ACAT 2014

- Prague -

1-5 September 2014

Clustering analysis on muon tomography data in the Muon Portal Project

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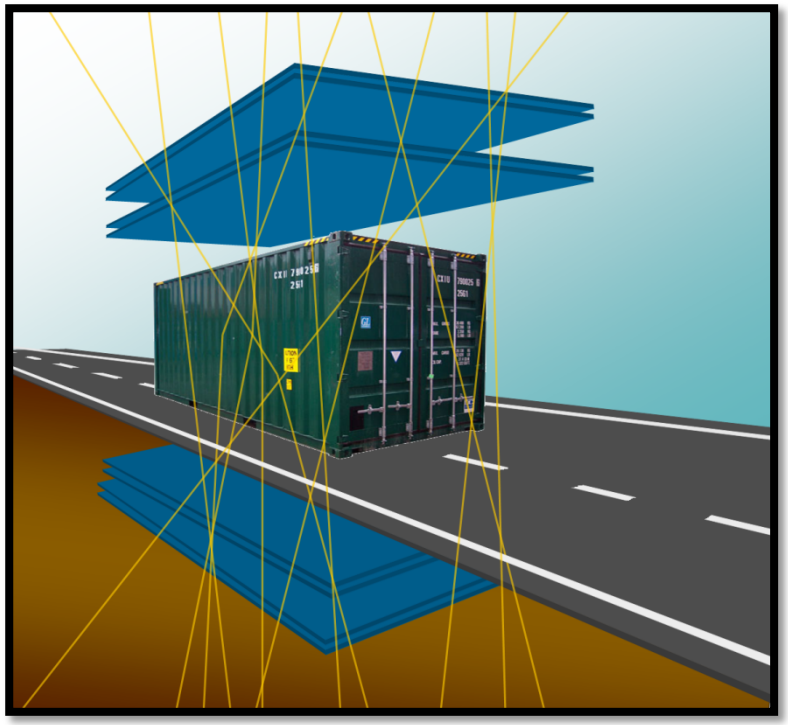
INAF

Outline

- **Borders security problem**
- **Muon Tomography goals and concept**
- **The Muon Portal Project**
  - Overall Design
  - Tracking and Image reconstruction
  - Density based clustering for muon tomography
  - Simulation scenarios and rendering results
- **Conclusions and future works**

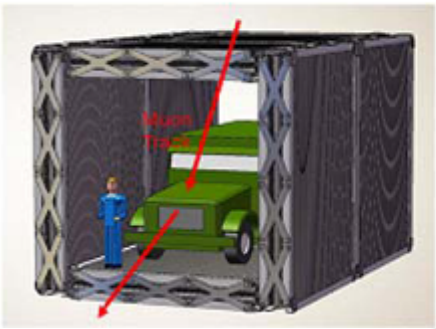


The problem

- Detection of **nuclear weapons** and **radioactive materials**
- Safety regulations are demanding a **better** and **faster** way to inspect containers, not possible by traditional techniques
- **Containers:** employed since 50 years as a standard way to transport goods by ships or trucks
  - Estimated yearly traffic: 200 M containers (in Catania ~ 15000 container /year)

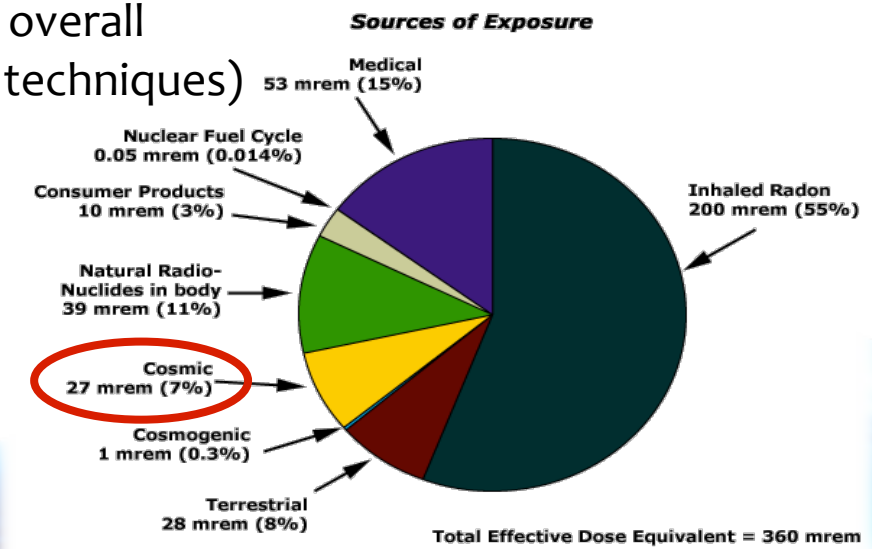
The problem

- Presently, only about 1% inspected
- **X-ray tomography**
  - Based on X-ray absorption (requires high fluxes)
  - Problems to traverse large thickness (Mean free path ~ 25 g/cm^2 ~ 2 cm Pb)
  - Mono or two-dimensional, not 3D (require multiple projections)
- Other possibilities
  - Directional imaging with **gamma rays**
  - **Neutron** radiography



Why Muon Tomography

- Secondary cosmic muons: **“Natural” radiation,** hence no additional dose delivered to users and goods
- Highly **penetrating radiations** (even more than X-rays)
- **Muon flux** at sea level relatively large: 10^{-2} cm^{-2} s^{-1}
- **Muonic interactions** well understood
- Muon scattering strongly **dependent on the Z of the material**
- **Each muon may contribute** to determine the overall imaging result (contrary to muon absorption techniques)

