLN-Zero**

Source shadowgram is **subtracted** from iteration detector image, optimised parameters are **stored**



Conditioning

- src PSF map
- src extracted params

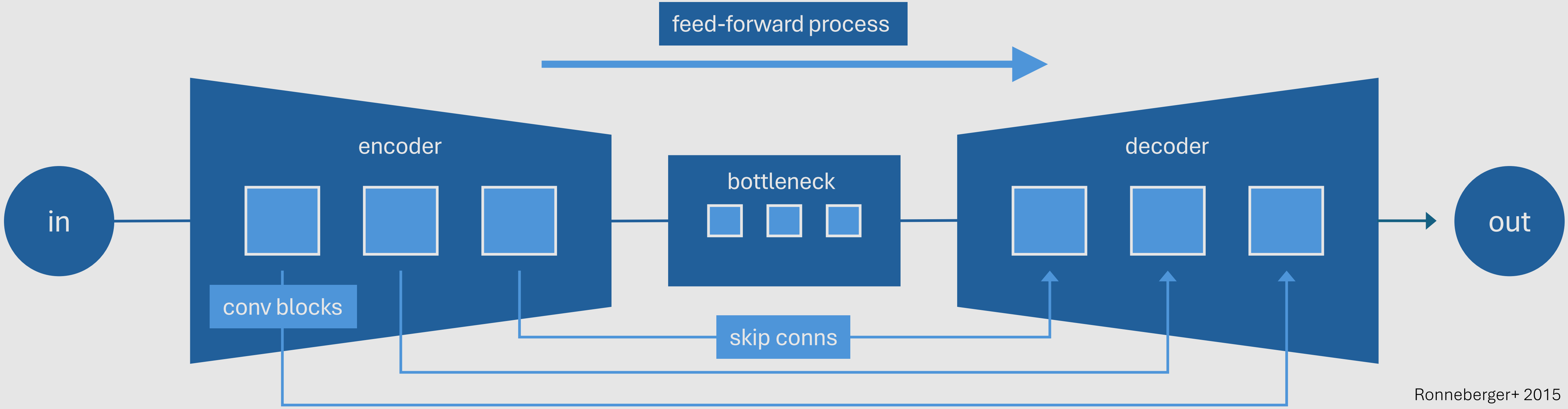
Samples generation is performed using **Classifier-Free Guidance**

Source PSF and params are **extracted** from sky image

spark!

@github/EdoardoGiancarli/SparkLab

IROS Joint-Diffusion: Model Architecture



But why use a U-Net architecture?

- U-Net architectures rely on conv blocks which excel at capturing **local patterns and spatial hierarchies**; preserve **fine-grained details** across different resolution levels; require less computational effort; perform well on **small dataset**; show good but limited scalability

- Diffusion Transformers (DiT) operate on signal patches relying on self-attention, retaining global context and modelling long-range spatial dependencies but losing local structures; require greater computational resources and show excellent scalability; need more data

IROS Joint-Diffusion: Training Objective

Training Loss

- **Shadowgrams Term** → **MSE Loss** between ground-truth and generated **images**
- **Parameters Term** → **Smooth-L1 (Huber) Loss** between ground-truth and generated **params**
- **PINN Term** → **MSE Loss** between conditioning **source PSF maps** and **decoded PSF maps** from generated shadowgrams

About the PINN term:

- Source shadowgrams and PSF maps are linked by CAI framework
- Source PSFs are computed through cross-correlation (linear operation), which satisfy PINN requirements for the Loss
- Relative (optionally adaptive) weights between loss terms, to balance output value levels

IROS Joint-Diffusion: Analysis Flow

TEST			CAMERA INSTRUMENTAL EFFECTS			
Phase	**Camera Regime**	**Status**	**Vignetting**	**Detector Spatial Resolution**	**Photons Inclined Penetration**	**Geometrical Deformations**
1st	Ideal	ON-GOING	🔴	🔴	🔴	🔴
2nd	Semi-Real	Planned	🟢	🔴	🔴	🔴
3rd	Semi-Real	Planned	🟢	🟢	🔴	🔴
4th	Real	Planned	🟢	🟢	🟢	🔴
5th	Real	TBD	🟢	🟢	🟢	🟢

