2D and 3D analysis improvements with Machine Learning for Muography Applications

Pisa Meeting 2024

Baptiste Lefevre, Héctor Gomez, David Attié

Outline

1. Muography with Micromegas detectors
2. Tomography analysis pipeline
3. Machine learning methodology

Context

Method with
examples and results

Outline

1. Muography with Micromegas detectors
2. Tomography analysis pipeline
3. Machine learning methodology

Context

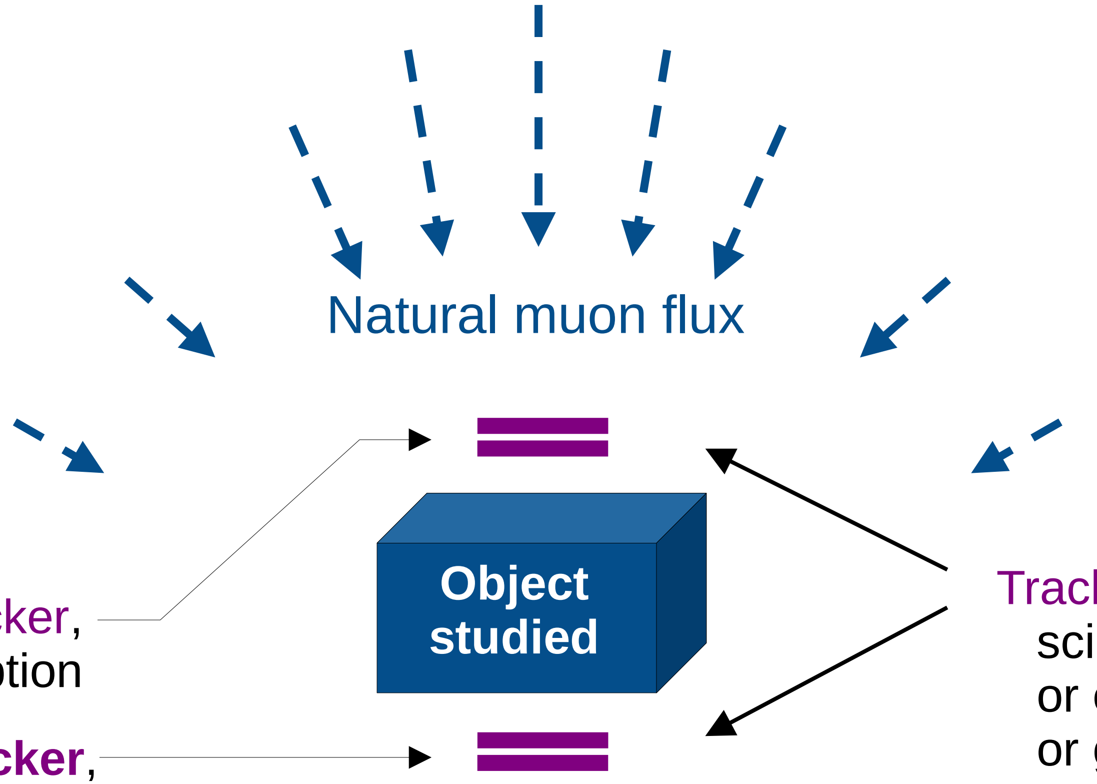
Method with examples and results

Goals

- ~~Give technical details about neural networks~~
- Explain some limitations in muography (at CEA Irfu)
- Discuss how we added machine learning in an existing pipeline

1. Muography with Micromegas detectors

Muography general idea



Muography techniques
rely on trackers (or vetos):

Upper muon tracker,
for scattering and/or absorption

Lower muon tracker,
for all techniques,
including **transmission**

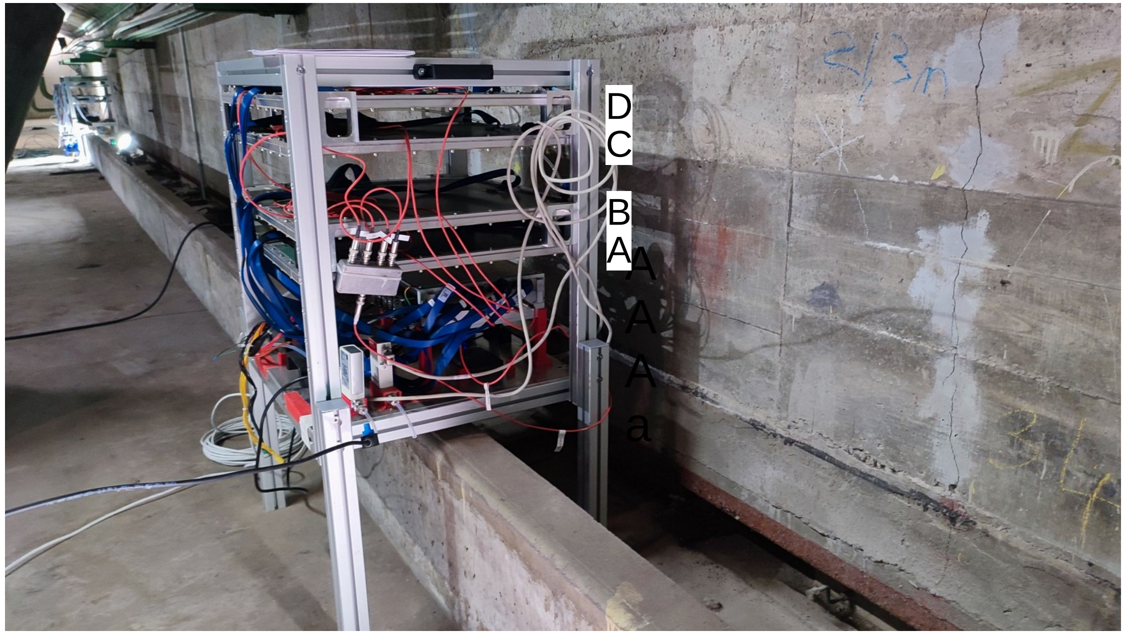
Tracker(s) composed of detectors:
scintillators,
or emulsion films,
or **gaseous detectors,**
or a TPC, ...

Applications :
- Archeology (pyramids)
- Homeland security (containers)
- Geosciences (volcanology)
- **Nuclear** (reactor monitoring, waste package study, ...)

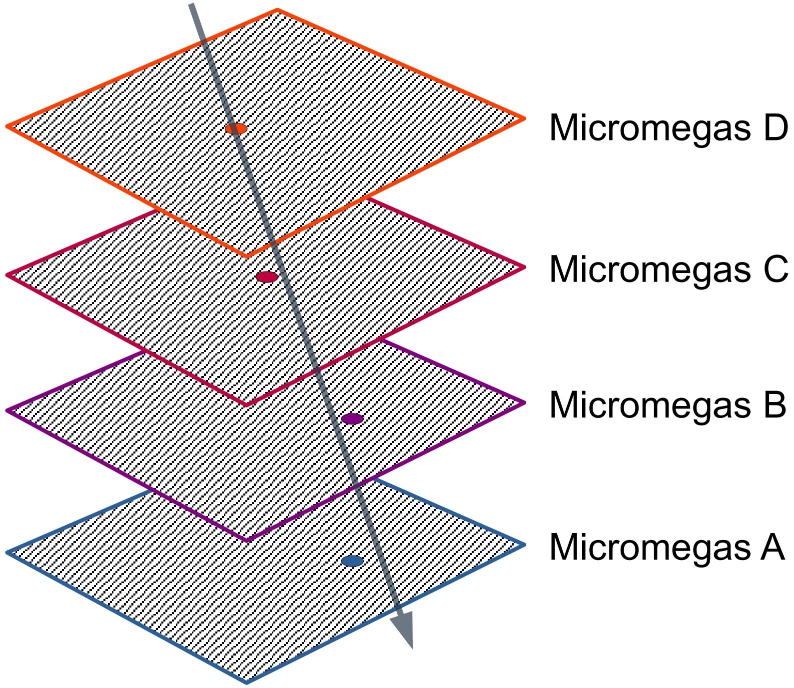
Muography project at CEA / Irfu

Friday 10:40 → talks about Micromegas detectors !

Talk focus :
Transmission muography technique, with **multiplexed Micromegas** detectors, for **nuclear** applications



Muon telescopes under the G3 nuclear reactor:
← Picture
Diagram →



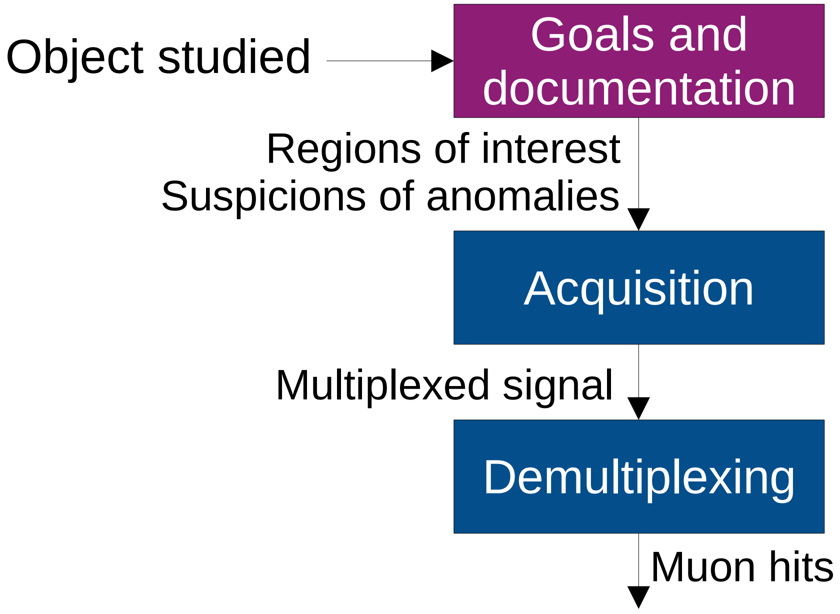
Hits on detectors
Track reconstructed

Picture of the reactor →

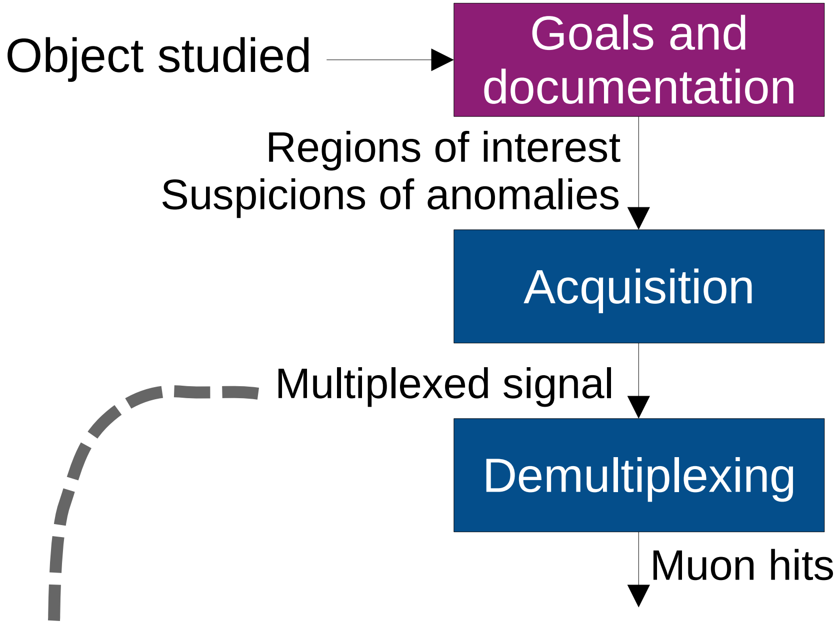
Images from
doi.org/10.1051/epjconf/202328807001
and francetnp.gouv.fr

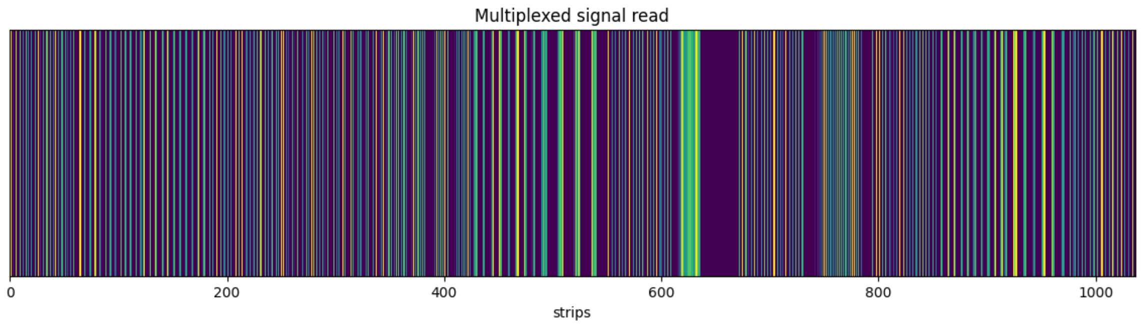
2. Tomography analysis pipeline

Data analysis pipeline: acquisition



Data analysis pipeline: acquisition





Simulation of multiplexed signal on 1 coordinate

Data analysis pipeline: demultiplexing 1/2

Object studied → **Goals and documentation**

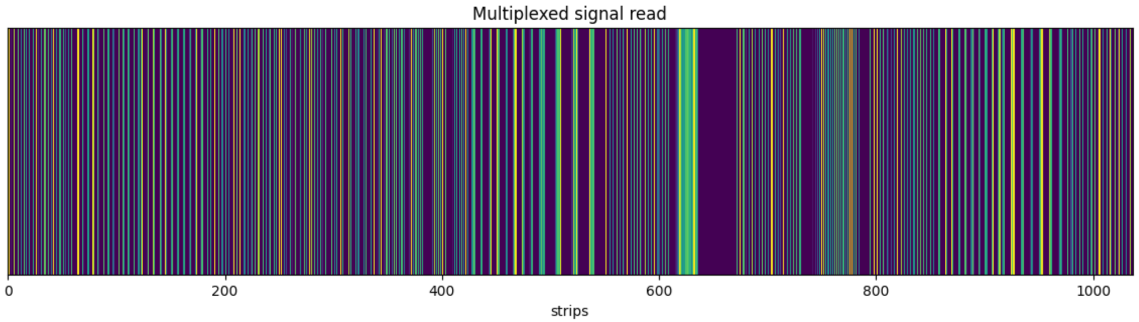
Regions of interest
Suspicions of anomalies
↓

Acquisition

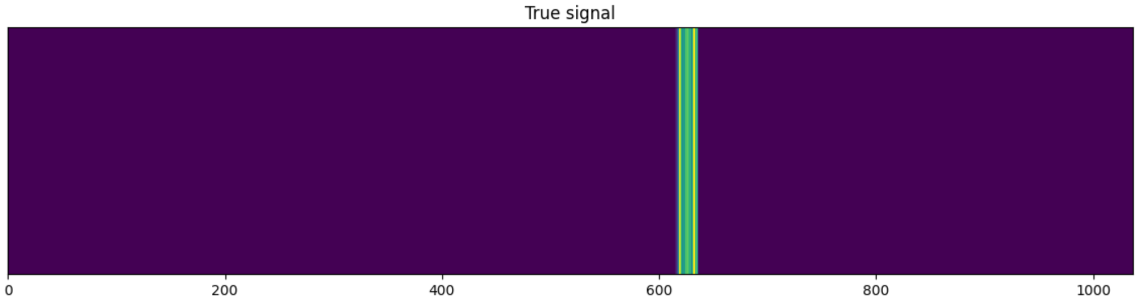
Multiplexed signal
↓

Demultiplexing

Muon hits
↓



Simulation of multiplexed signal on 1 coordinate



Demultiplexing of 1 coordinate

Data analysis pipeline: demultiplexing 2/2

Object studied → **Goals and documentation**

Regions of interest
Suspicions of anomalies

↓

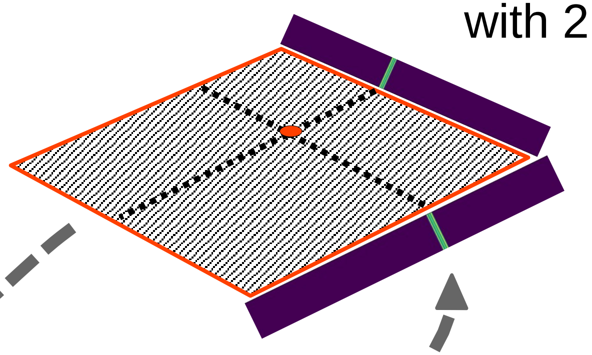
Acquisition

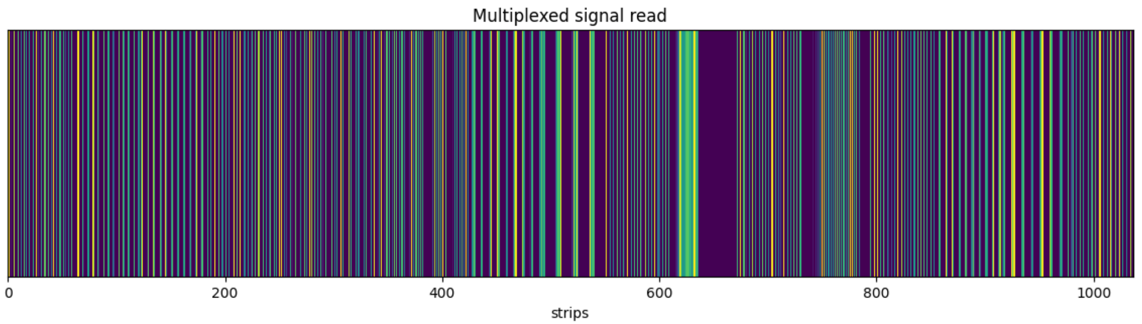
↓ Multiplexed signal

Demultiplexing

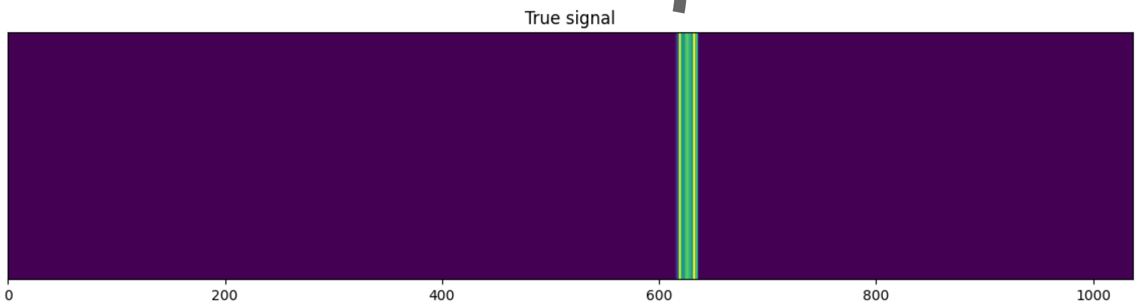
↓ Muon hits

Position on a Micromegas with 2 coordinates





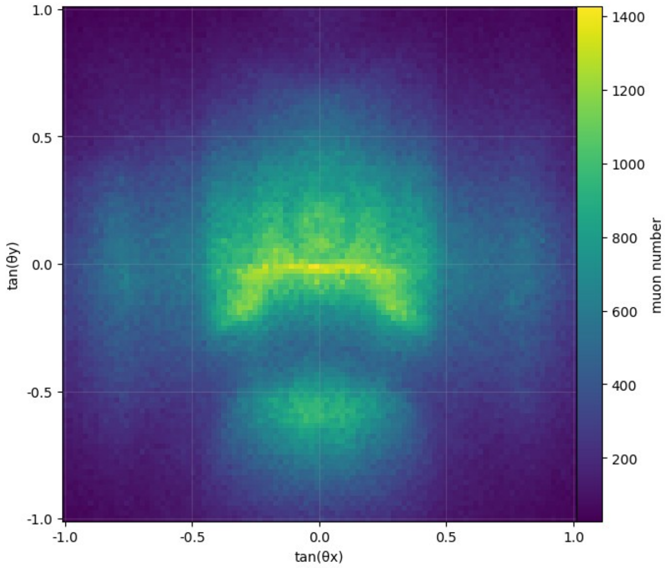
Simulation of multiplexed signal on 1 coordinate