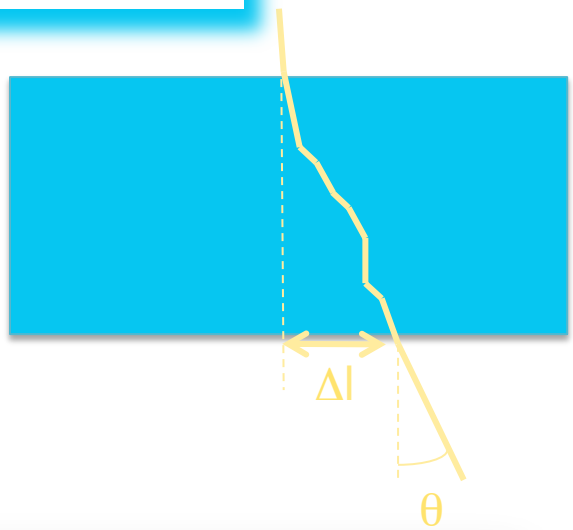


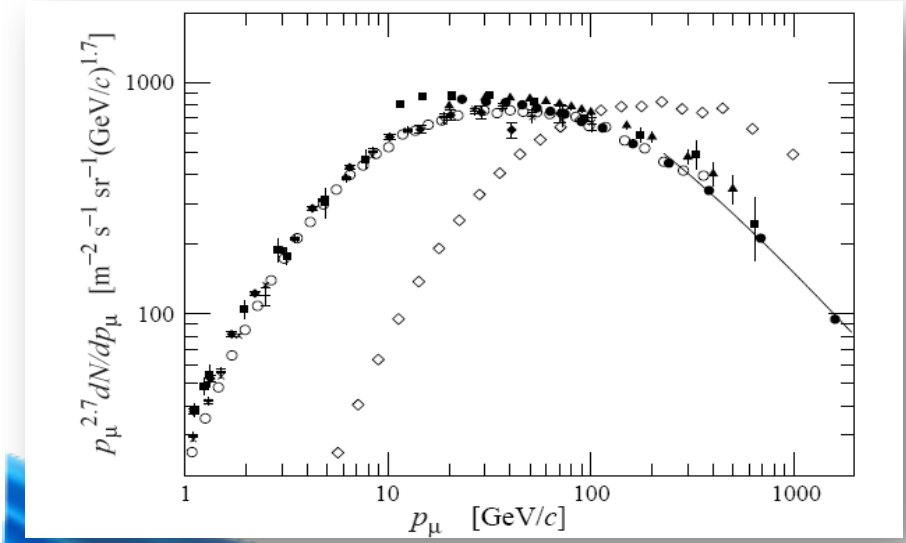
Muon Tomography

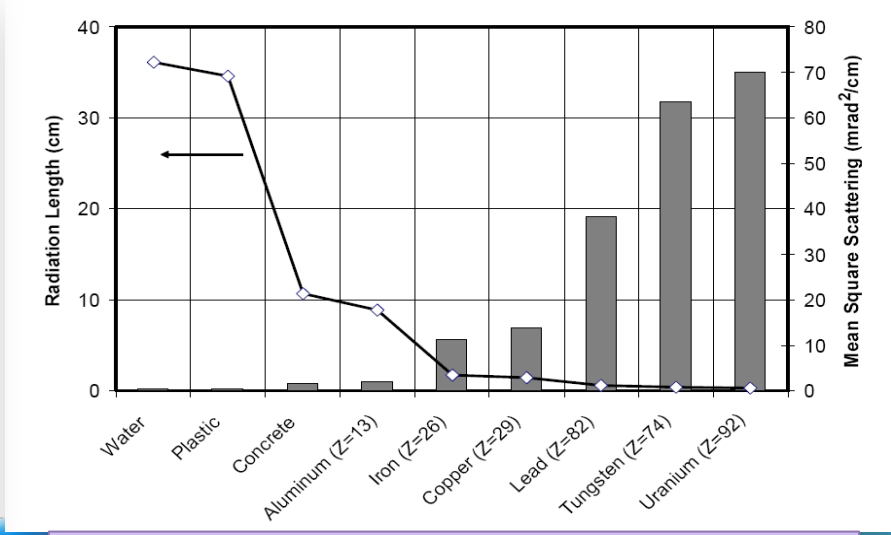
$$\theta_0 = \theta_{\text{plane}}^{\text{rms}} = \frac{1}{\sqrt{2}}\theta_{\text{space}}^{\text{rms}}$$

$$\theta_0 = \frac{13.6\text{MeV}}{\beta cp} \cdot z\sqrt{\left(\frac{x}{X_0}\right)} \cdot \left[1 + 0.038 \ln\left(\frac{x}{X_0}\right)\right]$$

$\beta c \rightarrow$ Velocity
$p \rightarrow$ Momentum
$z \rightarrow$ Charge Number
$x \rightarrow$ Width of Medium
$X_0 \rightarrow$ Radiation Length



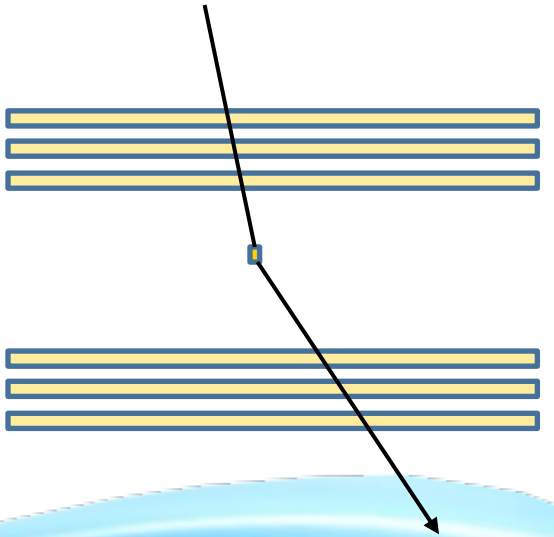




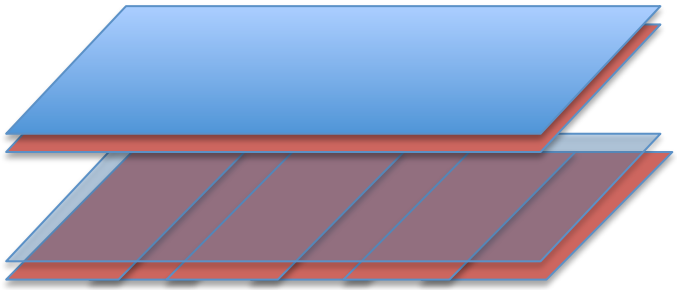
L. Schultz IEEE NSS Conference Record (2006)

Muon Tomography Detector

- A muon tomography detector is basically made by **several detection planes**, above and below the volume to be inspected
- Reconstruction of muon tracks allows, by different methods, to produce a **3D tomographic image**
- Performance of the system are given in terms of
  - **Sensitive** area / volume to be inspected
  - Spatial and angular **resolution**
  - **Time to scan** a volume
  - **Sensitivity & Efficiency** to high-Z objects
  - Sensitivity to **false positive**
  - **Discrimination** between high-Z vs low & medium-Z

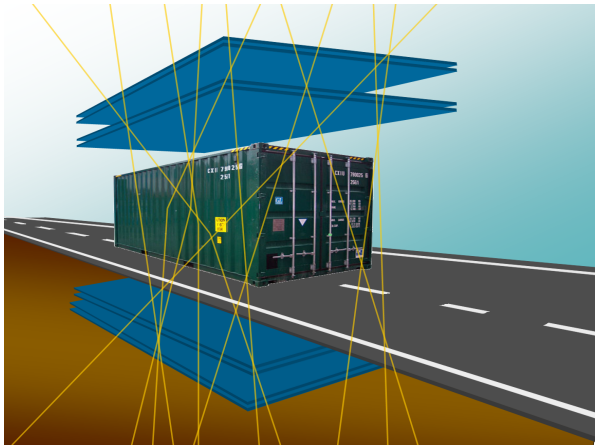


The Muon Portal project

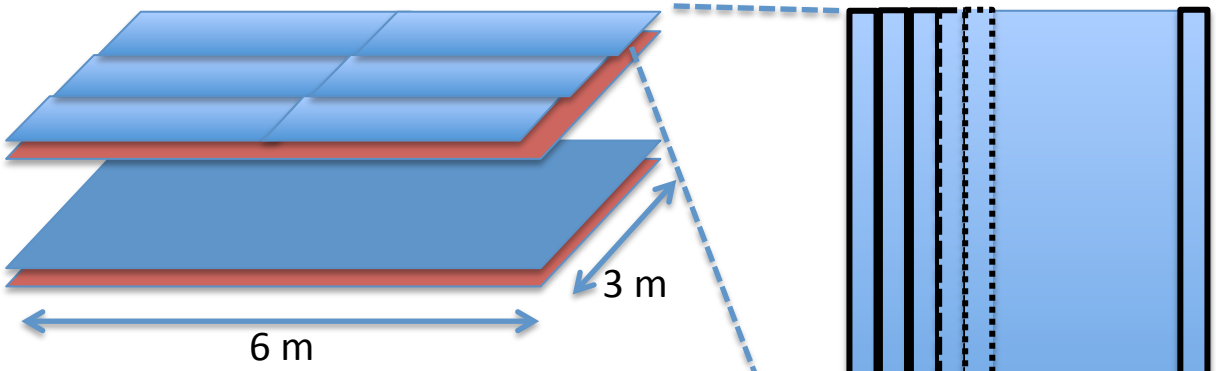


Plane X

Planes: 4 XY, 18m^2,
Separation[m]: 1.0-3.0-1.0
Modules: 2x3 in X, 6x1 in Y,
100 strips per module
Trigger: 4 planes crossed and
dE/dX > 0.5 MeV
A=10 m^{2}sr -> 20%
N_{events} ~2×10^5 for Δt=5 min
φ_μ = 1 m^{-2} s^{-1} integrated over the solid angle.