The tests on the IROS Diffusion framework are carried out starting from an **ideal instrumental setup**, analysing how the joint-diffusion process responds to each instrumental effect and **sequentially introducing realisms**

Observations are performed exploiting the WISEMAN* Monte Carlo simulator

*Ceraudo+ 2024b

Development of a custom
joint-diffusion framework for:

- source **shadowgrams** generation
- source **parameters** estimation

Integration into broader **IROS**-based pipeline for LEM-X coded-mask cameras **sky reconstruction**

on-going analyses

- Test **generative** process and assess **physics significance**
- Test **instrumental effects** influence on joint-diffusion process

challenges

- Specific pipeline for non-standard **image-parameter** joint conditioning, in different imaging domain (detector space + sky space)
- **High memory cost** when operating in full pixel space (shadowgrams have 308×1264 spatial dimension, at relatively low instrumental upsampling)
- Shift to **Latent Diffusion** approach

Thanks for your attention!

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LEM-X Coded-Mask Camera

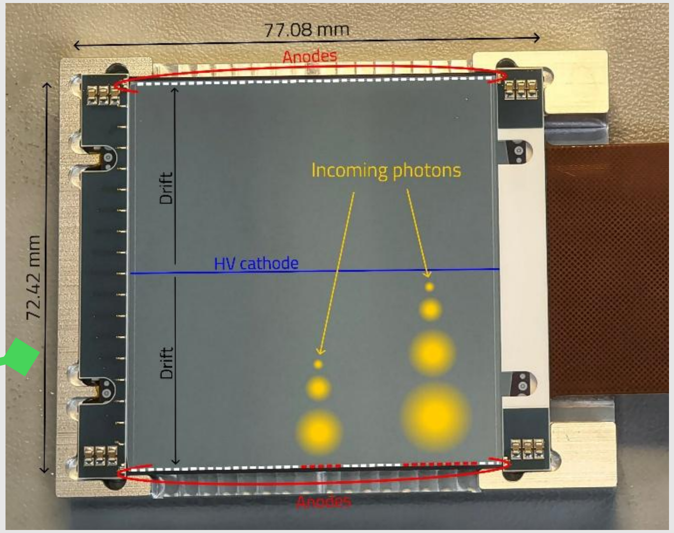
By **design**:

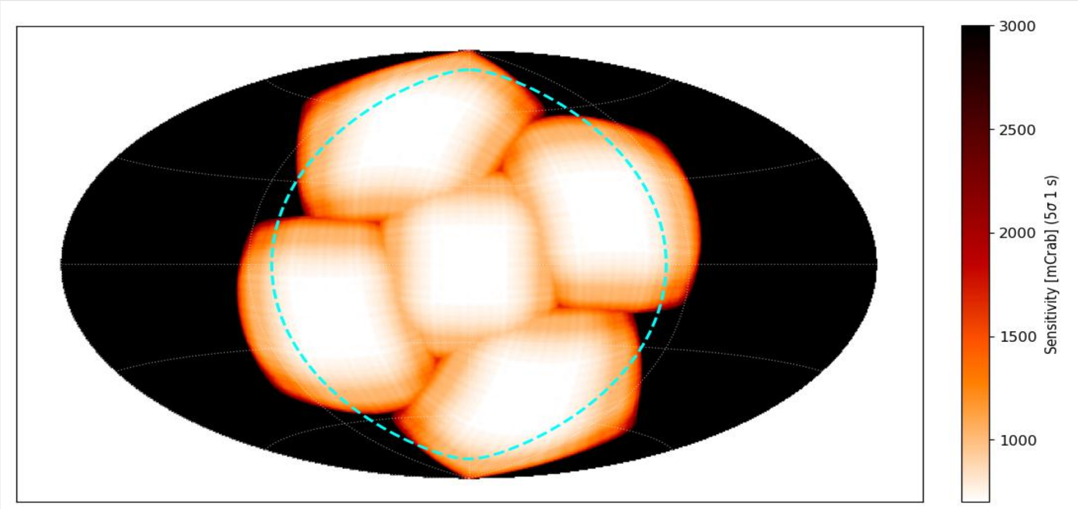
- 1.5D spatial resolution (typ. 65 µm × 8 mm FWHM)
- Low Energy threshold (2 keV)
- Good energy resolution (350 eV FWHM @ 6 keV)
- Good time resolution (better than 10 µs)
- Low power consumption (<1.2 W/DA)
- Low complexity (1D readout)