Demultiplexing of 1 coordinate

Data analysis pipeline: tracking

Raw muography



Muon number

Object studied → **Goals and documentation**

Regions of interest
Suspicions of anomalies

Acquisition

Multiplexed signal

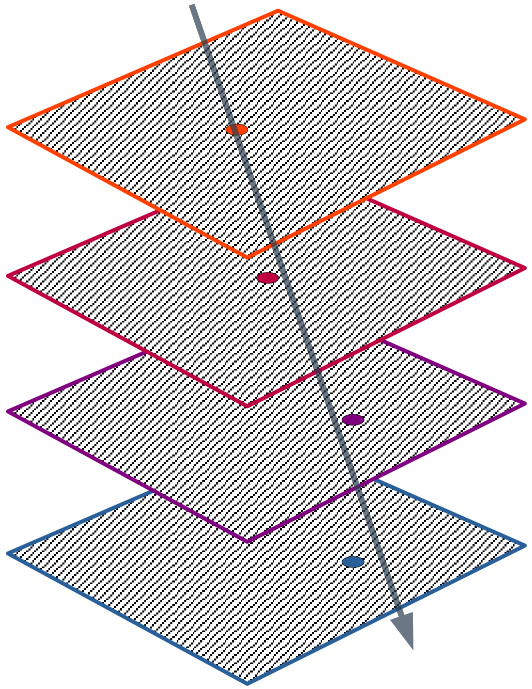
Demultiplexing

Muon hits

Tracking

Muographies

Tracking step :



Hits on detectors
Track reconstructed

Data analysis pipeline: opacity

Object studied → **Goals and documentation**

Regions of interest
Suspicions of anomalies
↓

Acquisition

Multiplexed signal
↓

Demultiplexing

Muon hits
↓

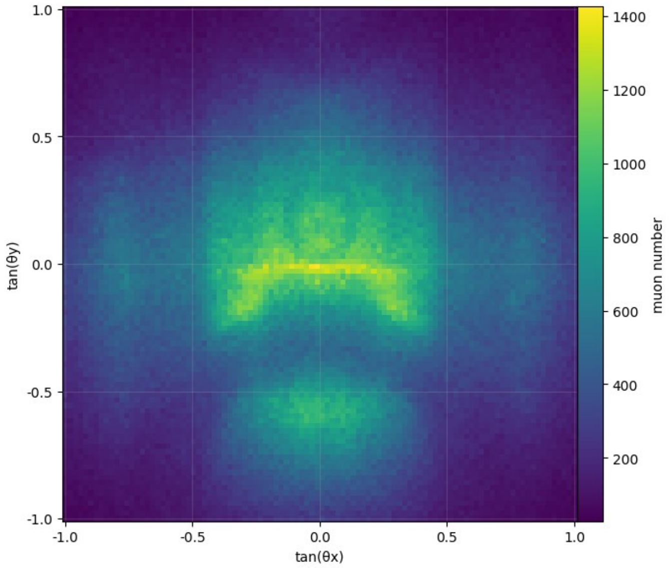
Tracking

Muographies
↓

Opacity estimation

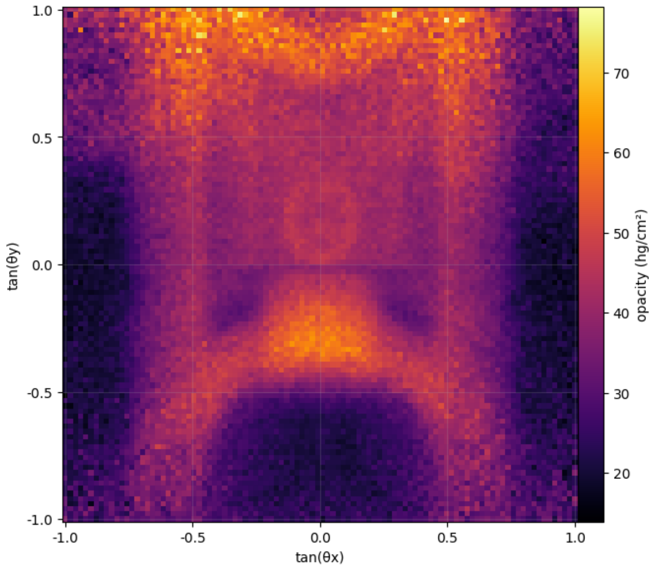
Opacities
↓

Raw muography



Muon number

Opacity estimation



$$o = \int \rho \cdot dl$$

Data analysis pipeline: 3D

Object studied → **Goals and documentation**

Regions of interest
Suspicions of anomalies

↓

Acquisition

Multiplexed signal ↓

Demultiplexing

Muon hits ↓

Tracking

Muographies ↓

Opacity estimation

↓

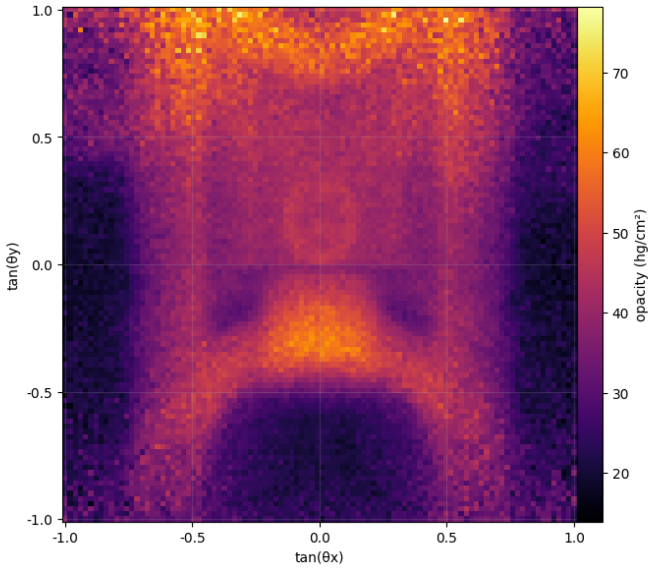
3D Reconstruction

↓

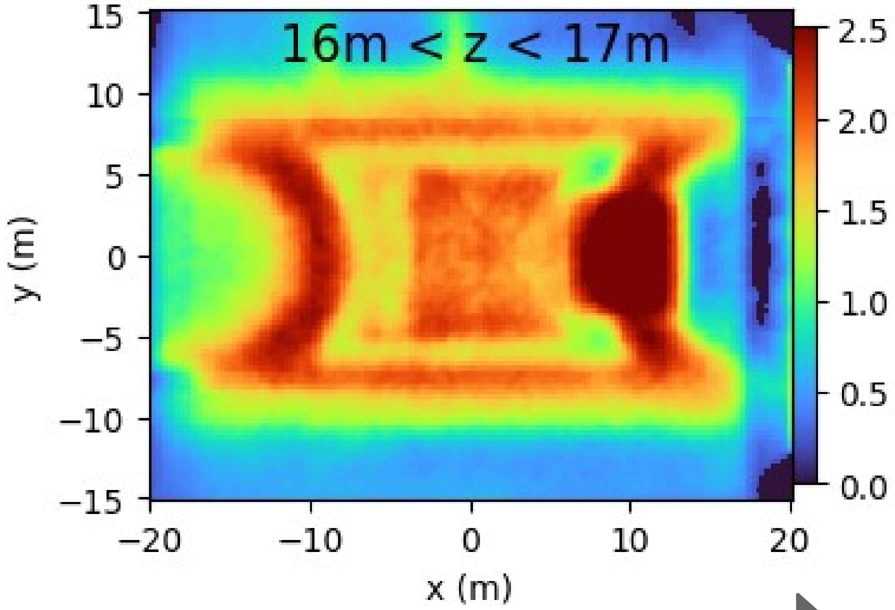
"Blind" tomography
(3D image)

Opacities

Opacity estimation



$$o = \int \rho \cdot dl$$



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Data analysis pipeline: 3D

Object studied → Goals and documentation

Regions of interest
Suspicions of anomalies

Acquisition

Multiplexed signal

Demultiplexing

Muon hits

Tracking

Muographies

Opacity estimation

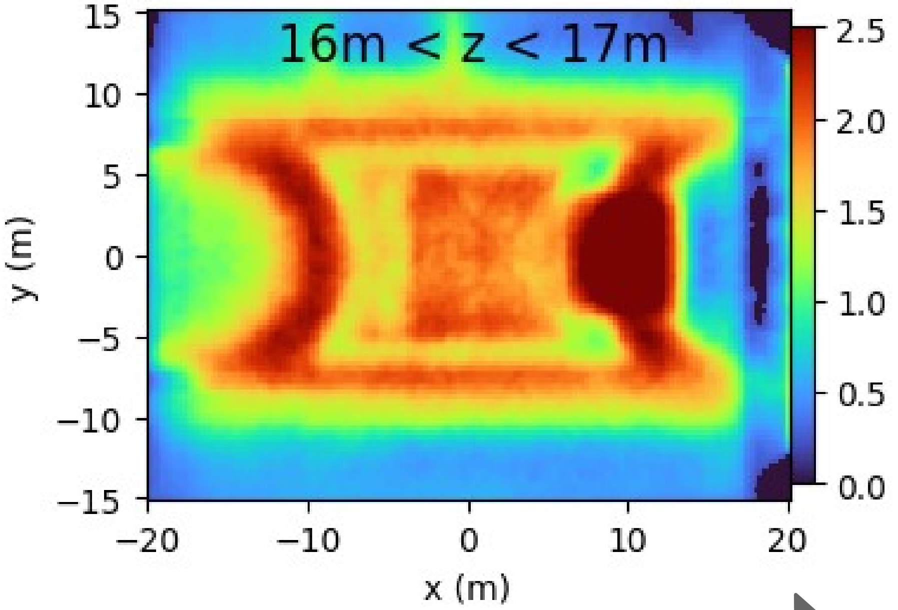
Opacities

3D Reconstruction

Analysis

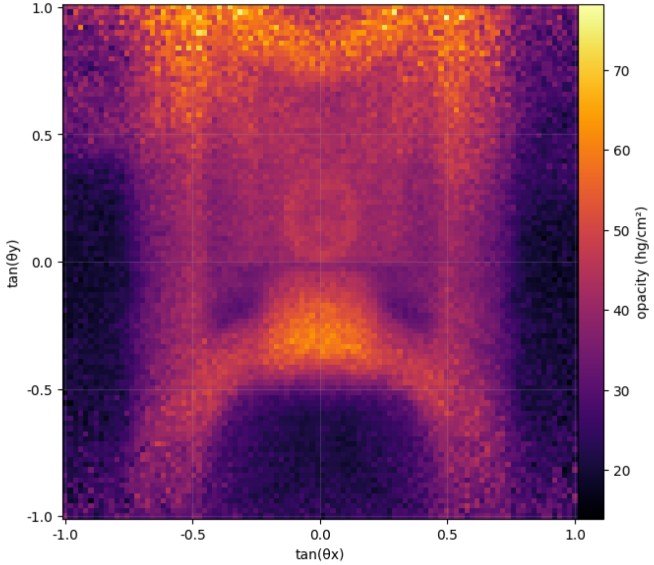
Observed anomalies
Defaults in the images

“Blind” tomography
(3D image)



ρ

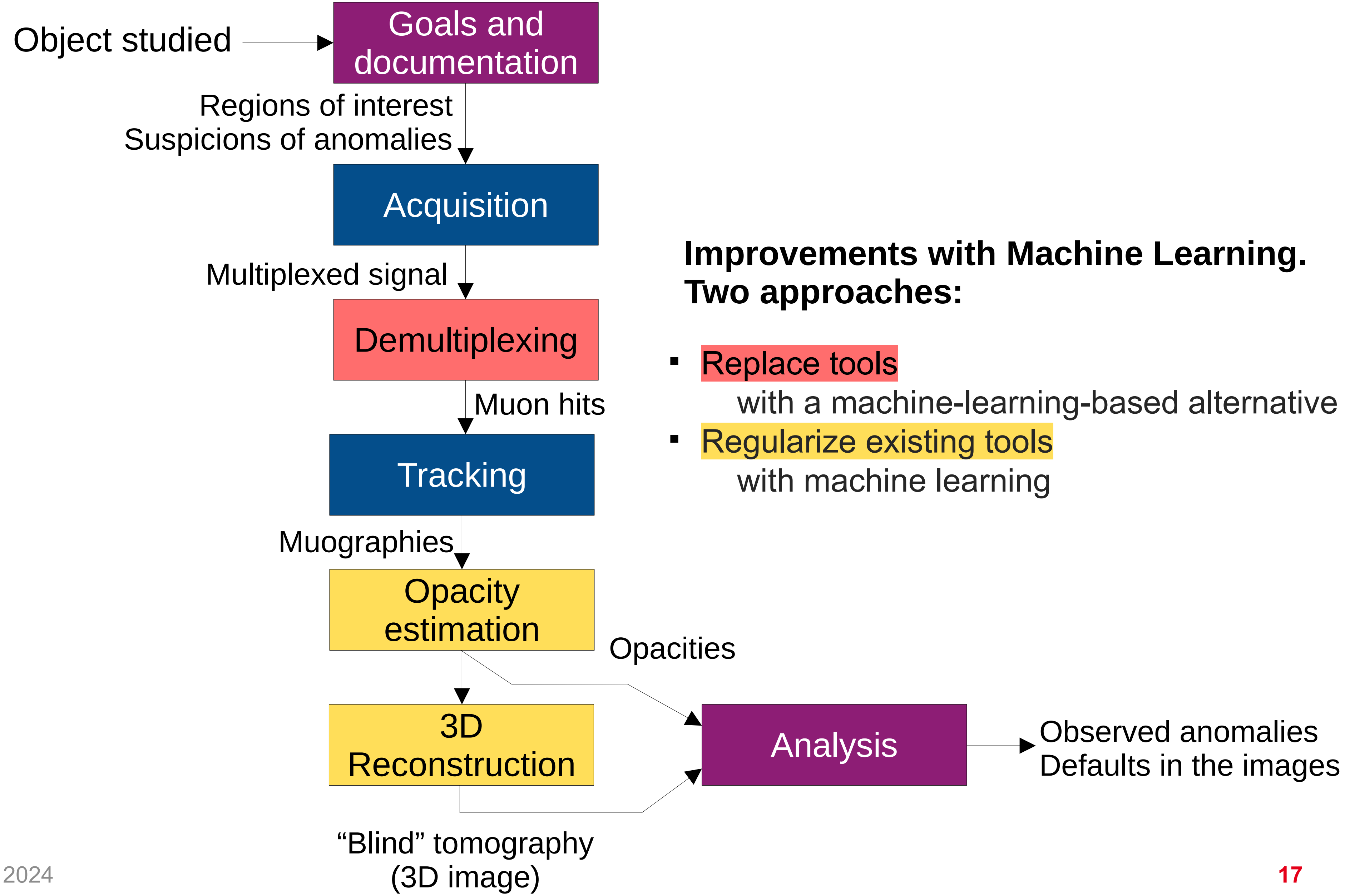
Opacity estimation



$$o = \int \rho \cdot dl$$

3. Machine Learning methodology

Data analysis pipeline: machine learning



Improvements with Machine Learning.
Two approaches:

- Replace tools
  with a machine-learning-based alternative
- Regularize existing tools
  with machine learning

Options considered

- Replace tools with a machine-learning-based alternative ?
- Regularize existing tools with machine learning ?