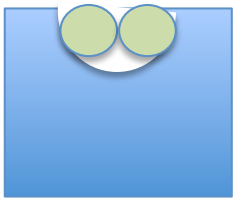


Plane Y



Module
1x3 m^2:100 extruded plastic scintillator strips 1x1 cm^2

Strip design with 2 WLS fibers



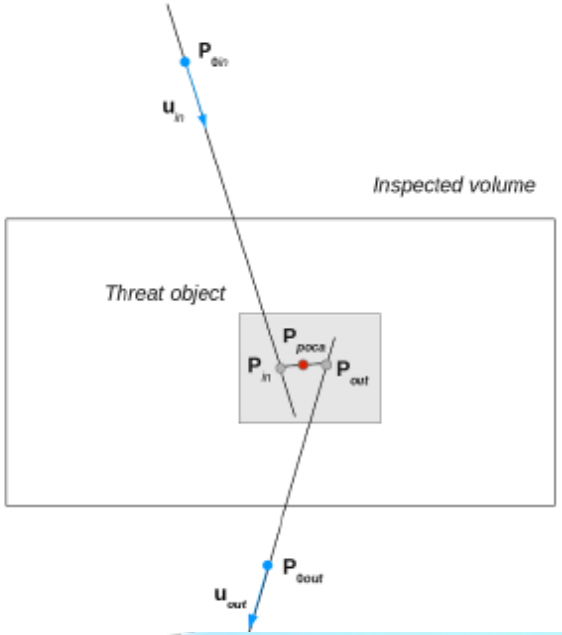
Poca Algorithm

- Simplest approach, fast and easy to implement
  - ✓ Geometrical **P**oint **O**f **C**losest **A**pproach between incoming and outcoming tracks

$$P_{poca} = \frac{1}{2} (P_{in} + P_{out})$$

  - ✓ Spatial distribution of the scattering centers, weights given by some power of the scattering angle

- However:
  - ✓ **Neglects multiple scattering** within the material
  - ✓ **Poor resolution** images
  - ✓ Critical behavior for material located close to **volume borders**

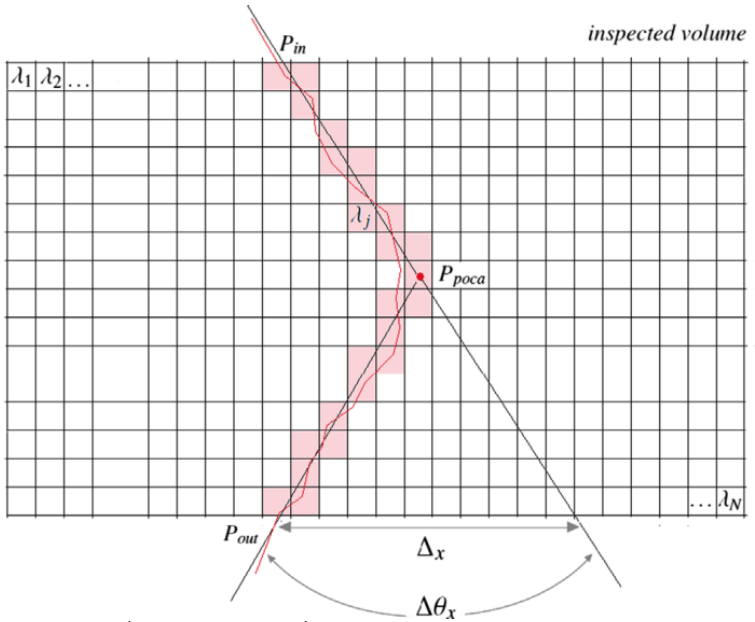


S.Riggi et al., NIM A 728 (2013) 59-68

EM-Likelihood algorithm

- Better statistical treatment of scattering processes by a log-likelihood method
  - ✓ Volume to be inspected divided into Nx ×Ny ×Nz 3D voxels
  - ✓ Scattering density defined for each voxel

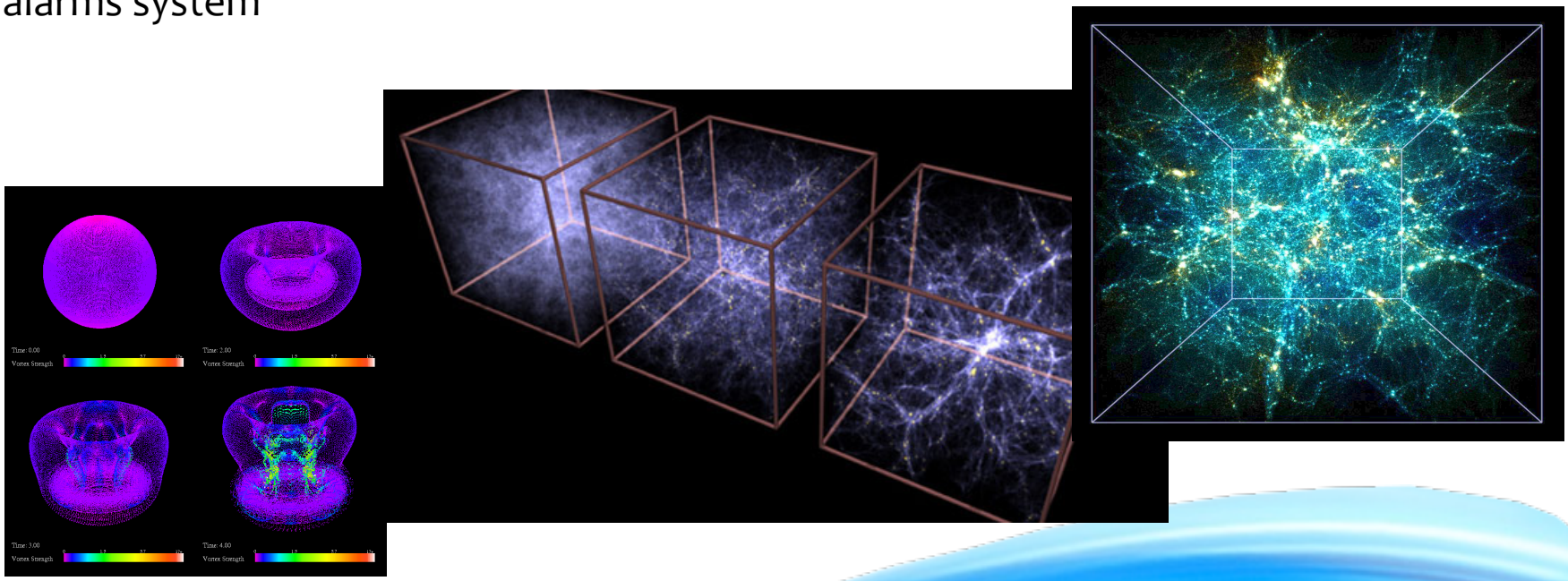
$$\lambda(X_0) = \left(\frac{15\ \text{MeV}}{p_0}\right)^2 \frac{1}{X_0}$$



  - ✓ Model the scattering and displacement data yi=(Δθi ,ΔXi) with a bivariate normal distribution
  - ✓ Iterative estimation with some stopping criteria