Each LEM-X module is:

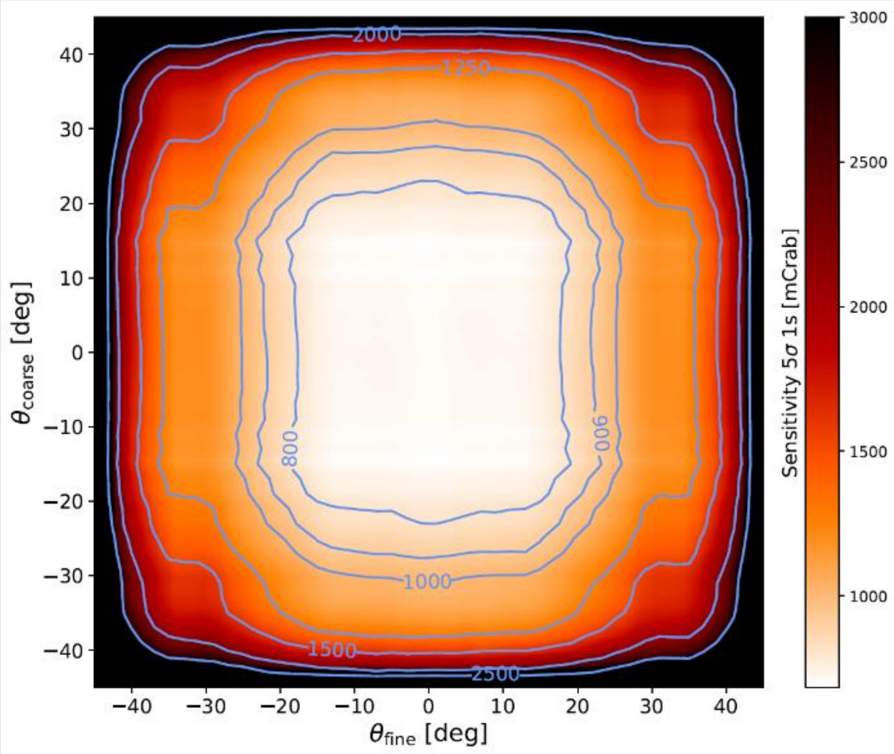
- **Autonomous** (with integrated BEE and PSU electronics)
- **Compact** (about 35×35×35 cm^3)
- **Light-weight** (~9 kg)
- With **low total power consumption** (13.2 W)

LEM-X camera and Unit performance have been thoroughly investigated and validated using the WISEMAN photon-by-photon Monte Carlo instrument simulator, alongside IROS procedures