Depends on the tool

- Demultiplexing
  - Long code based on empirical parameters
  - Known purity and efficiency issues

    → replace by a neural network
- Opacity computation
  - Physical parameterisation based on G4 simulations
  - Noise coming from the limited statistics

    → keep and develop a denoiser
- 3D reconstruction
  - SART algorithm, with known limitations (artifacts, ambiguities, ...)

    → keep and postprocess/regularize

In short, motivations :

- Complex code with lot of empirical parameters
- Issues hard to correct but easy to simulate
- Noise

3a. Demultiplexing

Context: article under review in *Engineering app. of artificial intelligence*

Demultiplexing and Electron-Muon identification in different Micropattern Readout Planes with common U-Net approach

Baptiste Lefevre[1 a], Etienne Gozillon[a], David Attié[a], Héctor Gomez[a], Irakli Mandjavidze[a], Philippe Mas[a]

[a] *Université Paris-Saclay, CEA, IRFU, 91191, Gif-Sur-Yvette, France.*

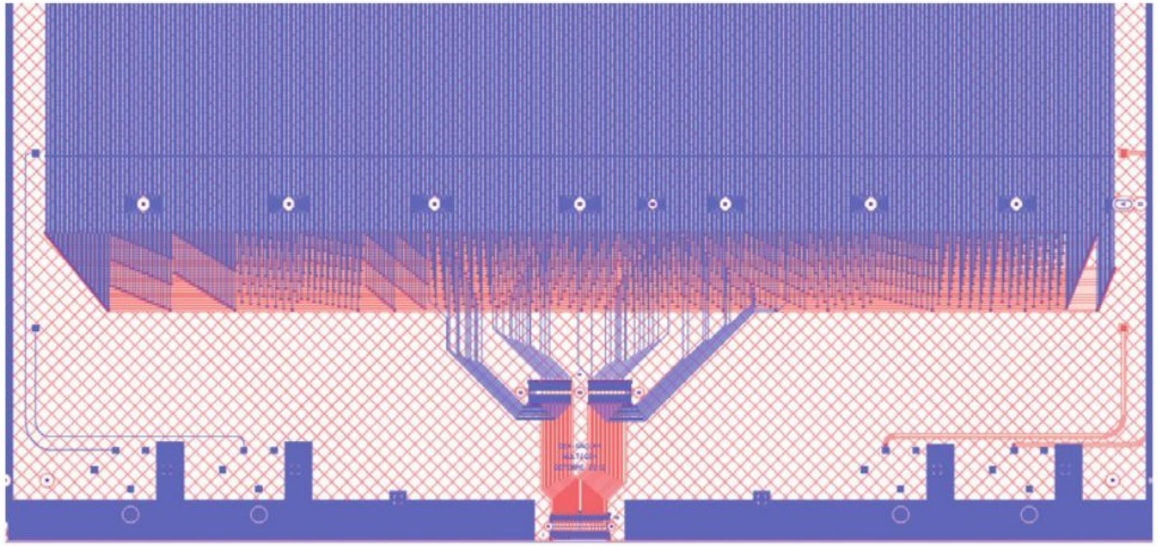
Abstract

Micropattern Gaseous Detectors, like Micromegas, are used in particle physics to detect charged particles like muons, which ionise gas. Micromegas detectors provide good spatial resolution that allows to do muography, an imaging method using the natural muon flux to study very opaque objects like pyramids, volcanoes or nuclear reactors. One of those detectors — called multiplexed Micromegas detector — allows to reduce significantly the volume and cost of the electronics. Multiplexed Micromegas need less electronics but produce ambiguous data that needs a demultiplexing step : an analysis to find the true position of the particle(s) on the detector.

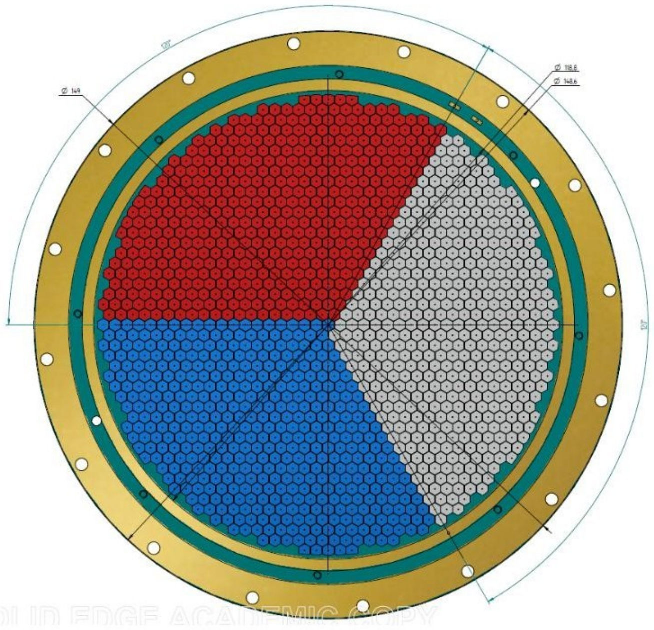
In this work we propose a new demultiplexing method, with a denoising approach using a U-Net architecture. We show that the same method allows to analyse two types of Micromegas detectors : a 1D detector with strips and a 2D detector with pixels in a Time Projection Chamber. We demonstrate that only a few changes have to be made to adapt to the 1D and 2D analysis. This makes the U-Net easily adaptable for a wide range of other high-granularity particle detectors, even others than gaseous ones, and for different sizes and dimensionalities. Moreover, we show that U-Net's capabilities also allow distinguishing muons tracks from electrons tracks in the 2D detector.

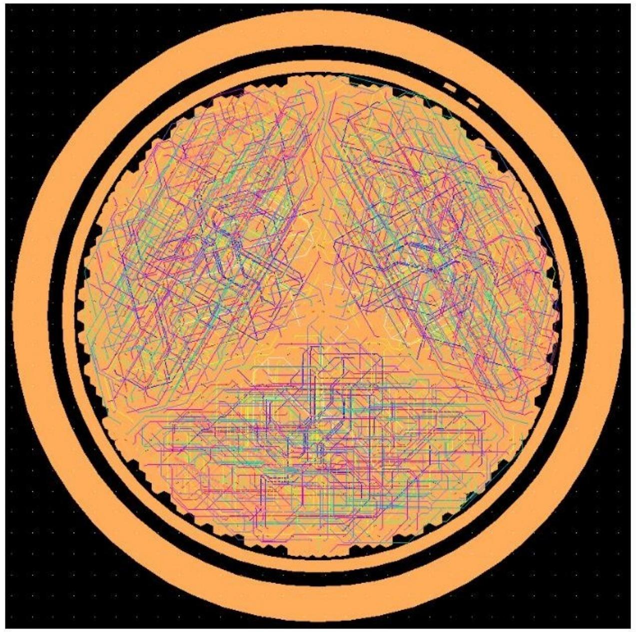
Keywords: Muon Tomography, Time Projection Chamber, Multiplexed Micromegas, Particle identification, U-Net

Multiplexed readout



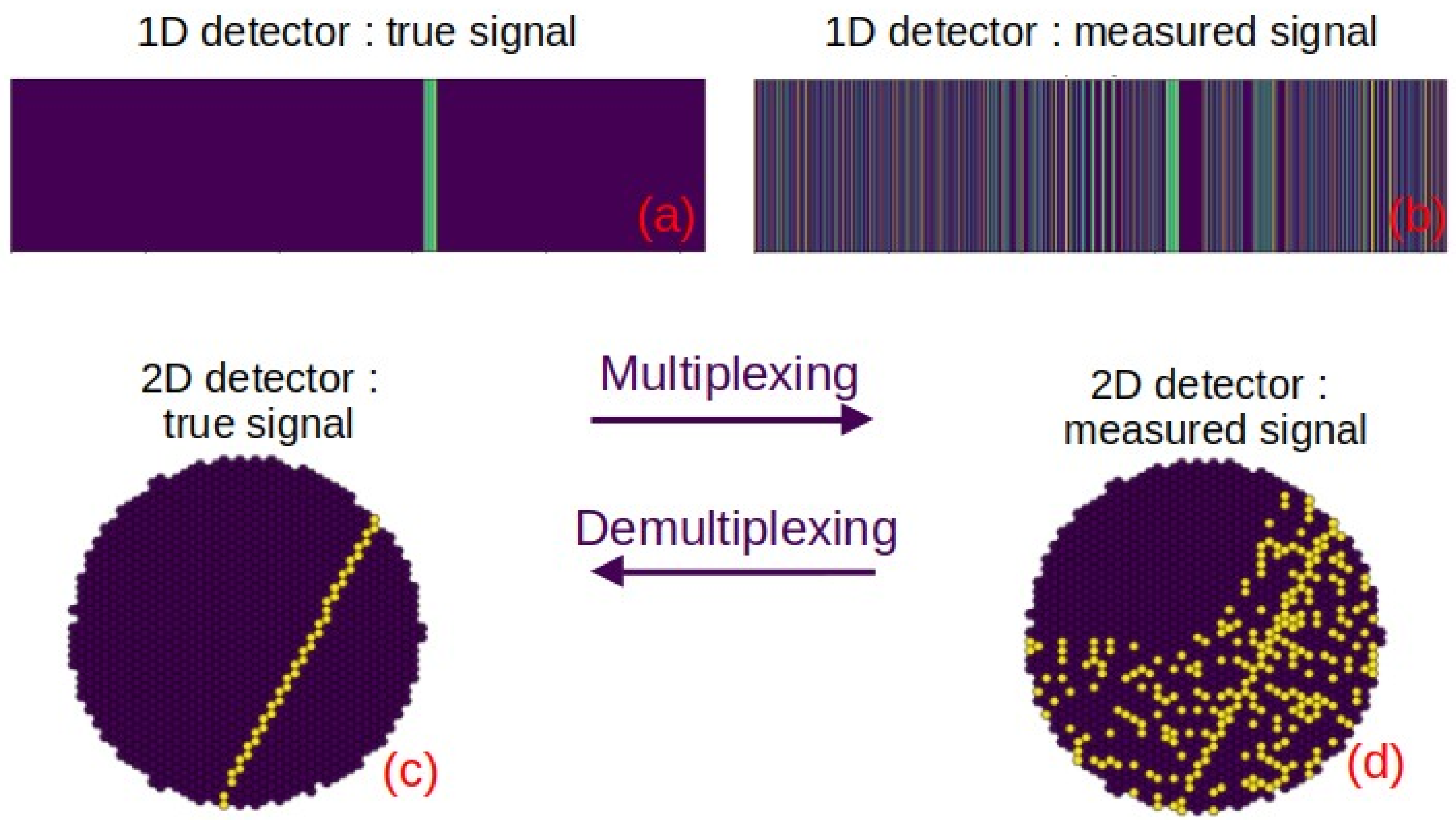
Stripped detector :
 1037 strips → 61 channels
 Multiplexing factor 17



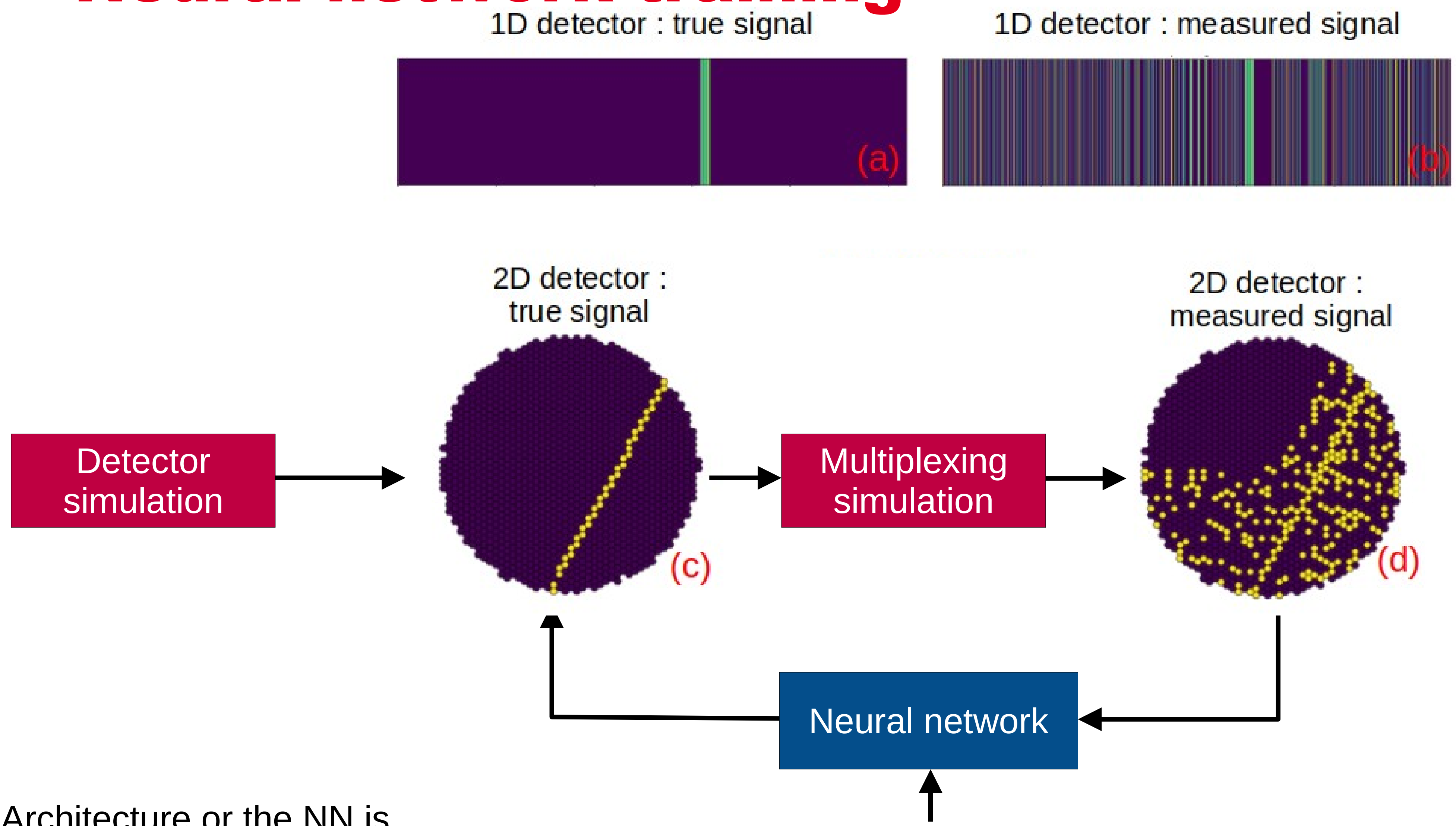


Pixelated detector :
 1344 pixels → 180 channels
 Mean multiplexing factor 7

Effect of the multiplexing



Neural network training

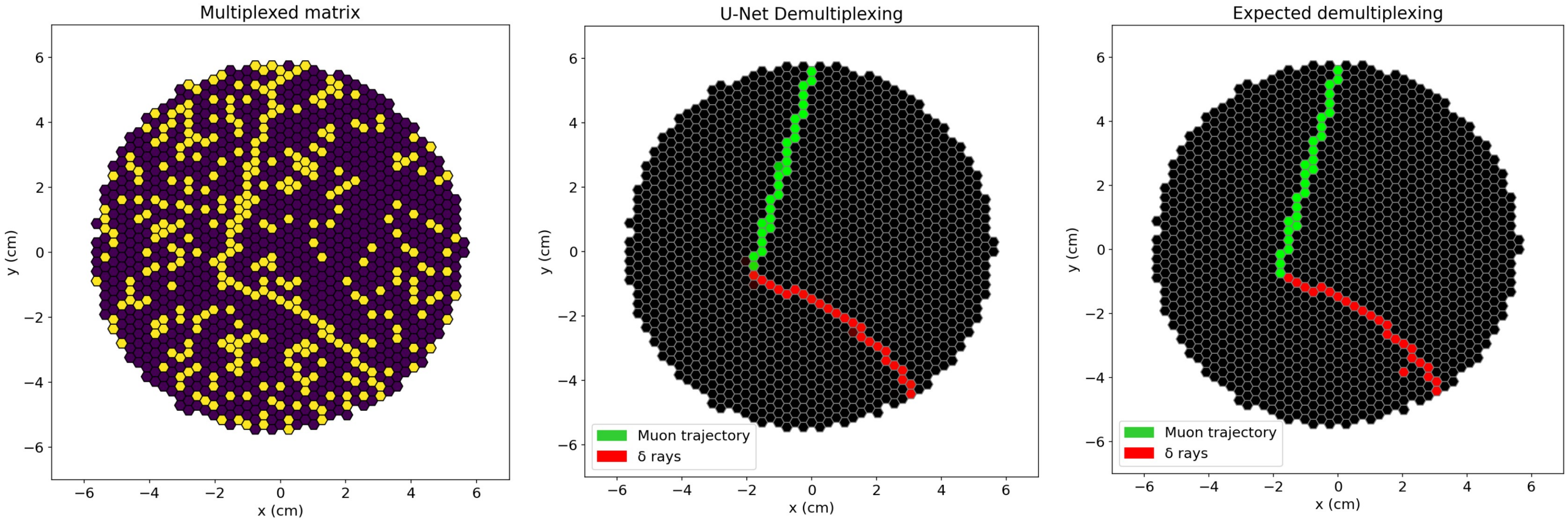


- Dimensionnality
- Number of filters (difficulty of the task)
- Activation and normalisation methods

Architecture or the NN is currently under review.

TPC Event displays

Example of typical simulated event.
No real data available for the moment.