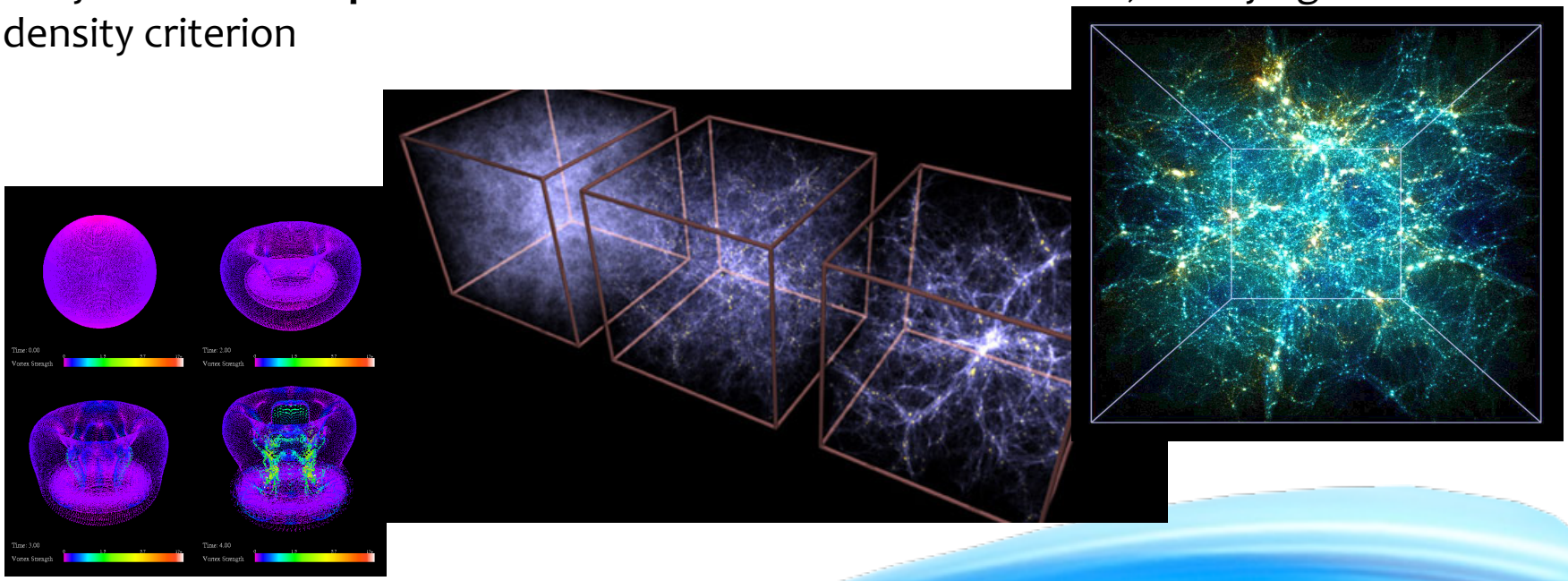
Density based Clustering: Why?

- ✓ The presence of a **three-dimensional grid** limits the automatic object identification process
- ✓ The problem is relevant in scenarios where the threat to be identified has a **comparable size** (or even smaller) to those of the single voxel and is located in a position **not aligned** with the grid.
- ✓ Risk **of losing useful statistical** and invalidate the automatic recognition and alarms system



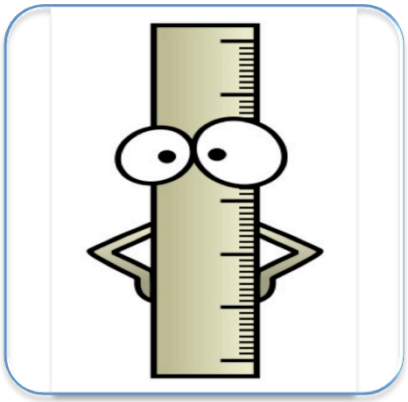
Density based Clustering: Why?

- ✓ Clustering analysis is traditionally applied to problems **like pattern recognition, image classification and color quantization.**
- ✓ It is used as a **data mining technique** to help distinguishing the structure of data and **to simplify the complexity** of huge quantities of data.
- ✓ The usage of these techniques allows **to infer the implicit information** in the data.
- ✓ They **connect data points** within a certain distance threshold ε, satisfying a density criterion



Friends of Friends Algorithm

- The **FOF** is a percolation algorithm normally used to identify dark matter halos from N-body simulations.



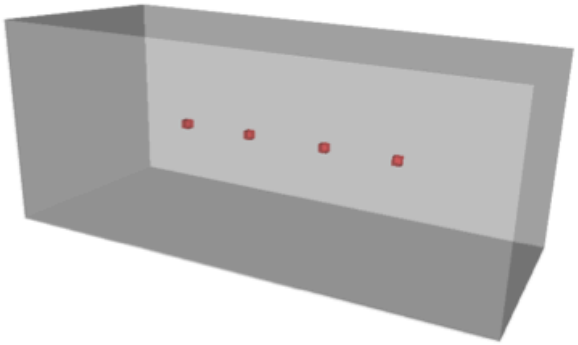
1) Defines a *Linking Length*.

2) Identifies all the pairs of "friends".

3) Identifies all the "friends of friends"

- The linking length is related to a parameter "*L*" that represents **the mean inter-particle separation** in simulations (related to the mean number density $\langle n \rangle$ as $L = \langle n \rangle^{-1/3}$
- Another parameter in FOF algorithm is **the minimum number of particles N_{min},** in a cluster. The aim is to reject spurious clusters, that is groups of friends who do not form persistent objects in the simulation

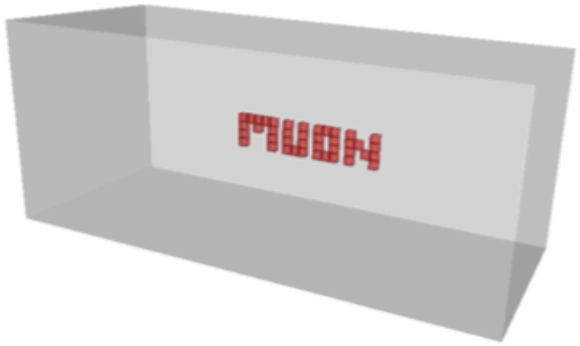
Simulated scenarios



(a) Scenario A

Four threat boxes Scenario

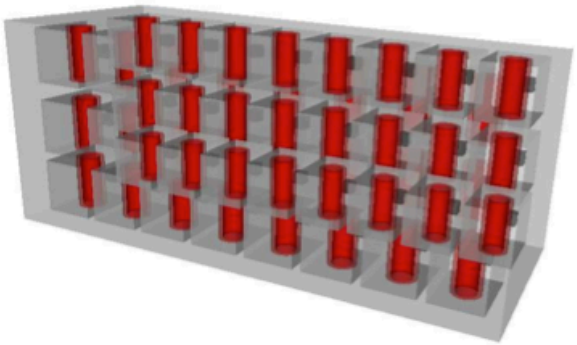
W, U, Pb, Sn of size 10 cm×10 cm×10 cm inserted at the center of a empty container.



(b) Scenario B

"Muon" Shape Scenario

'M'= Uranium (U)
'U'= Iron (Fe)
'O'= Lead (Pb)
'N'= Aluminium (Al)



(c) Scenario C

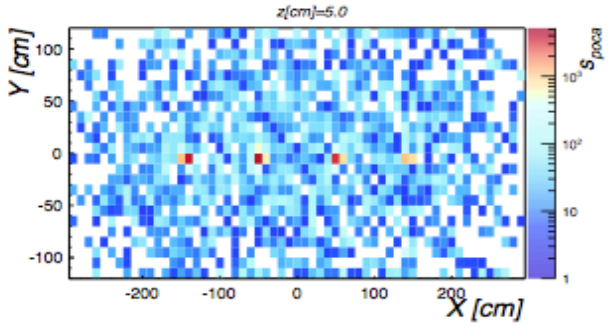
"Washing machines" Scenario

- **Fe** engine+ Concrete block+ **Al** structure

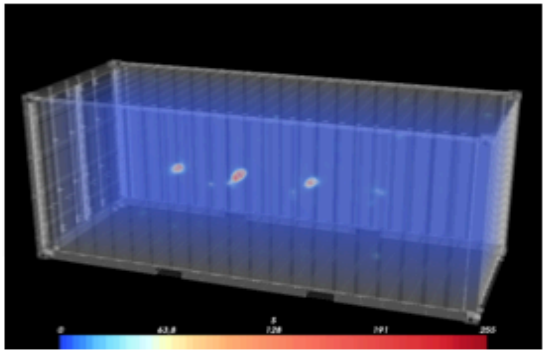
Simulations settings:

- GEANT4 simulations
- $5*10^5$ simulated events available ~ 10 min.
- realistic energy spectrum with range 0.1-100 GeV
- Only events passing the container → ~1% events rejected