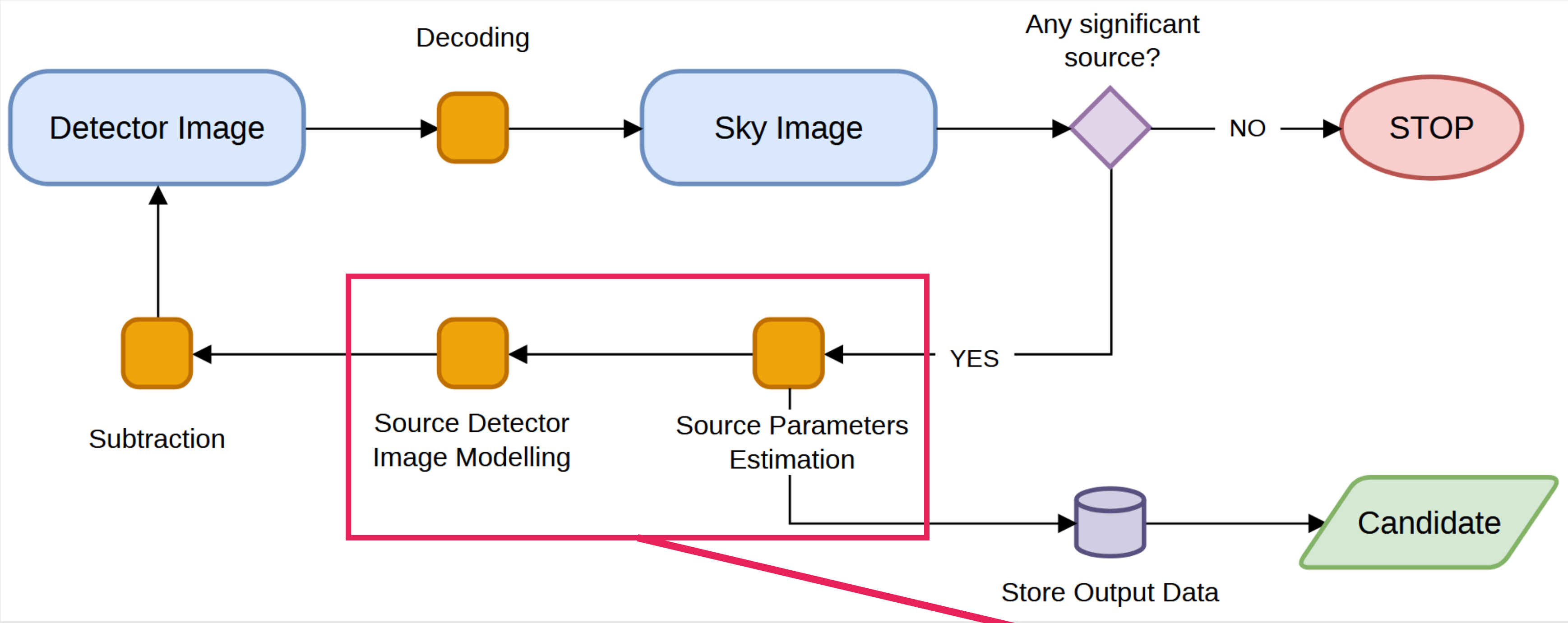


Camera Units combined sensitivity [mCrab] @ (5σ, 1s)



Camera sens. vs off-axis angle [mCrab] @ (5σ, 1s)

IROS Pipeline for Sky Reconstruction



Giancarli+ 2026, in prep.

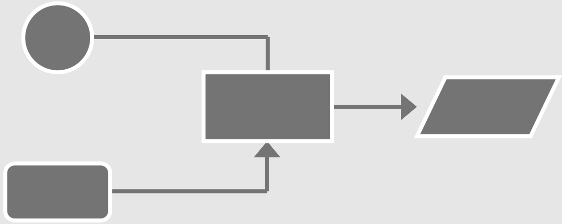
Source Extraction
(Sky Domain)

- **Selection** based on **detected counts** and **SNR level**
- **Double-camera** comparison for improved localisation
- Source parameters **optimisation**:
  - Camera local-frame **coordinates**
  - Collected photon **counts**

Source Subtraction
(Detector Domain)

- Source **modelling:**
  - Images inter-pixel **resolution**
  - **Mask** instrum. effects: **Vignetting**
  - **Detector** instrum. effects: **Spatial Resolution** for **fine** and **coarse** direction + **Inclined Penetration**
- Source **subtraction** and **storage**
- Catalogue **comparison** (during post-processing)

IROS Joint-Diffusion



- Source **modelling**
- Params **optimisation**

IROS Joint-Diffusion: Model Architecture