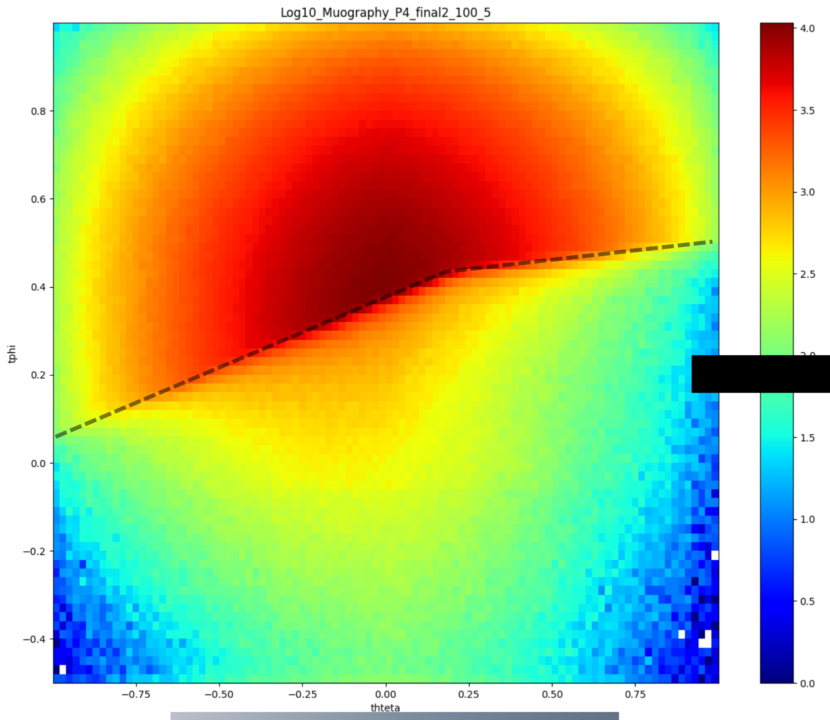


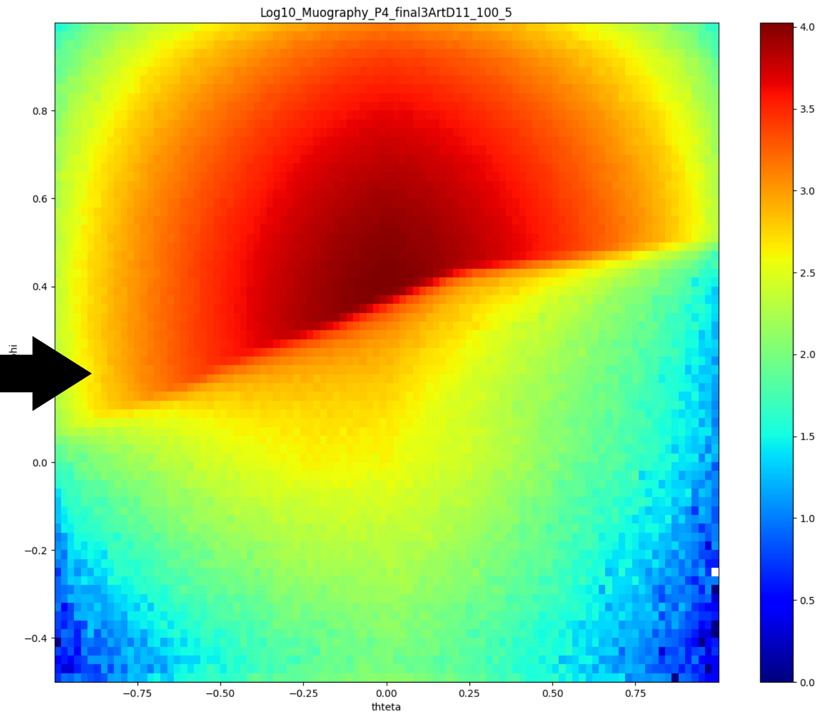
On 200k simulated events : **effiency**: 94% for muons , 63% for electrons , 99% for empty
purity: 94% for muons , 70% for electrons , 99% for empty

Demultiplexing is good (99%), the difficulty is the particle identification.
In the end, pixel metrics are not crucial. Only the track direction count.

Evaluation on real data: Reprocess of ScanPyramids

Data taken with multiplexed resistive strip Micromegas detectors





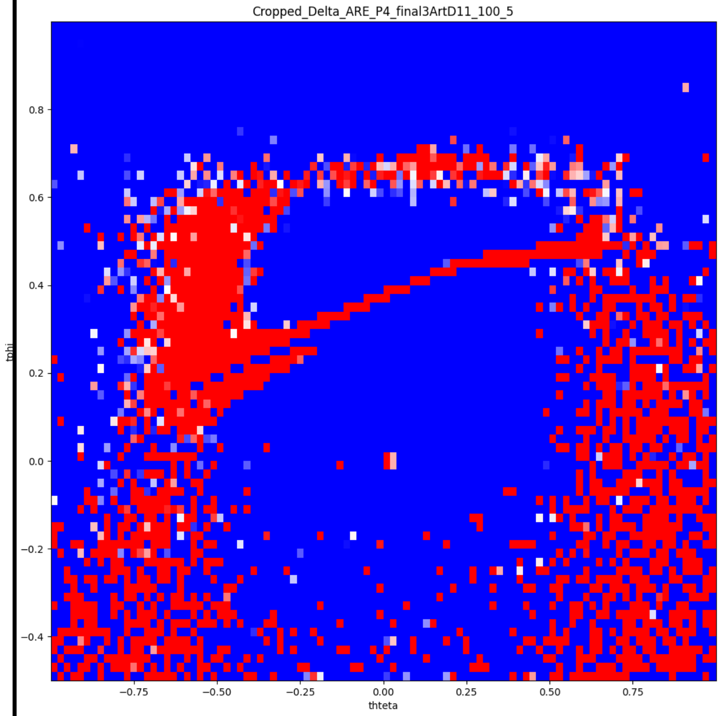
$$\overline{ARE} = \frac{1}{Npix} \cdot \sum_{i \in pixels} \left| \frac{\mu_i - \mu sim_i}{\mu sim_i} \right|$$

Current method	Neural network
0.72	0.60 (-27%)

Mean absolute relative error : -27%

Directions of

progress and regress



ARE(NN) < ARE(Cur. Meth.)

ARE(NN) > ARE(Cur. Meth.)

Improvement in 75% of the pixels (i.e. directions)

3b. Opacity images denoising

Context: article in preparation

3D reconstruction of a nuclear reactor by muon tomography: structure validation and anomaly detection

IRFU'S Muography Group

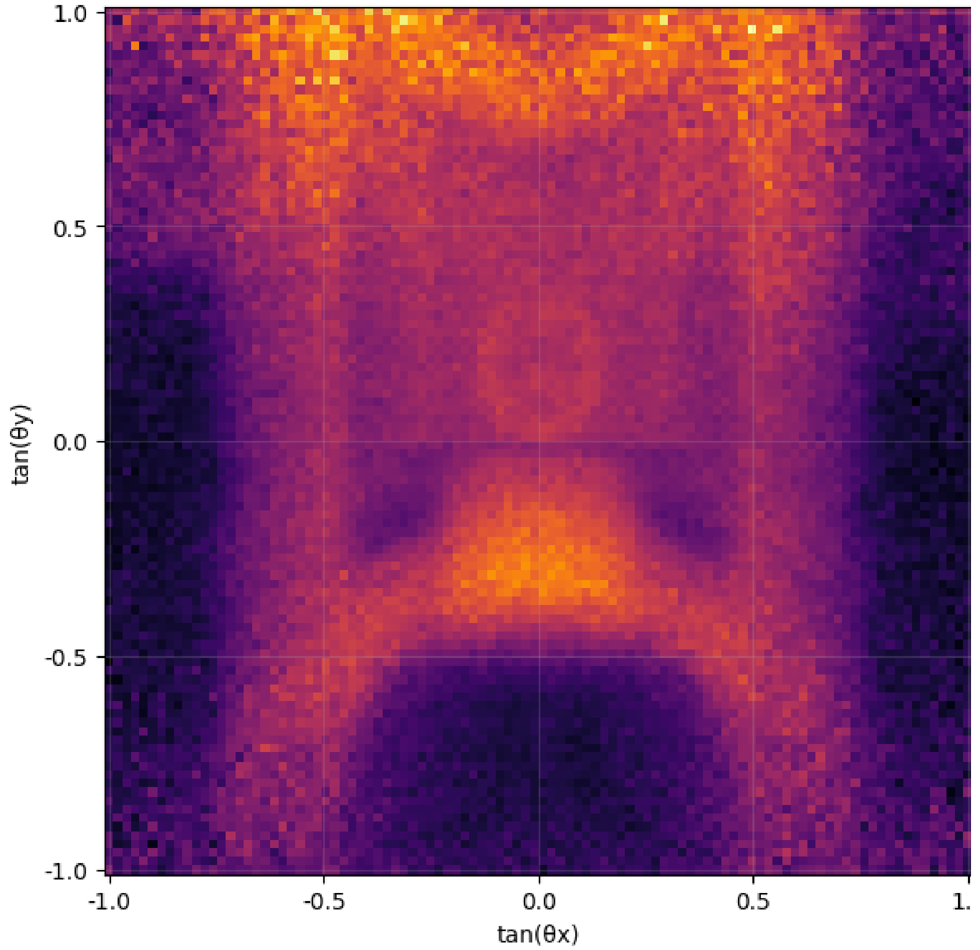
Recent developments in muon tomography have shown that the detection of atmospheric muons may be used to investigate the internal components of inaccessible high-opacity objects. This was demonstrated with the reconstruction of a french historical Natural-Uranium Graphite and Gas (UNGG) nuclear reactor. Muon telescopes with a high angular resolution are used to measure the directional muon flux (called muography image) below the reactor.

The results of a muography campaign of 46 points of view are given, which made three-dimensional reconstructions possible. In this work the methodology to analyze muographies and reconstruct three-dimensional images is described and its systematic errors are evaluated.

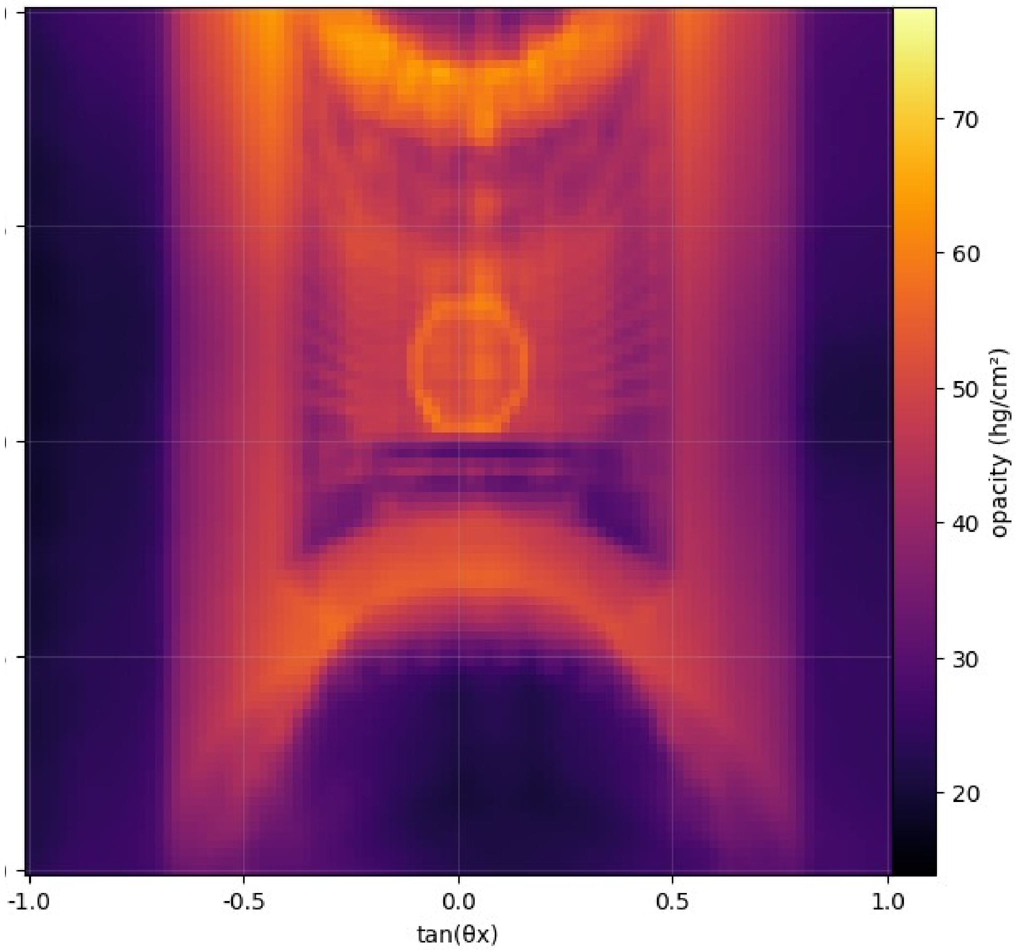
Moreover data-augmentation and machine-learning techniques were used to improve the quality of the muography images and the 3-dimensional reconstruction. Both techniques were proven to be very efficient on simulated data and useful on the true measures.

These method's precise characterizations allowed to compare the results to simulations obtained with a model of the reactor. The comparisons made the discovery of anomalies between the reactor and the model possible. These anomalies are commented in this work.