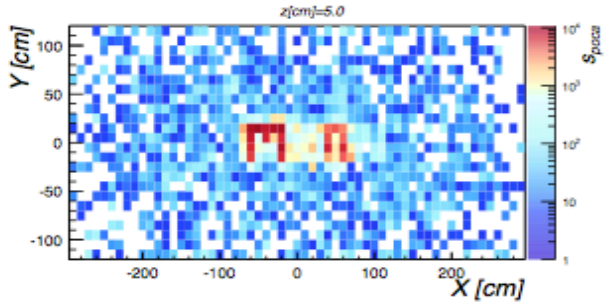
Algorithms results: POCA



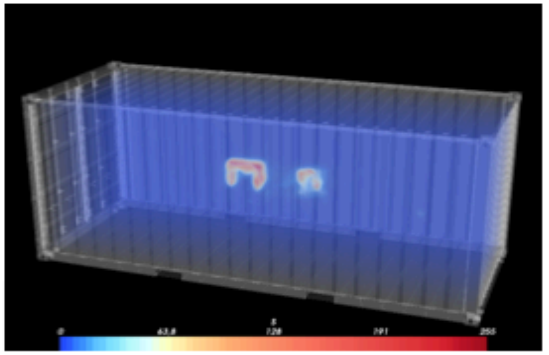
(a) POCA XY tomography - Scenario A



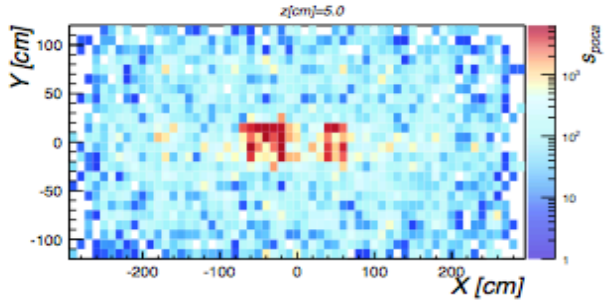
(b) POCA 3D rendering - Scenario A



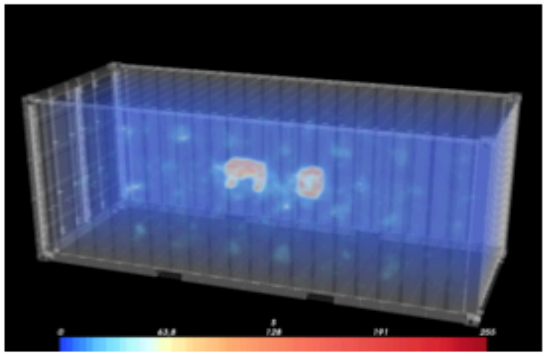
(c) POCA XY tomography - Scenario B



(d) POCA 3D rendering - Scenario B

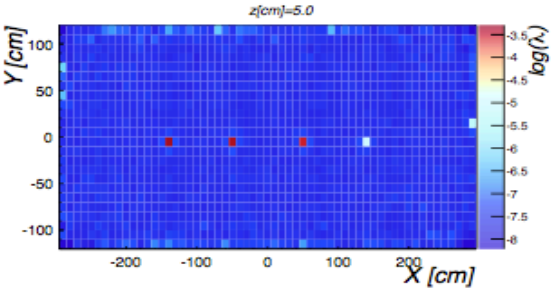


(e) POCA XY tomography - Scenario C

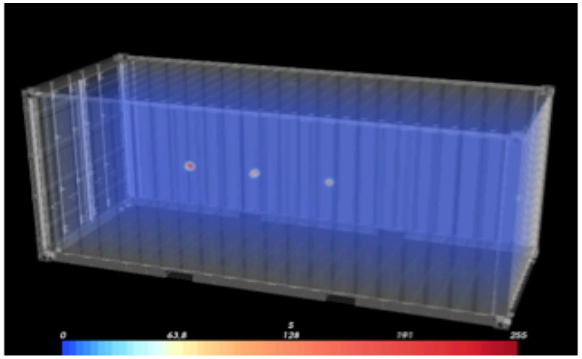


(f) POCA 3D rendering - Scenario C

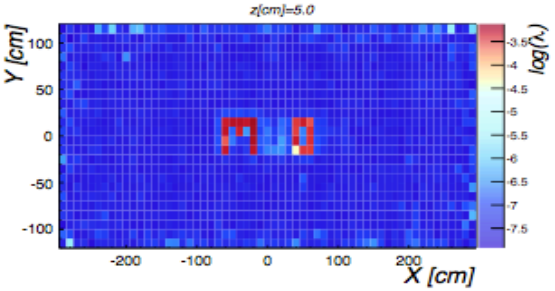
Algorithms results: EM-Likelihood



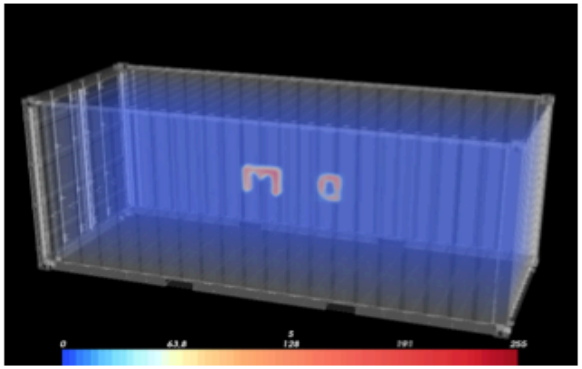
(a) EM-ML XY tomography - Scenario A



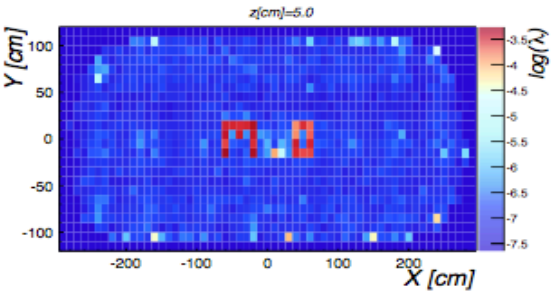
(b) EM-ML 3D rendering - Scenario A



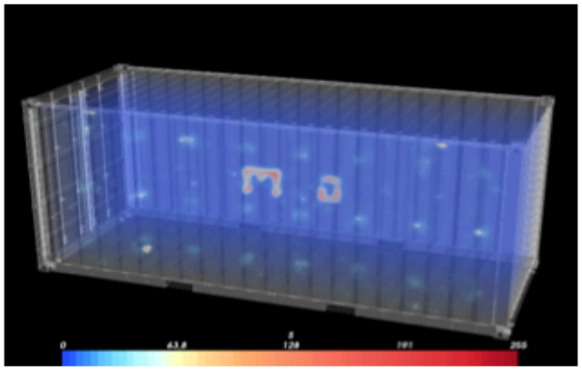
(c) EM-ML XY tomography - Scenario B



(d) EM-ML 3D rendering - Scenario B

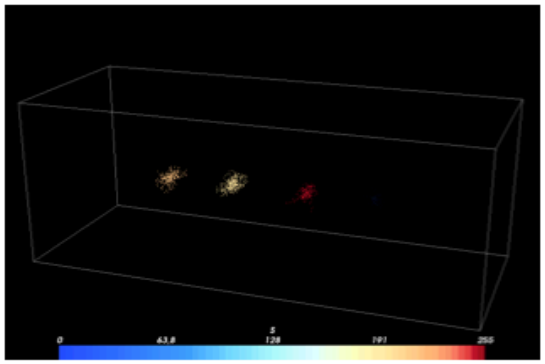


(e) EM-ML XY tomography - Scenario C

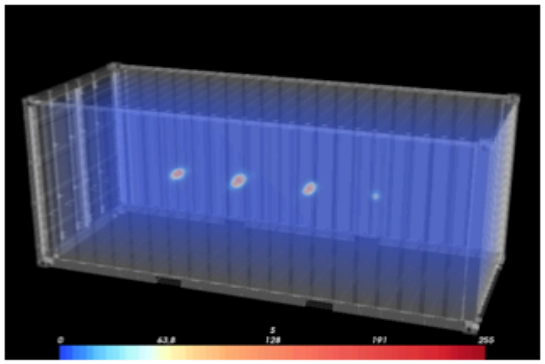


(f) EM-ML 3D rendering - Scenario C

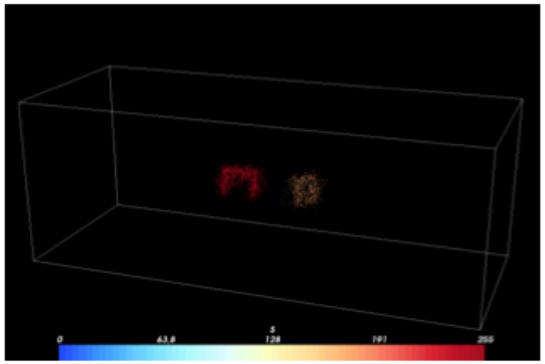
Algorithms results: Fof clustering



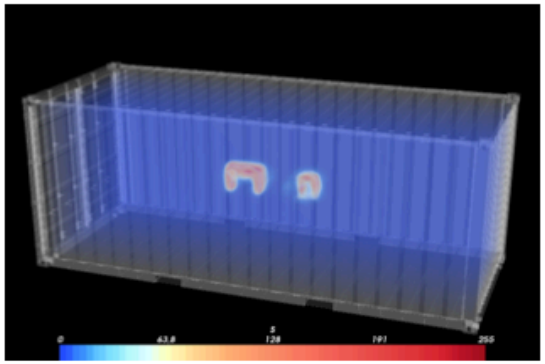
(a) Clustering - Scenario A



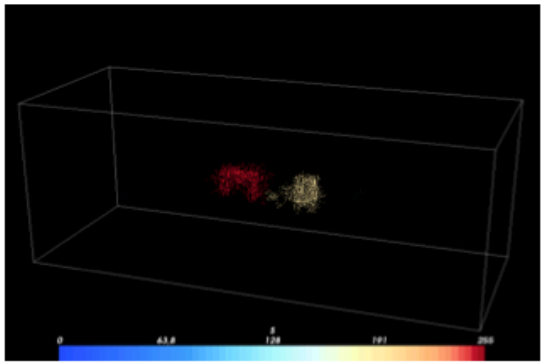
(b) Clustering 3D rendering - Scenario A



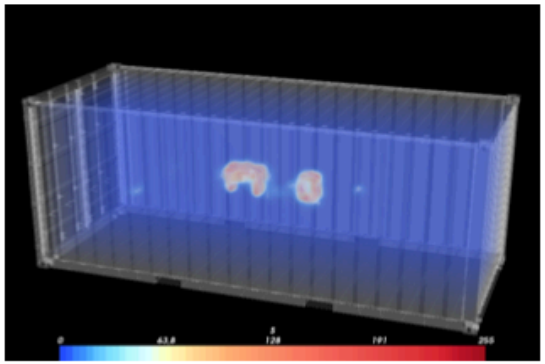
(c) Clustering - Scenario B



(d) Clustering rendering - Scenario B

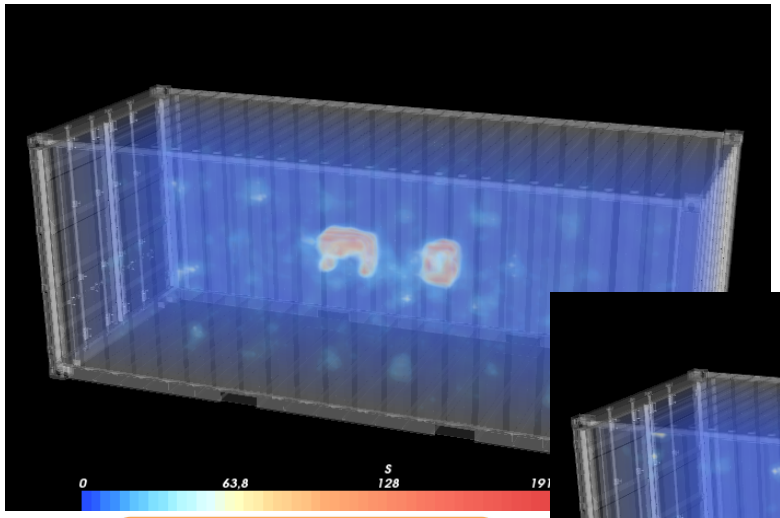


(e) Clustering - Scenario C

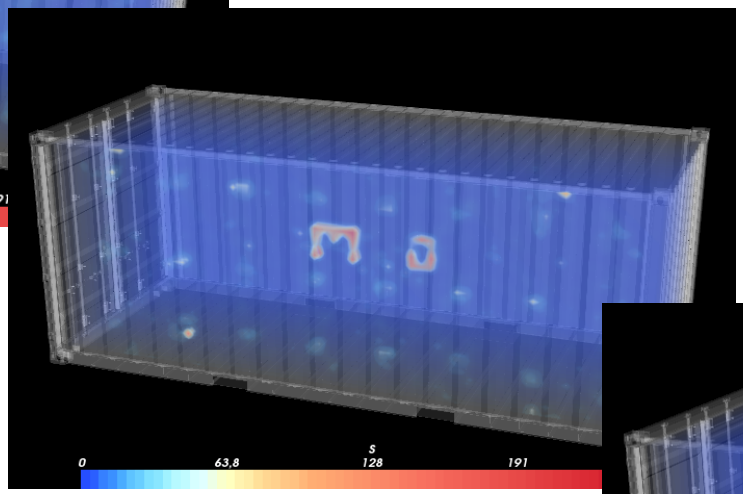


(f) Clustering 3D rendering - Scenario C

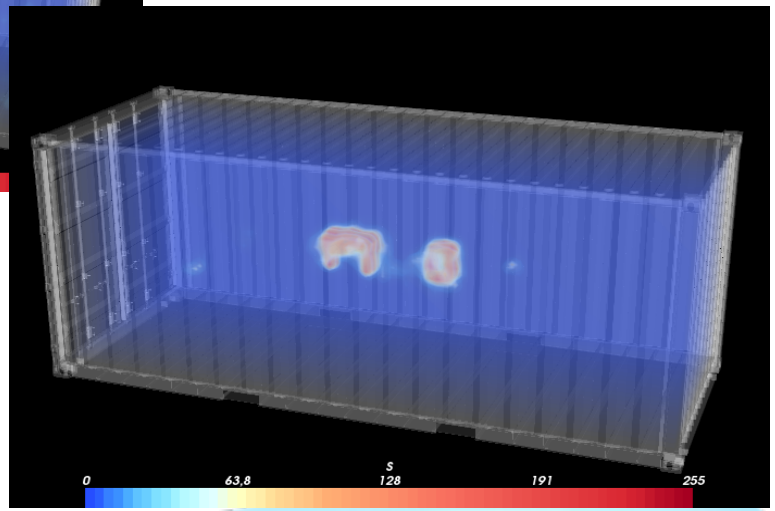
Algorithms in comparison



Poca Volume Rendering

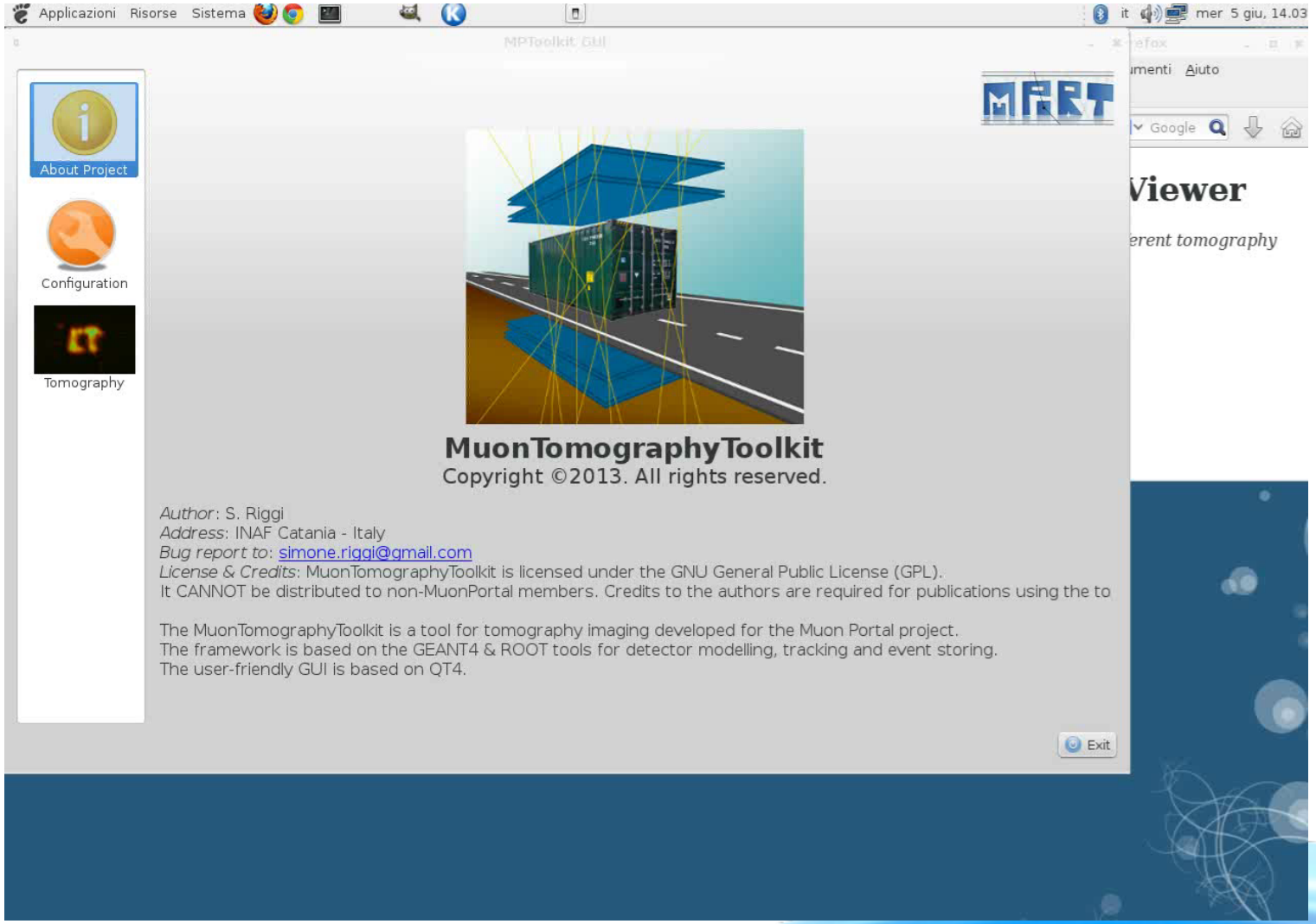


EM-LM Volume Rendering



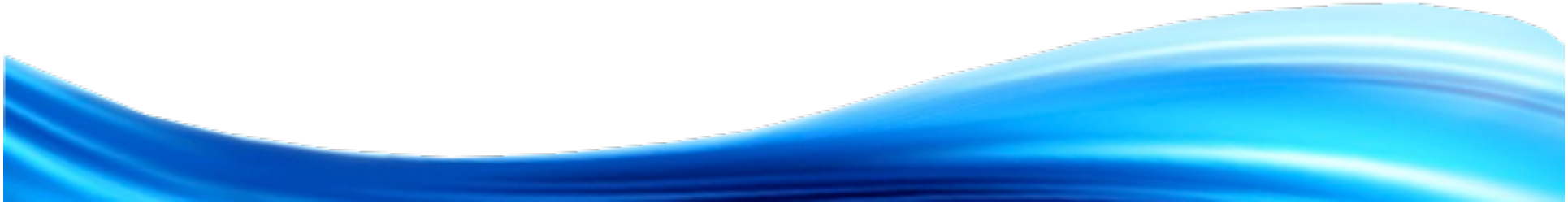
FoF Volume Rendering

Demo


Applicazioni
Risorse
Sistema
mer 5 giu, 14.03
MPToolkit GUI
About Project
Configuration
Tomography
MuonTomographyToolkit
Copyright ©2013. All rights reserved.
Author: S. Riggi
Address: INAF Catania - Italy
Bug report to: simone.riggi@gmail.com
License & Credits: MuonTomographyToolkit is licensed under the GNU General Public License (GPL).