Noise issue in opacity images



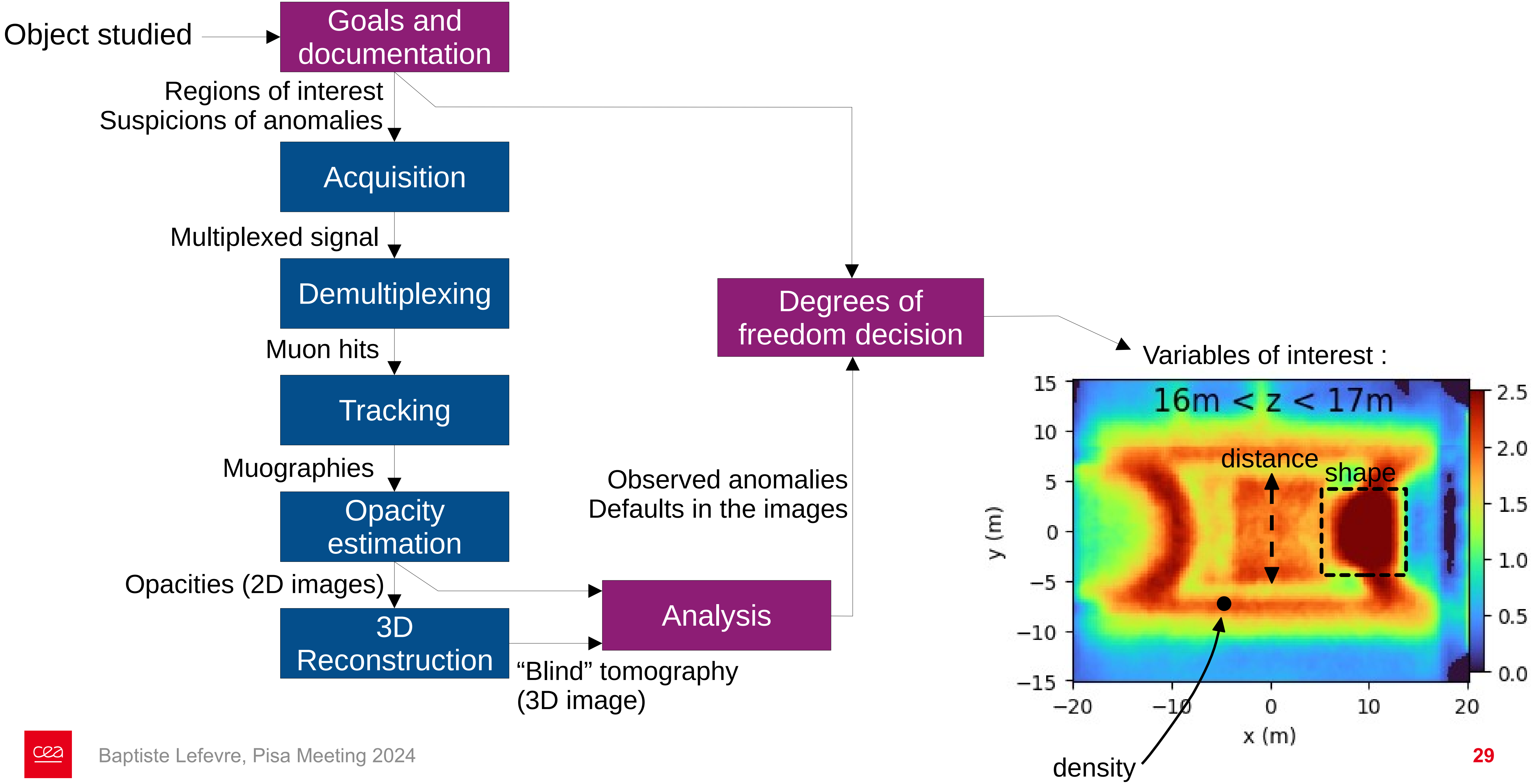
Opacity with 22 days of **real data**



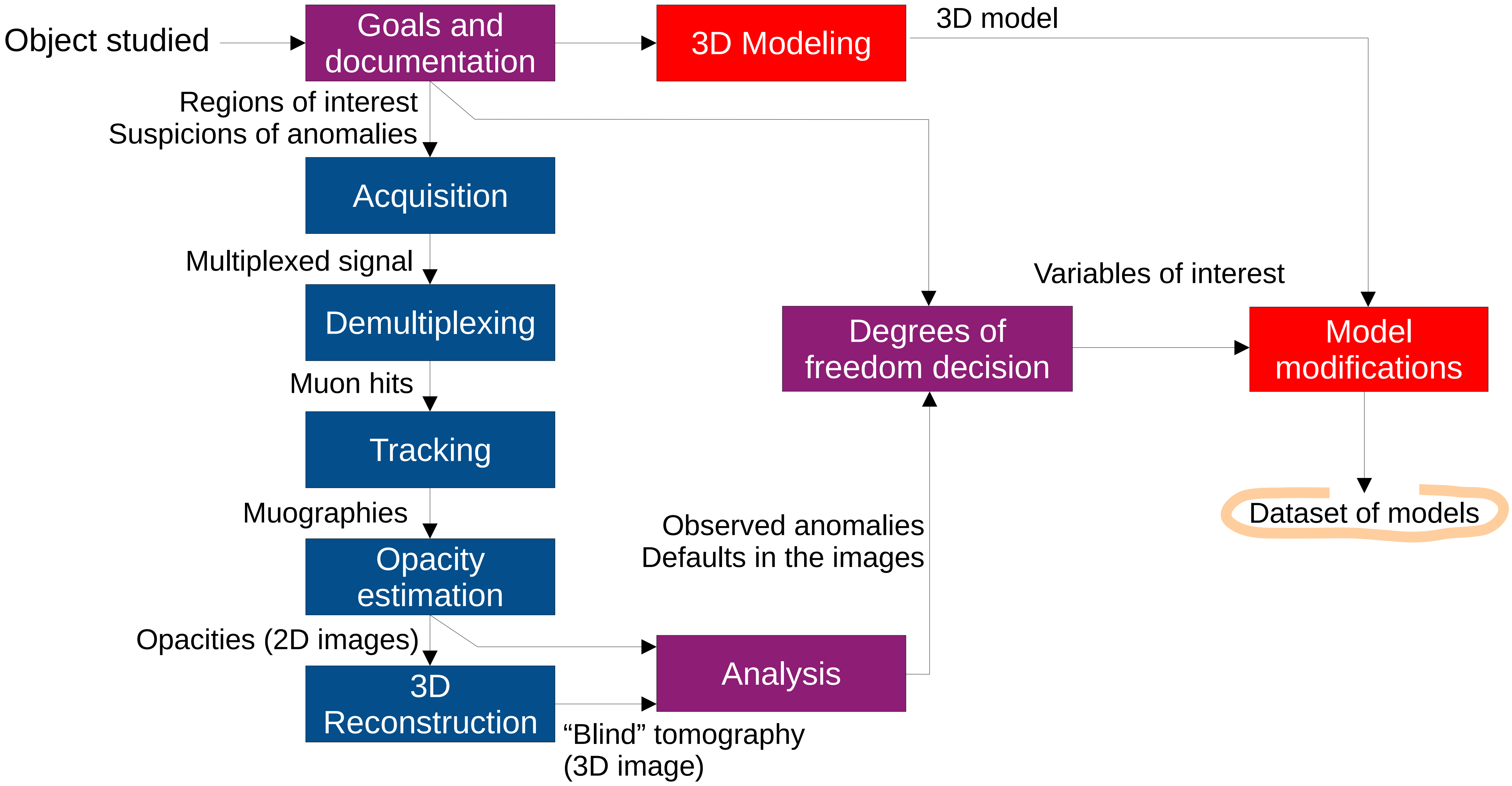
Opacity map from the **reactor model**

Noise is mainly due to a lack of statistics.
(i.e. 22 days is a short duration)

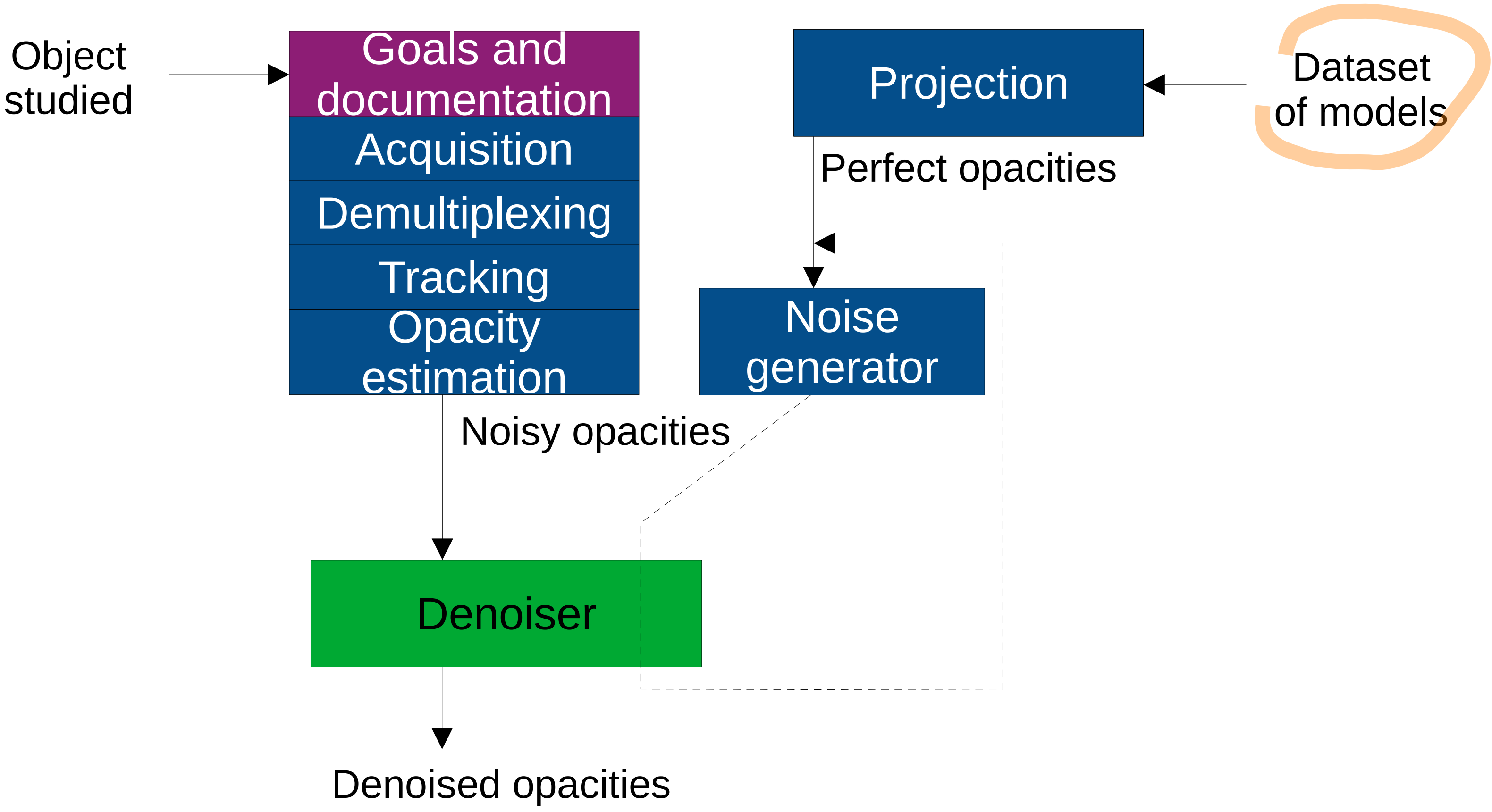
Data analysis pipeline



Data analysis pipeline



Data analysis pipeline

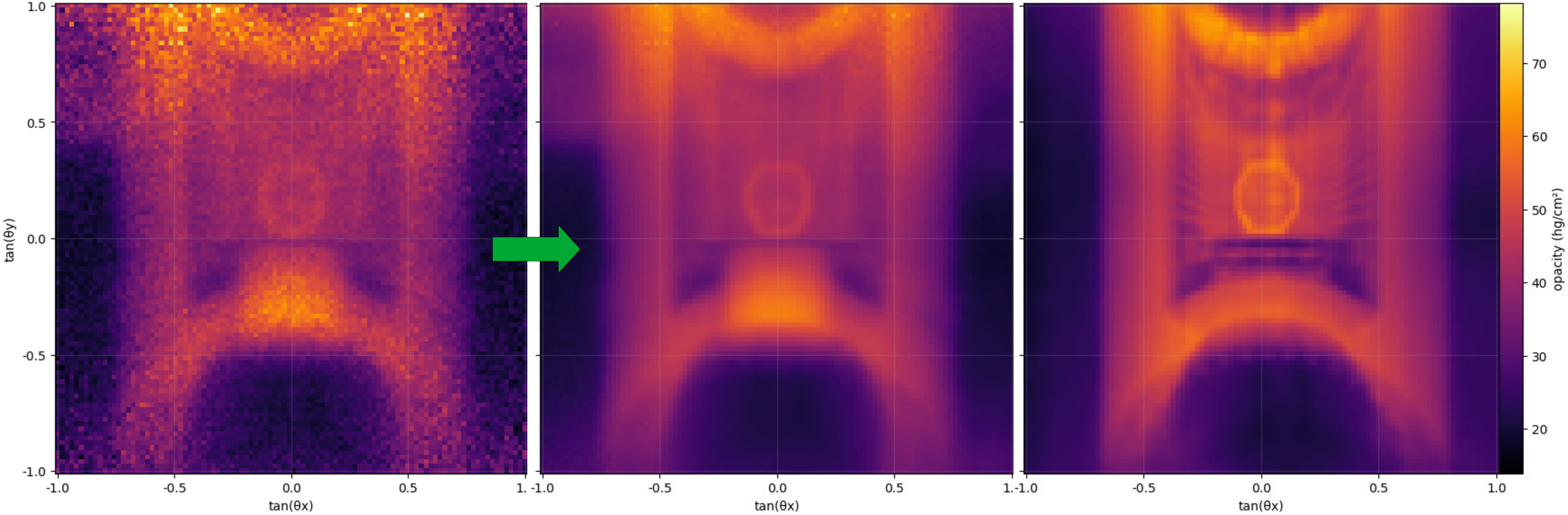


Perfect opacity images may be obtained by projection of a 3D model :

$$o = \int \rho \cdot dl$$

Denoising qualitative performances

On real data : visually working.
But **real object** ≠ **model**.



Opacity
with 22 days of **real data**

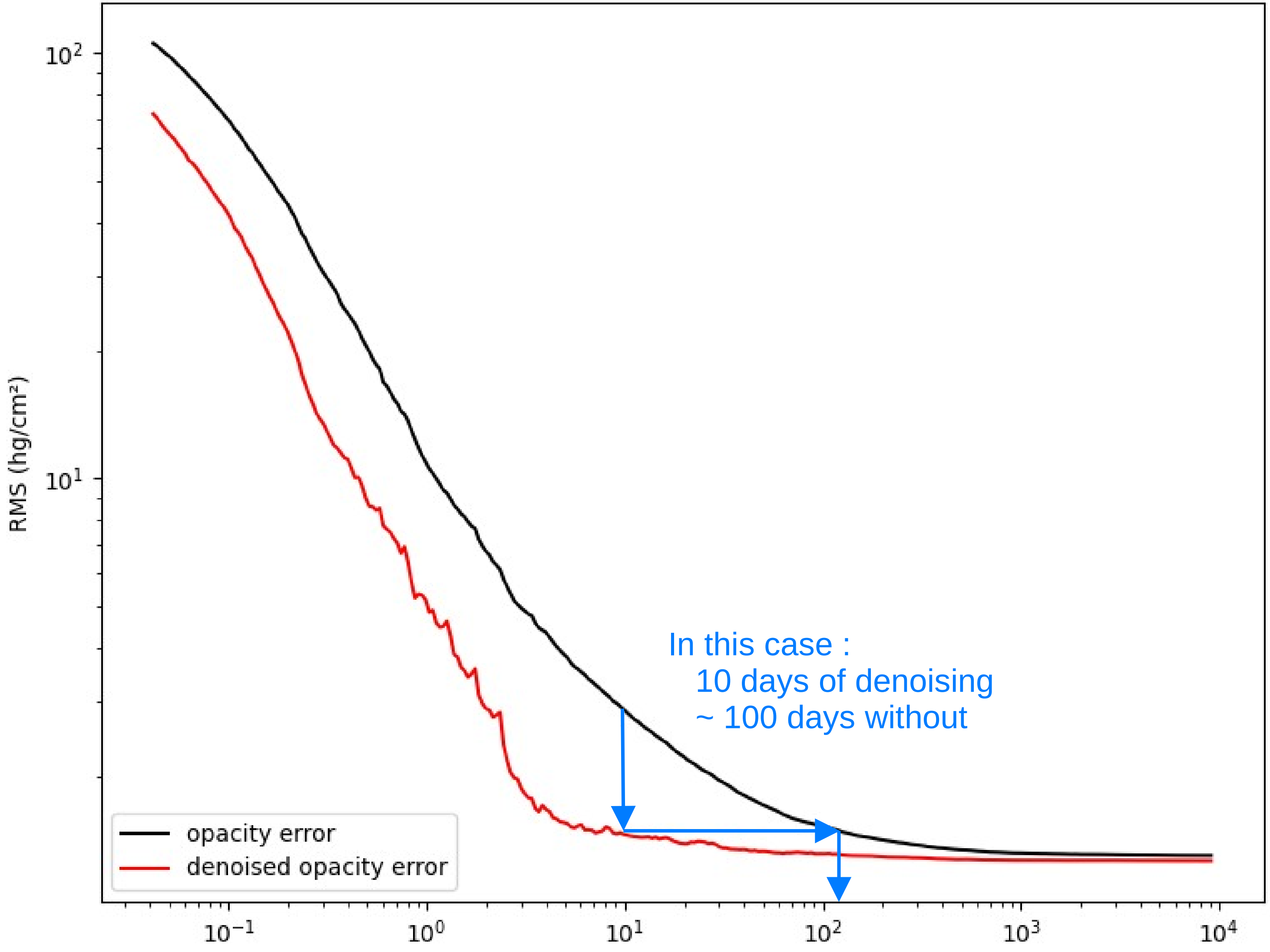
Opacity
with 22 days of **real data**
and **denoising**

Opacity map in the **model**

Denoising quantitative performances

Measured on simulations

Image quality improves (log)

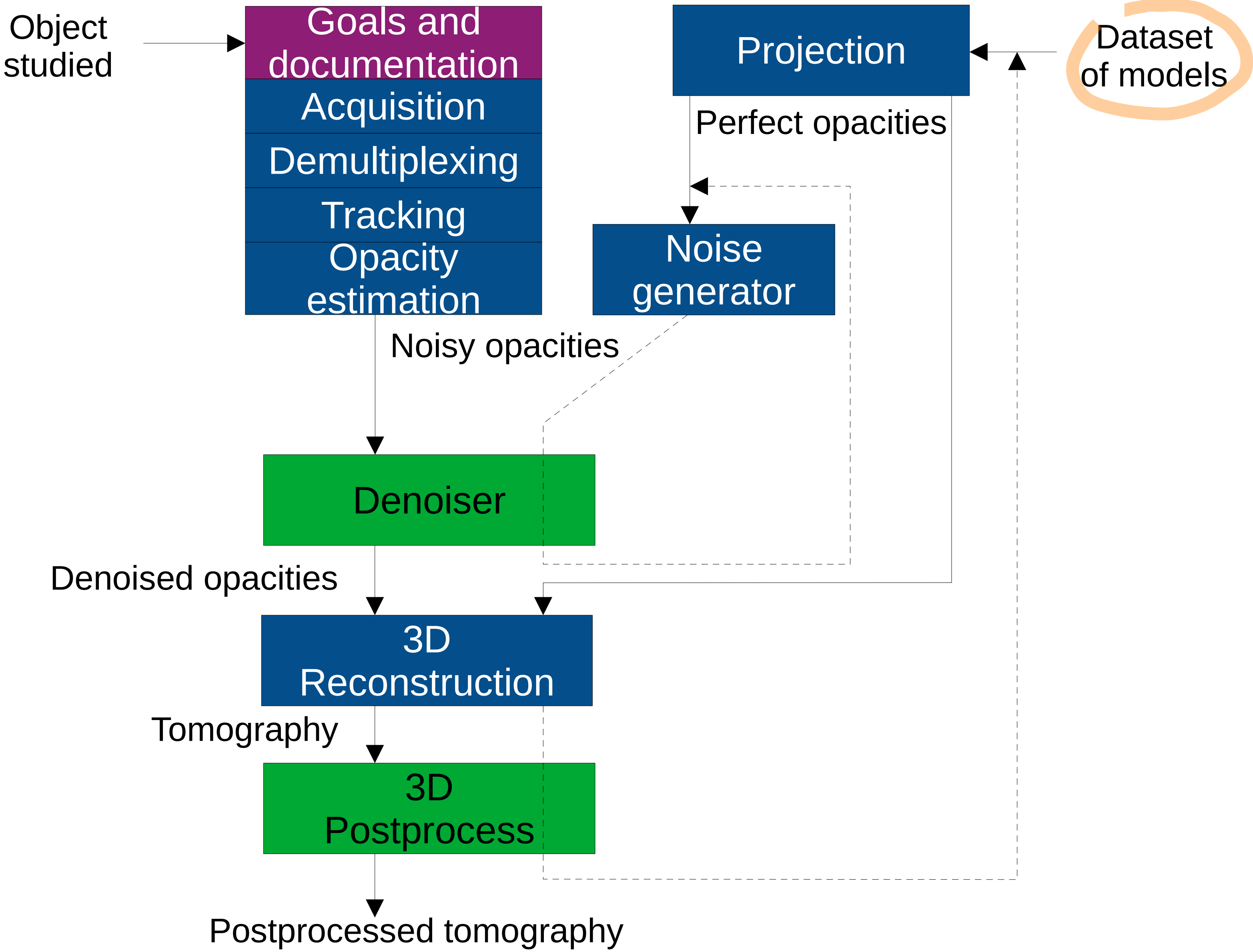


Measurement duration increases (log)

i.e. gain factor 10
in measurement durations

3c. 3D images postprocess

Data analysis pipeline



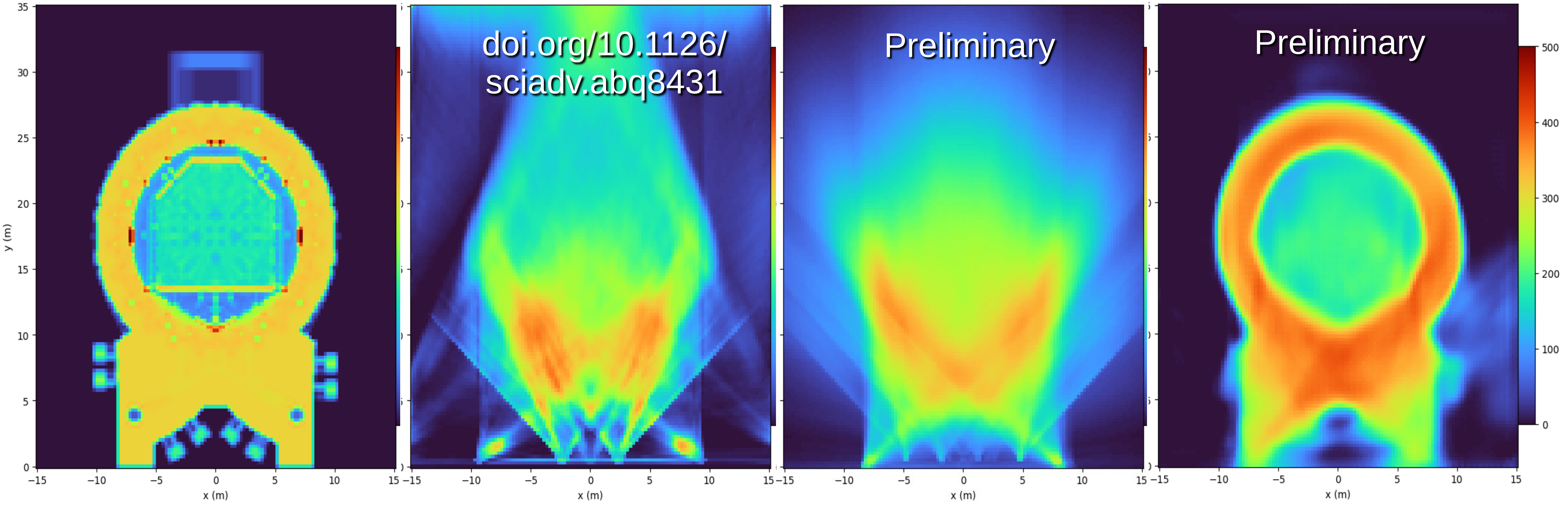
Perfect opacity images may be obtained by projection of a 3D model :

$$o = \int \rho \cdot dl$$

Postprocess the 3D results

- Projections on the North-South directions of the reactors

Model of the reactors | G2 Reconstruction | G3 Reconstruction | G3 Reconstruction and postprocess

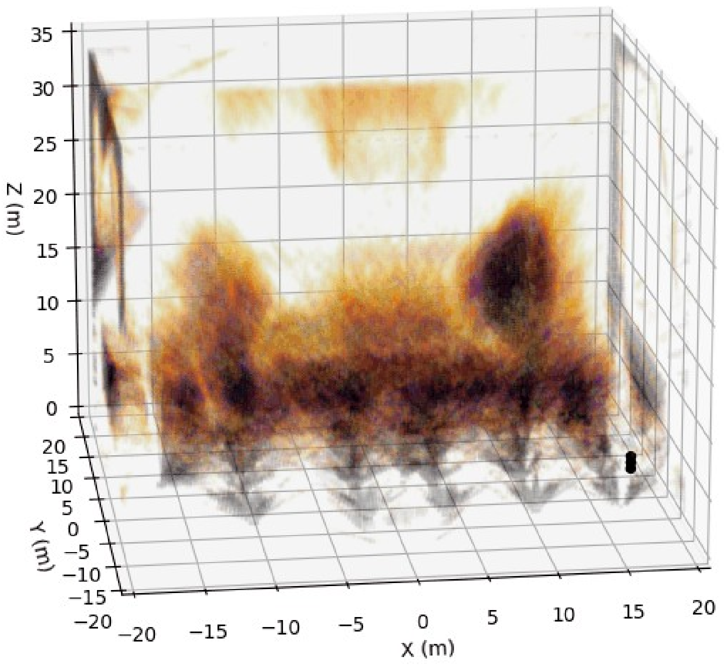


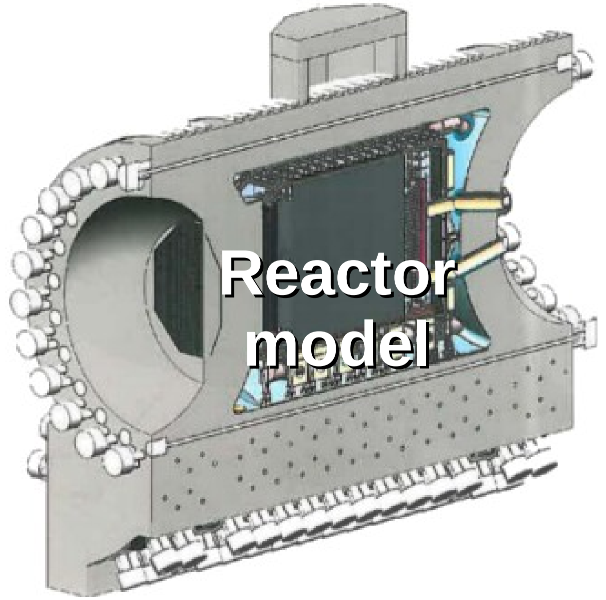
Data taking optimization
doi.org/10.1051/epjconf/202328807001

Postprocess

Postprocess
Preliminary results

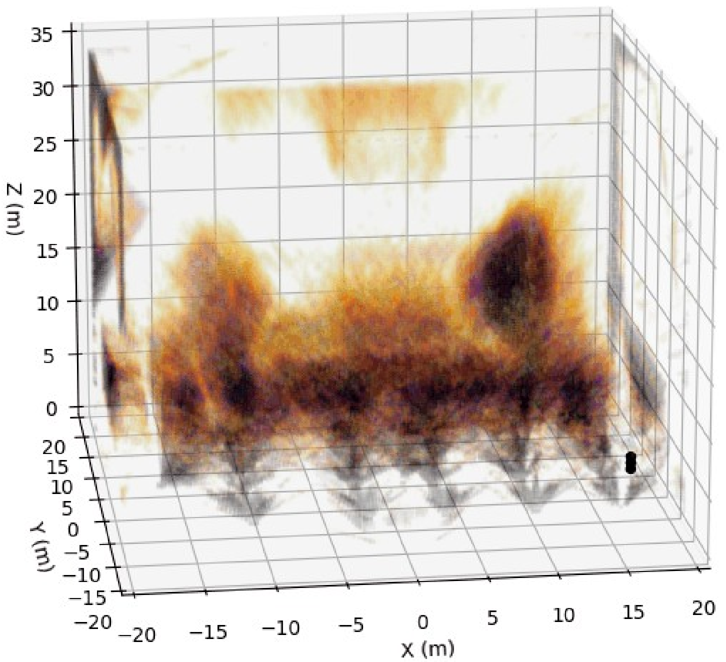
Published in ScienceAdvances
doi.org/10.1126/sciadv.abq8431

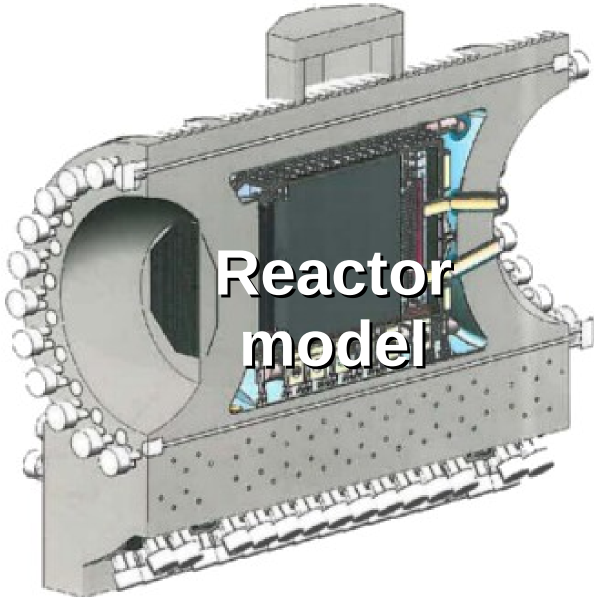




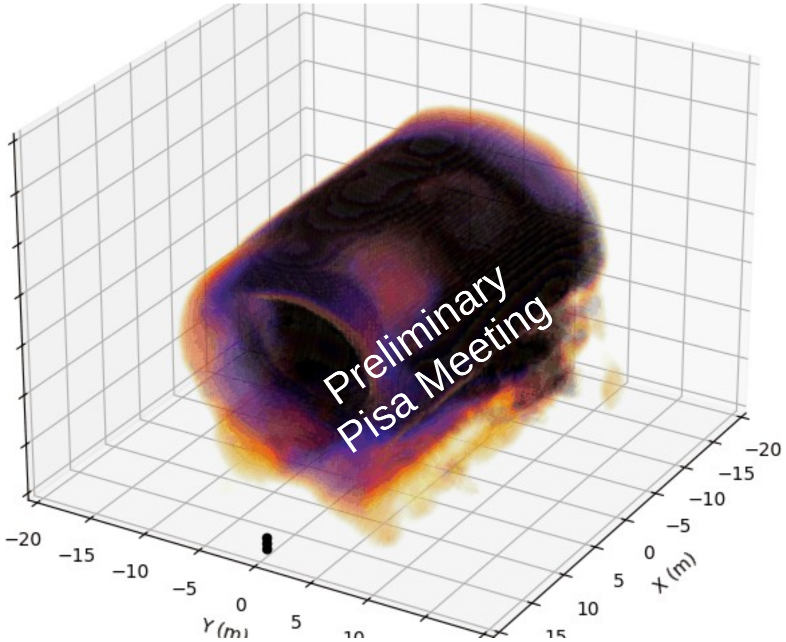
Postprocess Preliminary results

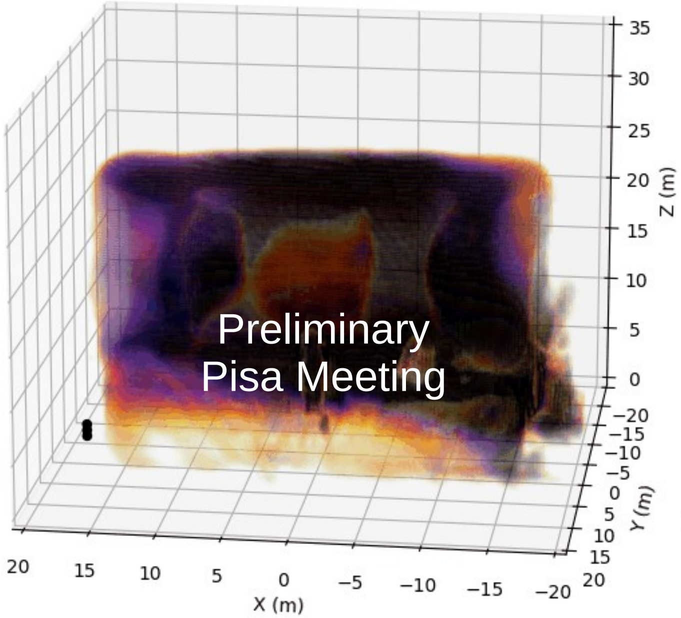
Published in ScienceAdvances
doi.org/10.1126/sciadv.abq8431

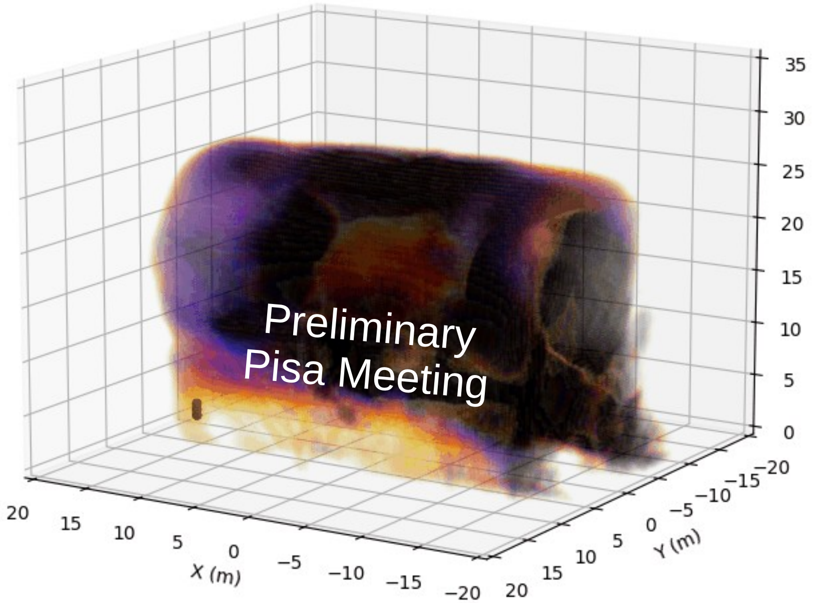




Postprocess,
To be published







■ Conclusion

Summary

- Neural networks may replace some parts of the analysis...
- … or be added to the existing pipeline

- New techniques improved the images...
  - With better demultiplexing (low level analysis for more reliable muon tracks)
  - With denoising (to compensate the low statistics)
- … and the 3D reconstruction
  - With a postprocess of the 3D reconstruction

- Work done for my **PhD thesis: ending in november 2024**

Thank you !

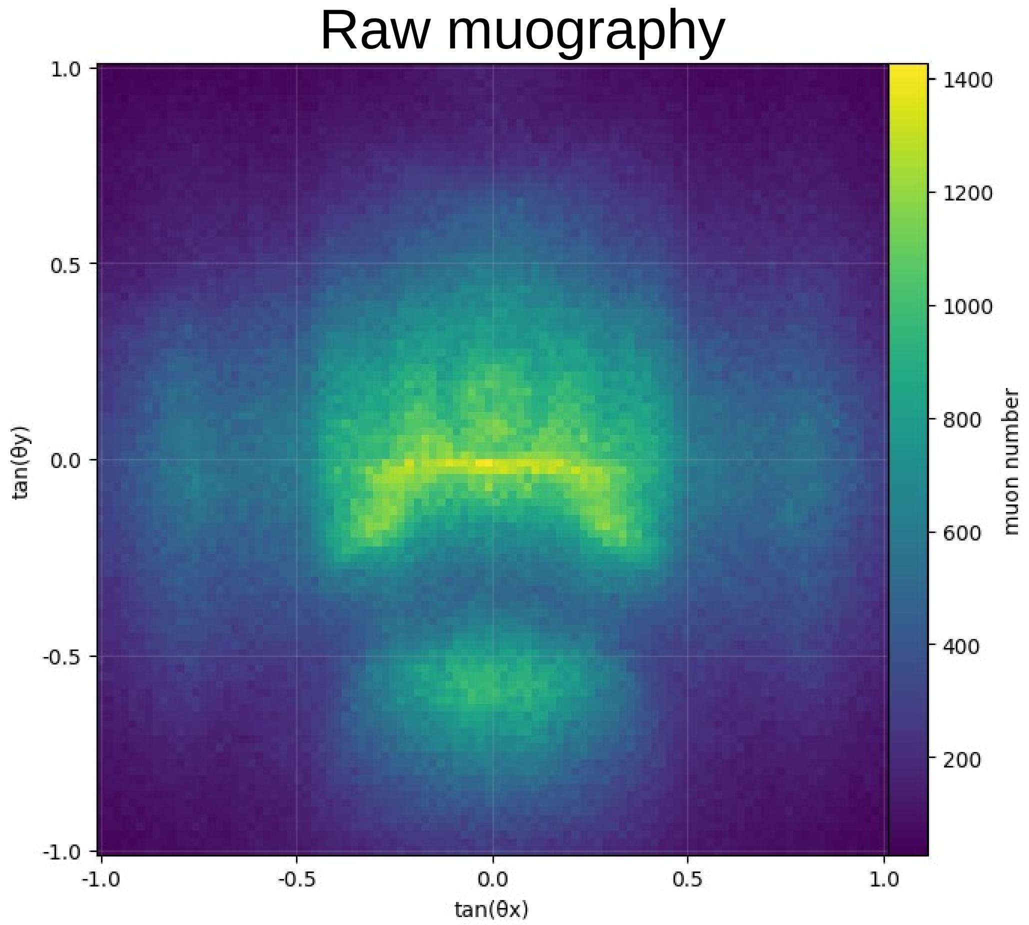
Baptiste Lefevre,
Héctor Gomez,
David Attié