It CANNOT be distributed to non-MuonPortal members. Credits to the authors are required for publications using the to
The MuonTomographyToolkit is a tool for tomography imaging developed for the Muon Portal project.
The framework is based on the GEANT4 & ROOT tools for detector modelling, tracking and event storing.
The user-friendly GUI is based on QT4.
Exit
Aiuto
Google
Viewer

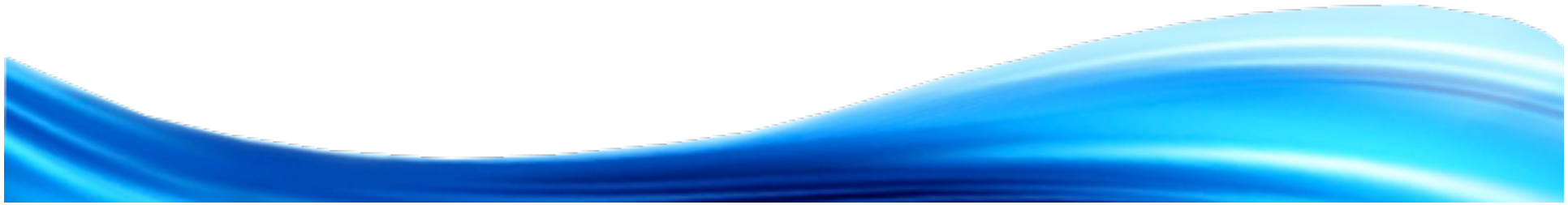
Conclusions and future works

- ✓ **Development of an integrated recostruction algorithm in order to combine the Clustering results with the E-M for better efficiency and accuracy**
- ✓ **Statistical analysis of false positive and false negative variation depending on the threshold and the scanning time**
- ✓ **Use of the particle momentum classification and borders effects study in order to improve algorithm performances**