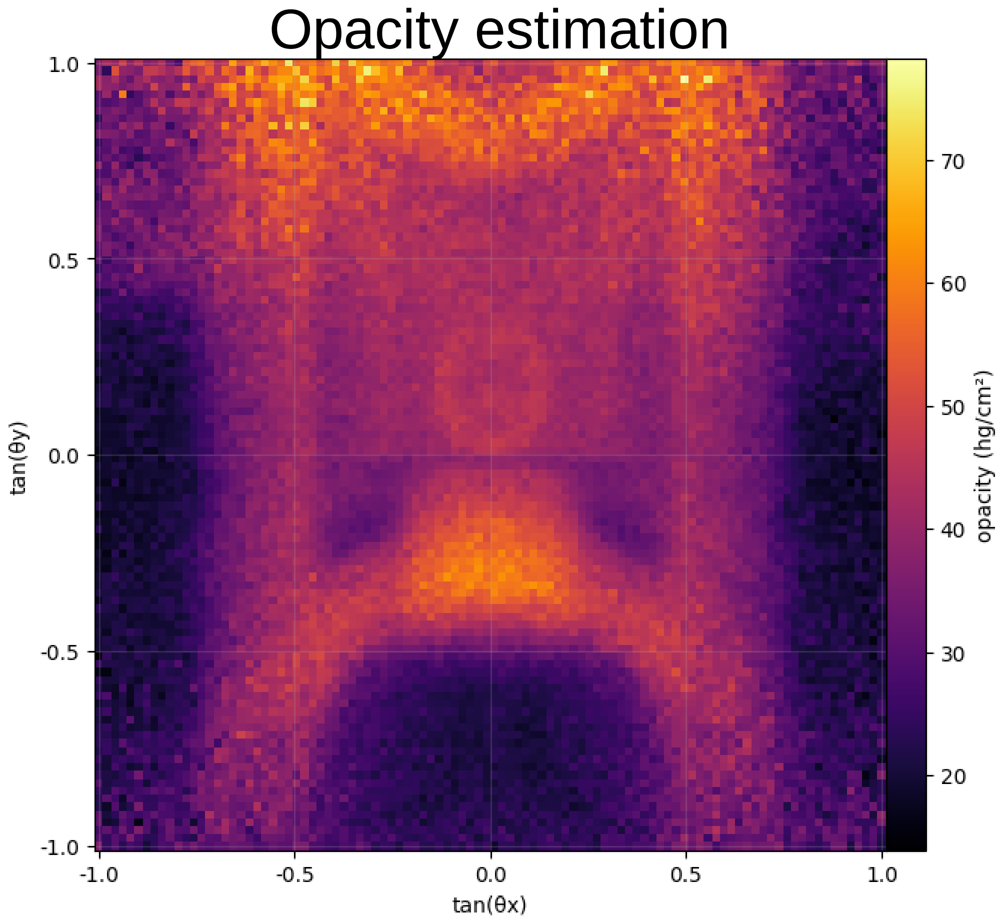
baptiste.lefevre@cea.fr

Image : G2 nuclear reactor in Marcoule (France) →

■ Backup slides

Muography project at CEA / Irfu





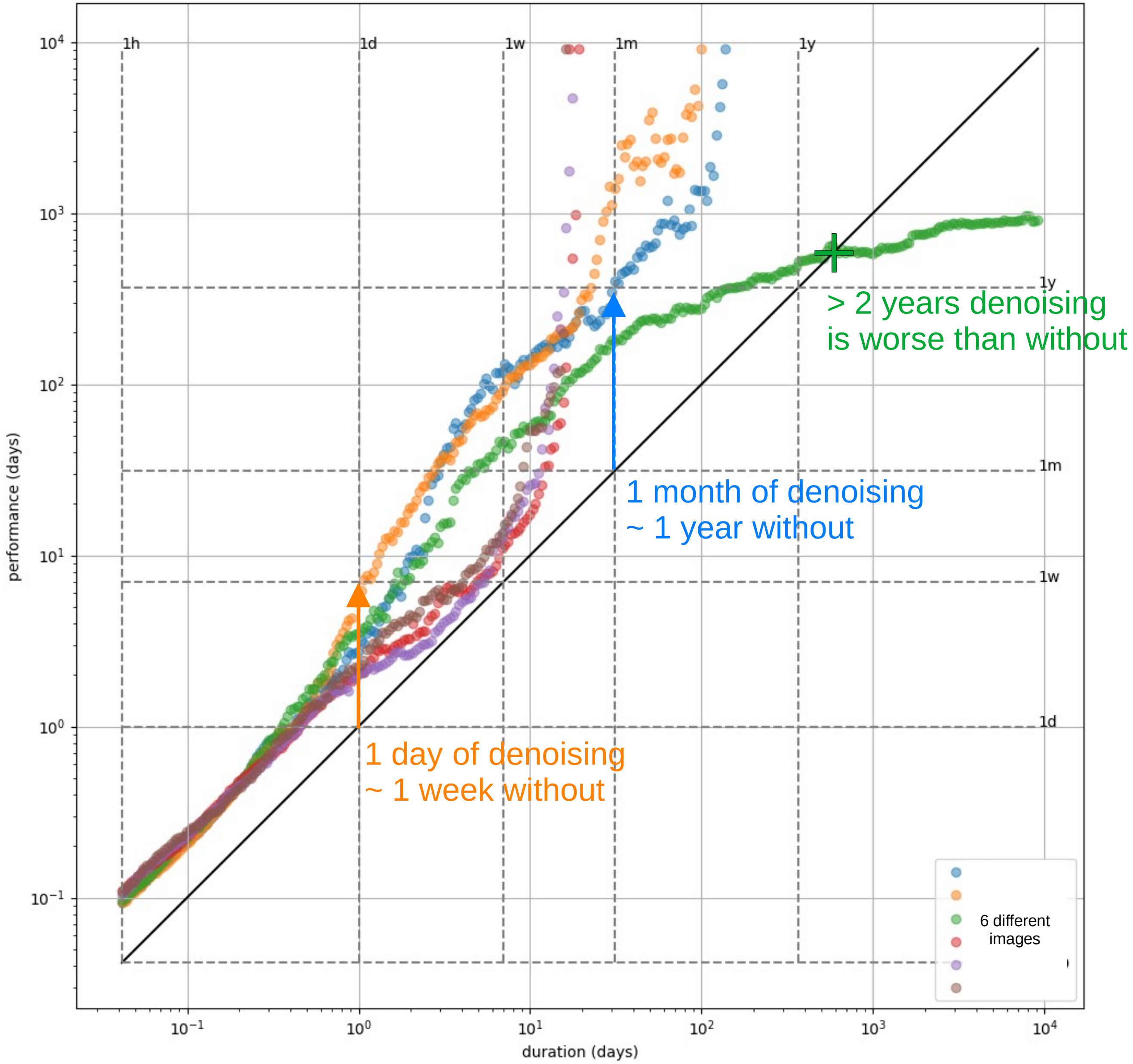
Angles of the reconstructed tracks

$$o = \int \rho \cdot dl$$

Denoising performances

Can only be measured on simulations.

The performance of the denoising depends on the position of the telescope.



G2 3D Reconstruction

SCIENCE ADVANCES | RESEARCH ARTICLE

PHYSICAL SCIENCES

3D imaging of a nuclear reactor using muography measurements

Sébastien Procureur[1]*, David Attié[1], Laurent Gallego[2], Hector Gomez[1], Philippe Gonzales[3], Baptiste Lefèvre[1], Marion Lehuraux[1], Bertrand Lesage[4], Irakli Mandjavidze[1], Philippe Mas[1], Daniel Pomarède[1]

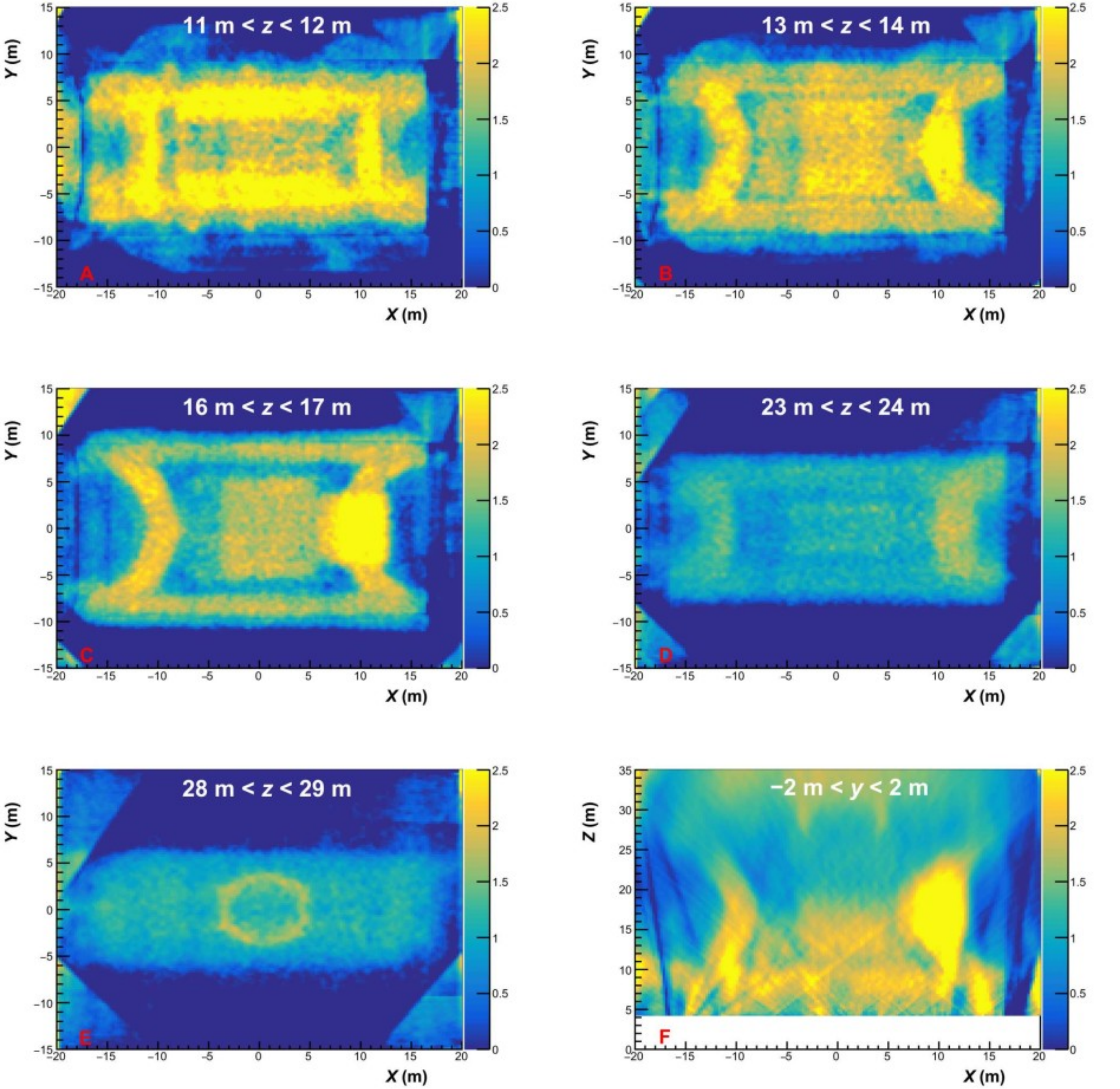


Fig. 4. Some tomographic slices obtained from the 3D reconstruction of the reactor, revealing several details of the structure. (**A** to **E**) *x-y* slices at different heights. (**F**) *x-z* slices close to the *y* axis. See text for more details.

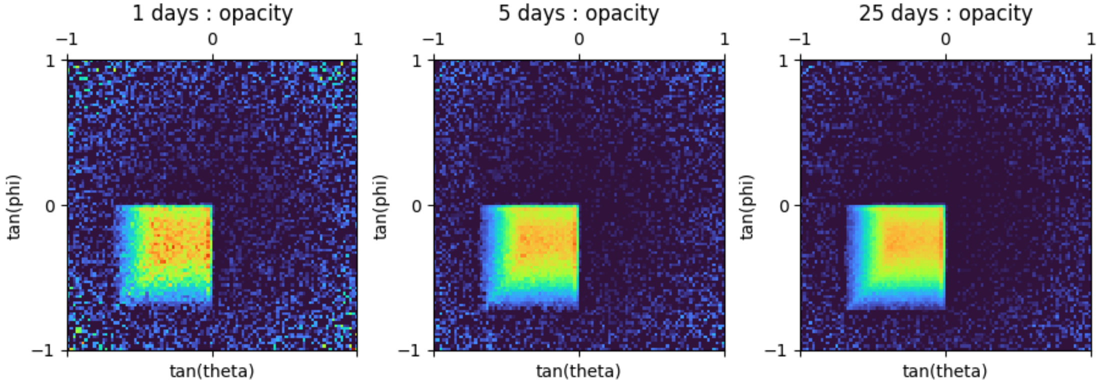
Data taking optimization

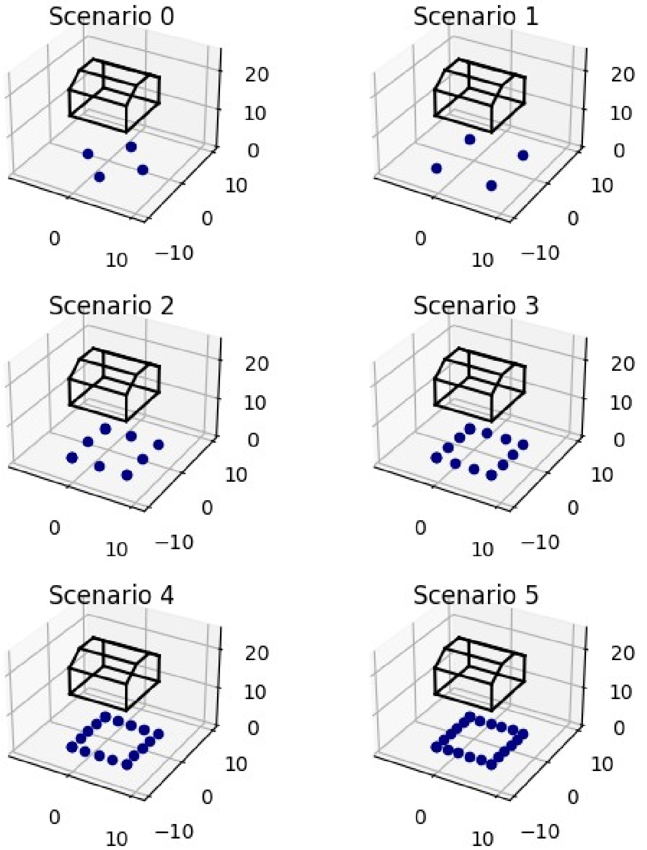
EPJ Web of Conferences **288**, 07001 (2023)
https://doi.org/10.1051/epjconf/202328807001

3D imaging of a nuclear reactor using muography measurements with Micromegas detectors

Baptiste Lefevre[1*], Héctor Gomez[1], Sébastien Procureur[1], David Attié[1], Laurent Gallego[2], Philippe Gonzales[3], Marion Lehuraux[1], Bertrand Lesage[4], Irakli Mandjavidze[1], Philippe Mas[1] and Daniel Pomarede[1]

[1] CEA/DRF/Irfu, France
[2] CEA/DES/DDSD, France
[3] Assystem Engineering and Operation Services, France
[4] SOM-LIGERON, France



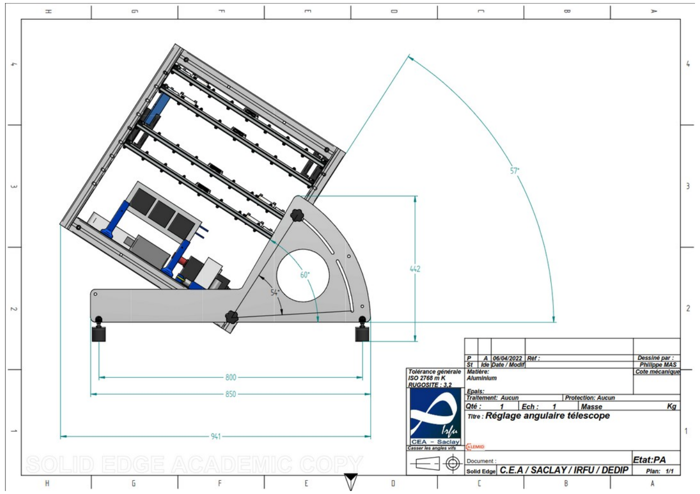


Conclusions :

- **Number of positions is more important than duration**
- Trained and available staff on site are a key asset
- Methodology has to be modified between G2 and G3
- Need high number of telescopes

G2-G3 Differences - Acquisition

	G2 (published)	G3 (preliminary)
Positions	27	46
Used duration (months)	24	12



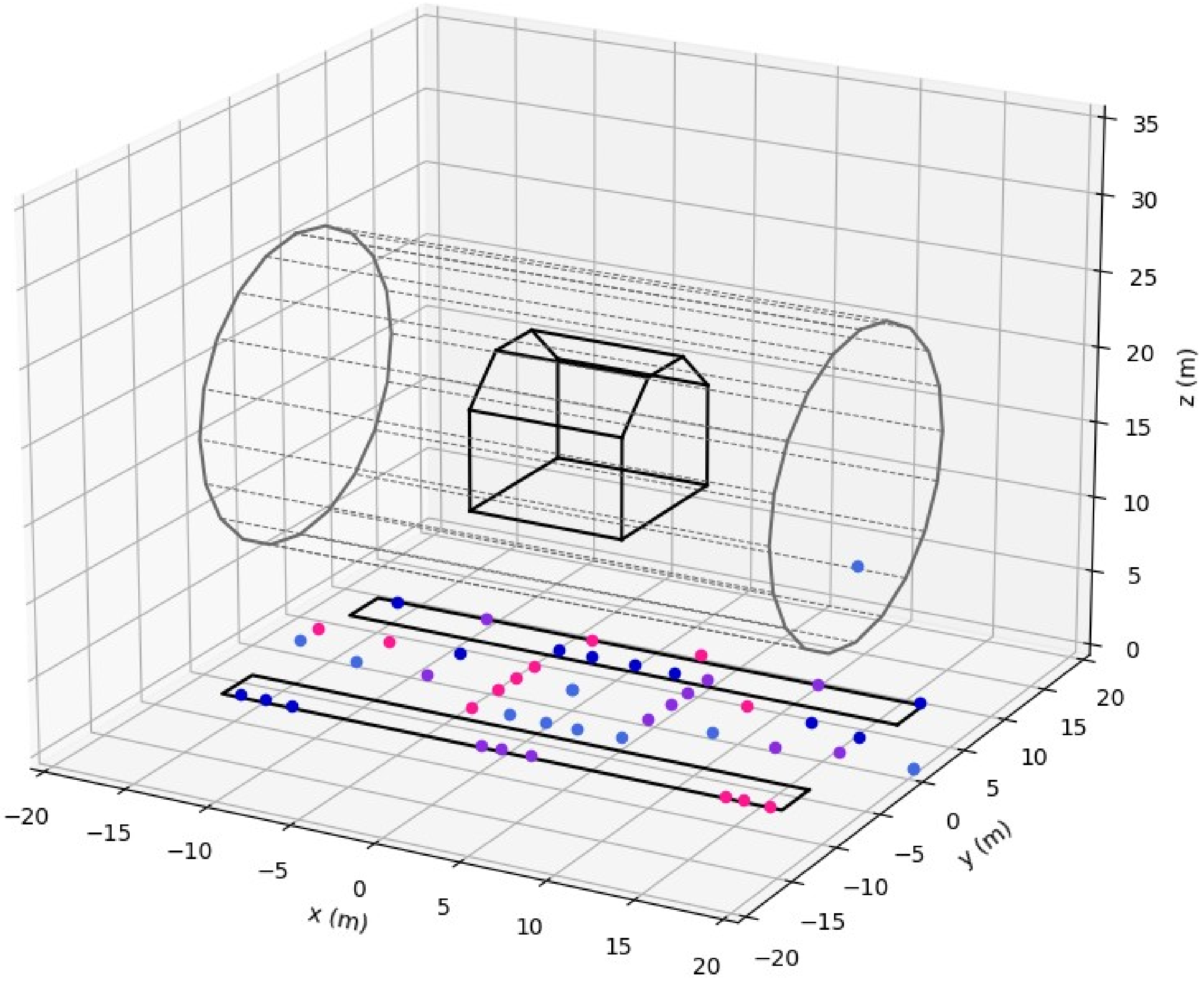
New mechanic


Installation in small corridors


Installation in complicated environment

G2-G3 Differences - Acquisition

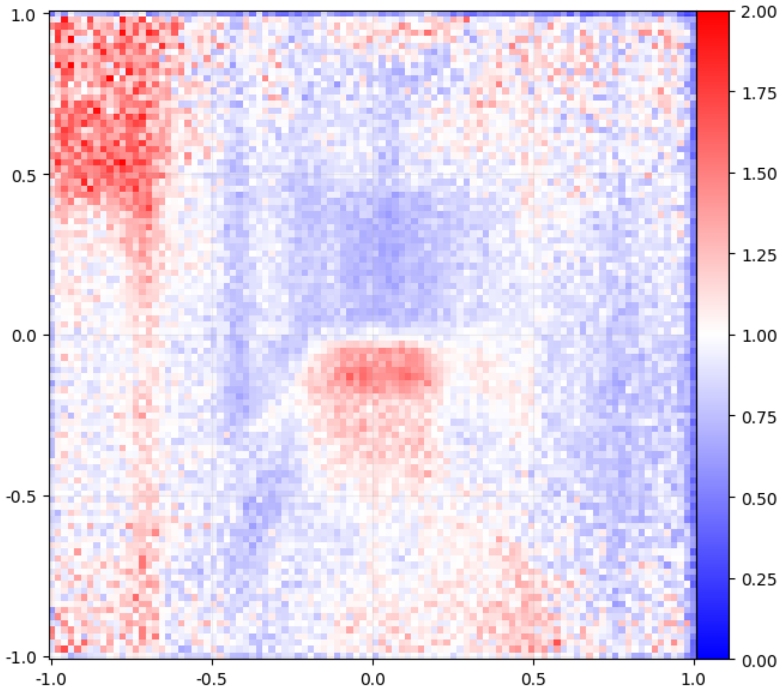
View below the reactor



Map of the positions at the G3 reactor

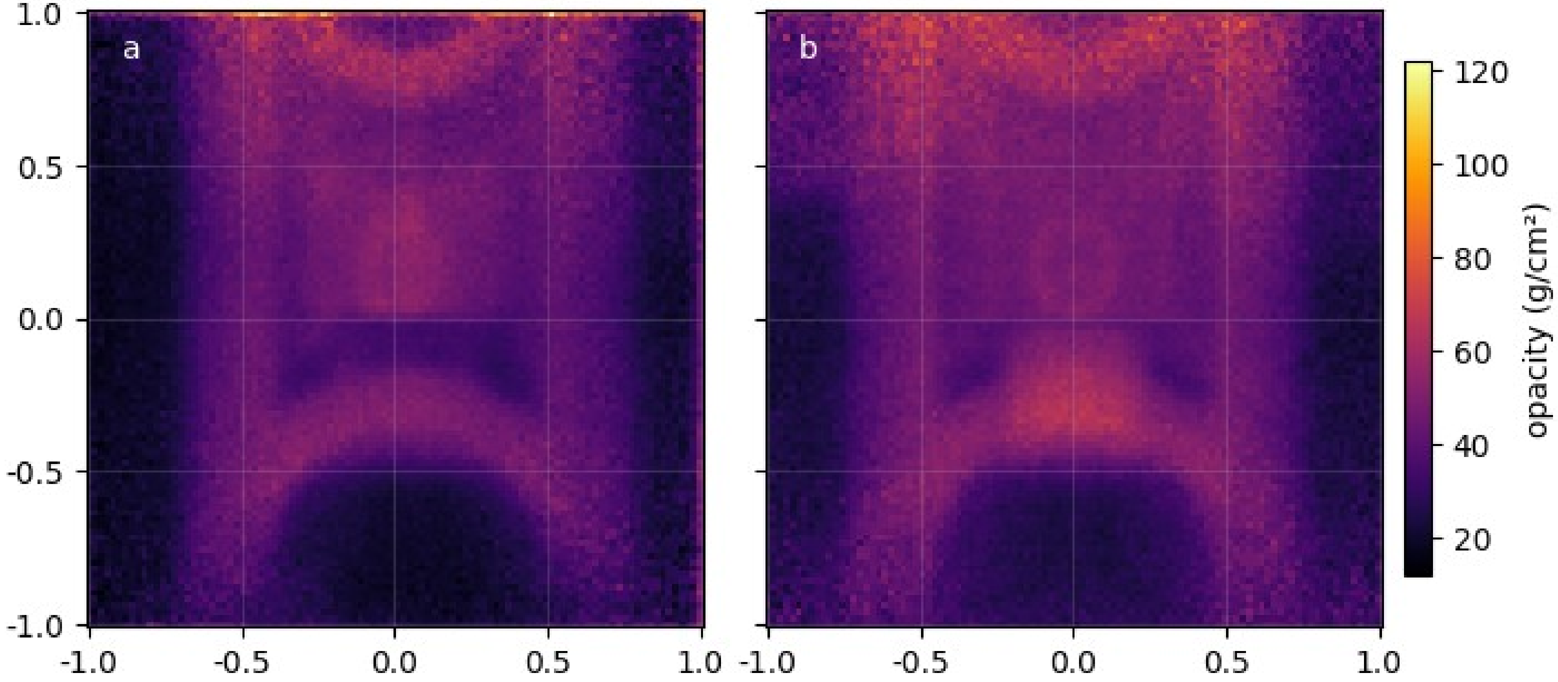
Large anomalies detected

Division



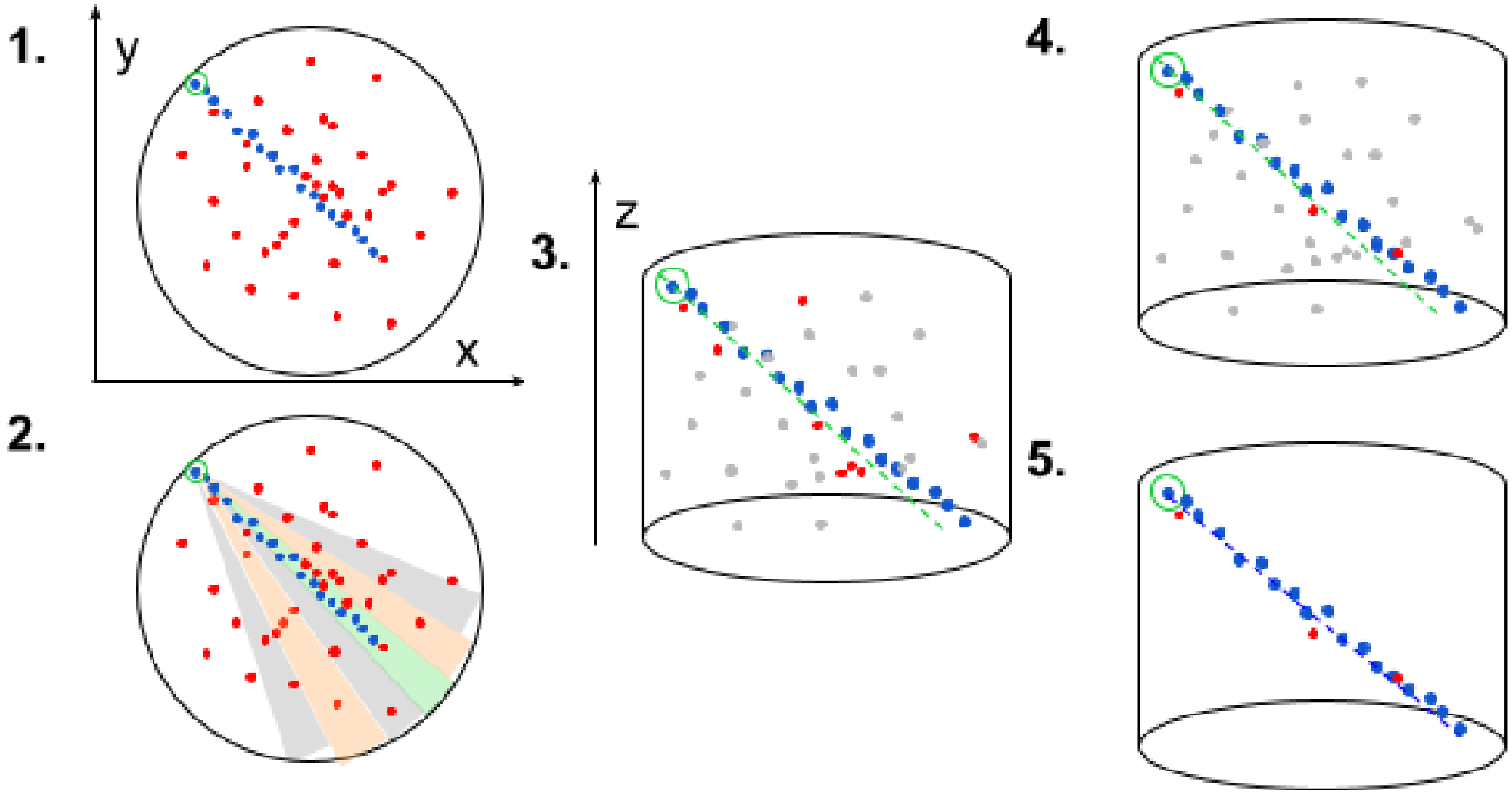
Simulated opacity

Measured opacity



Previous TPC demultiplexing algorithm

Marion Lehuraux,
Development of new Time Projection Chambers for societal and academic applications : muon tomography in confined environment and T2K upgrade of the near detector,
Ph.D. thesis, Université Paris-Saclay, 2022



- Consider the multiplexed points as noise
- Uses multiple fits in 2D and 3D
- Needs constraining hypothesis (number of pixels hit, no delta rays)

Inputs and outputs of the TPC demultiplexing

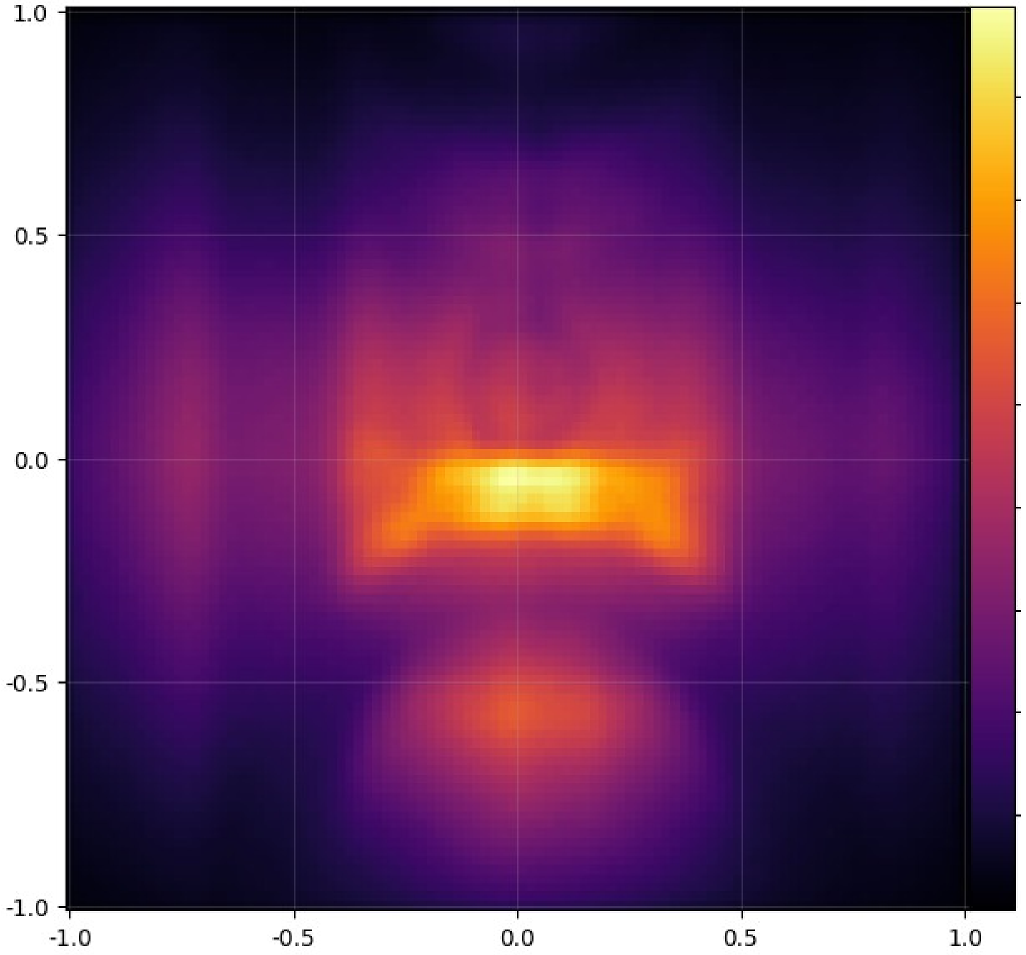
Inputs:

- Activated pixels (boolean matrix)
- Energy deposit per pixel
- Time of arrival per pixel

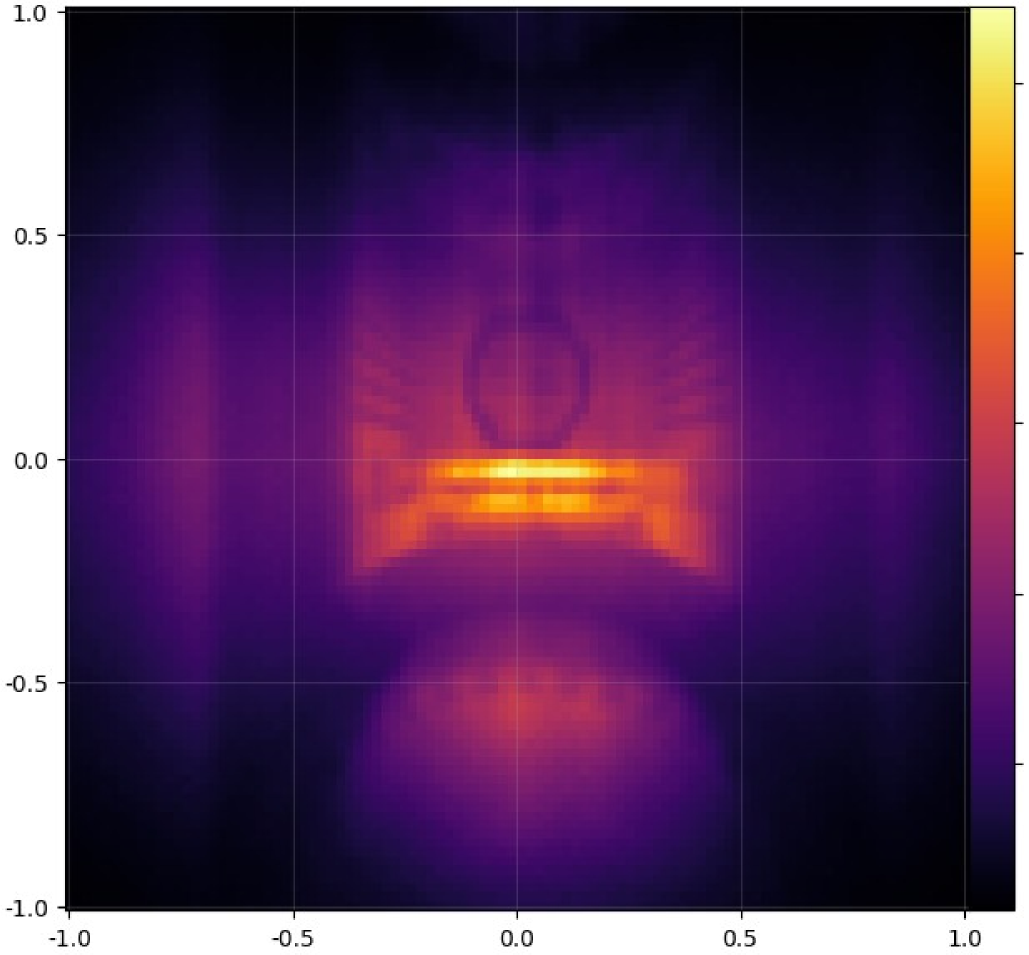
Outputs:

- Muon probability matrix
- Electron probability matrix
- « Empty » probability matrix

What is the best muography possible ?



Simulated infinite time



Simulated infinite time
& no scattering