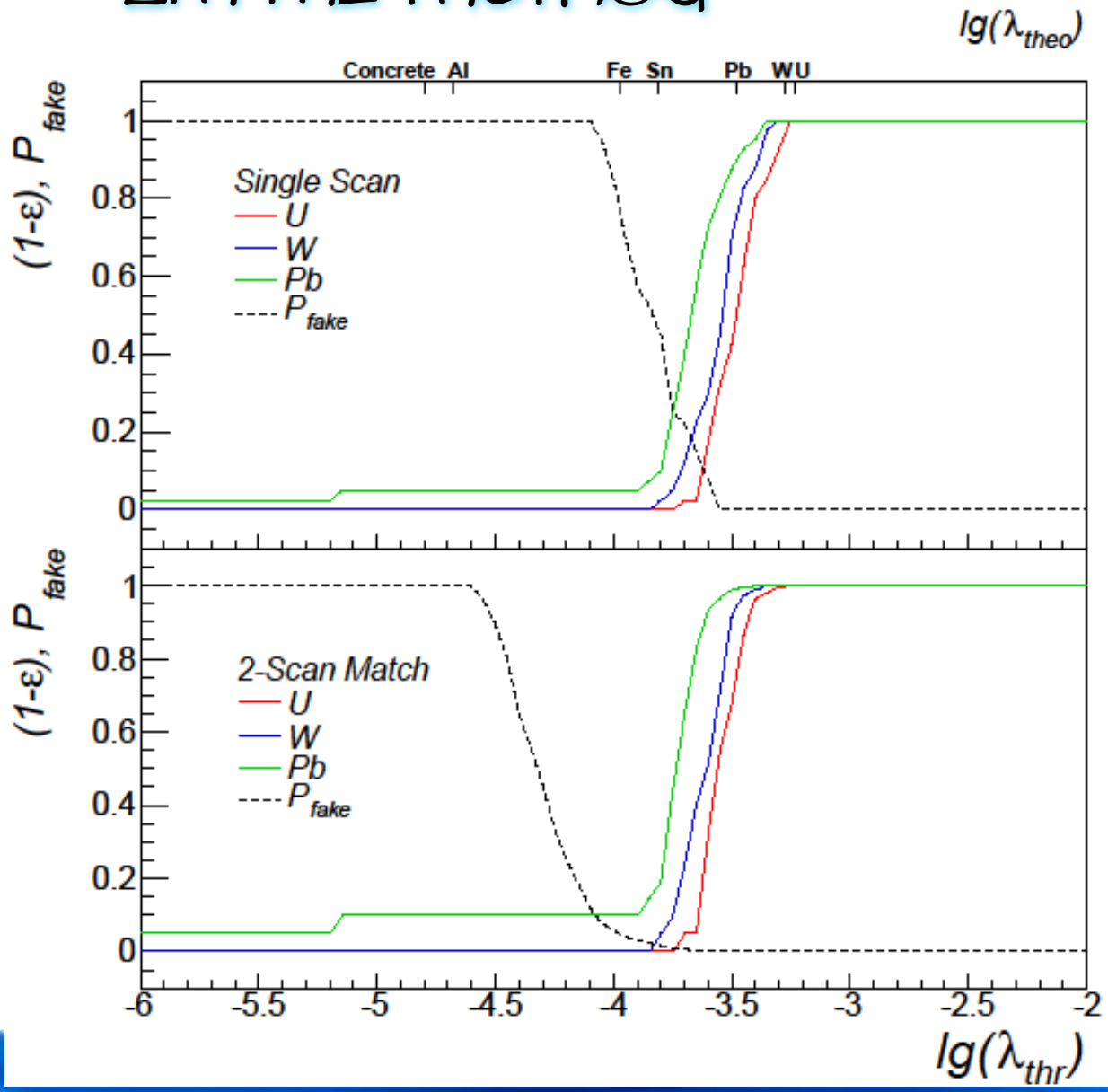


Stay human.

Backup slides



Fake probability and efficiency EM-ML method

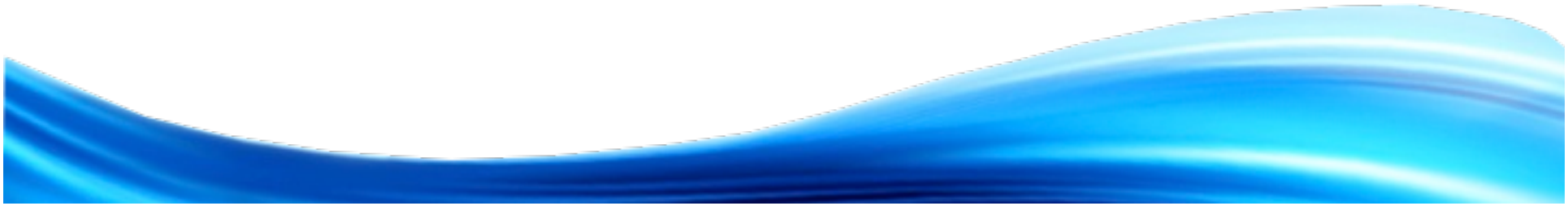


Optics algorithm

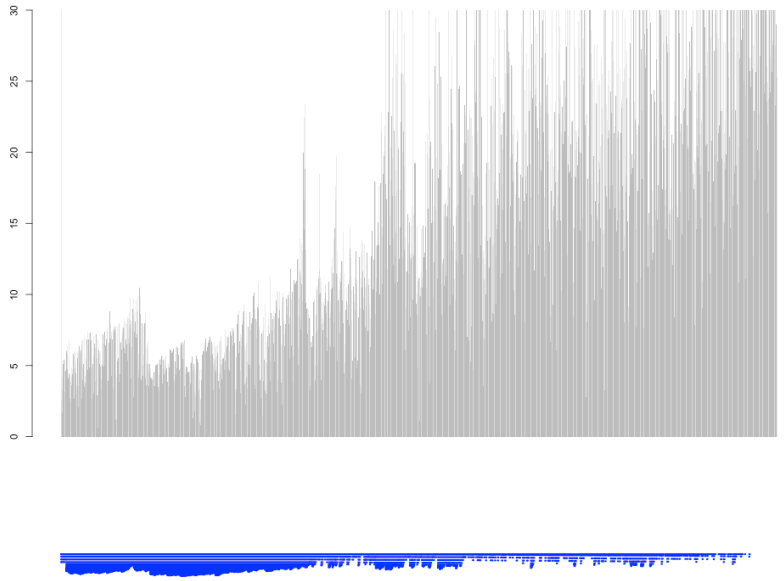
- Its basic idea is similar to DBSCAN, but it addresses one of DBSCAN's major weaknesses: the problem of detecting meaningful clusters in data of varying density.

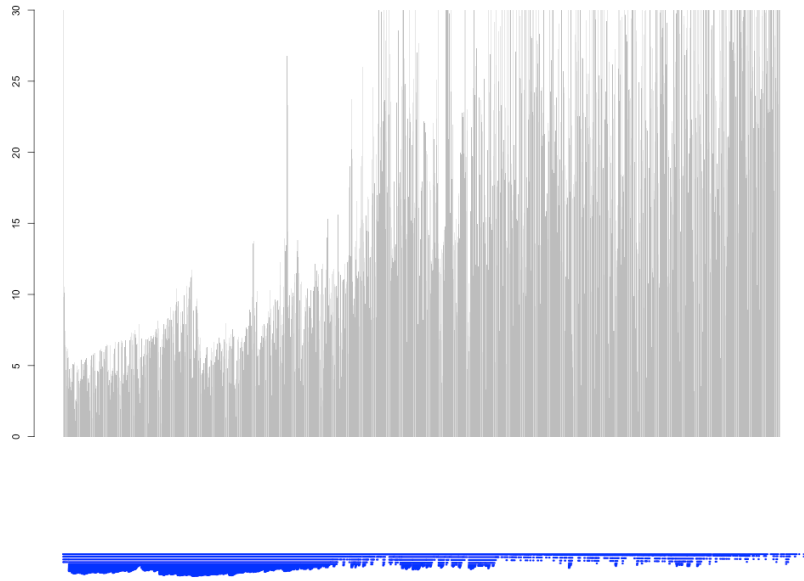
- In order to do so, the points of the database are (linearly) ordered such that points which are spatially closest become neighbors in the ordering.

- Additionally, a special distance is stored for each point that represents the density that needs to be accepted for a cluster in order to have both points belong to the same cluster. This is represented as a dendrogram.



Optics - MuonAtCenterScenario



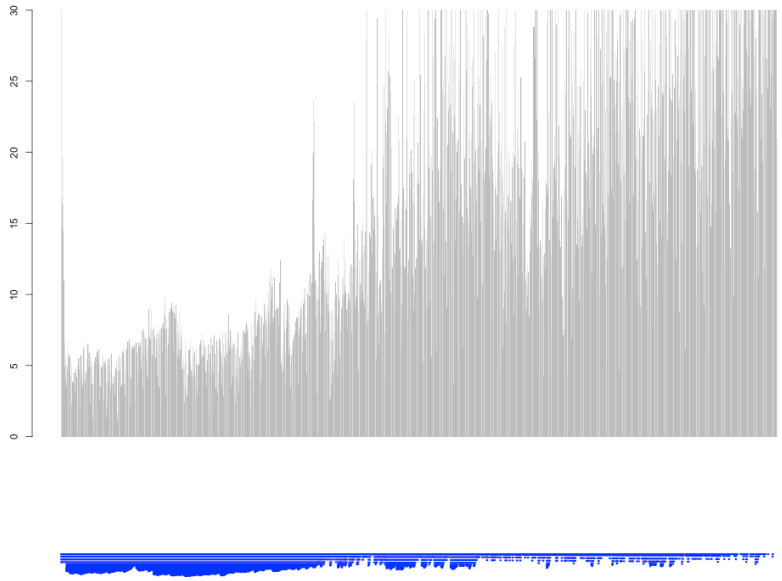


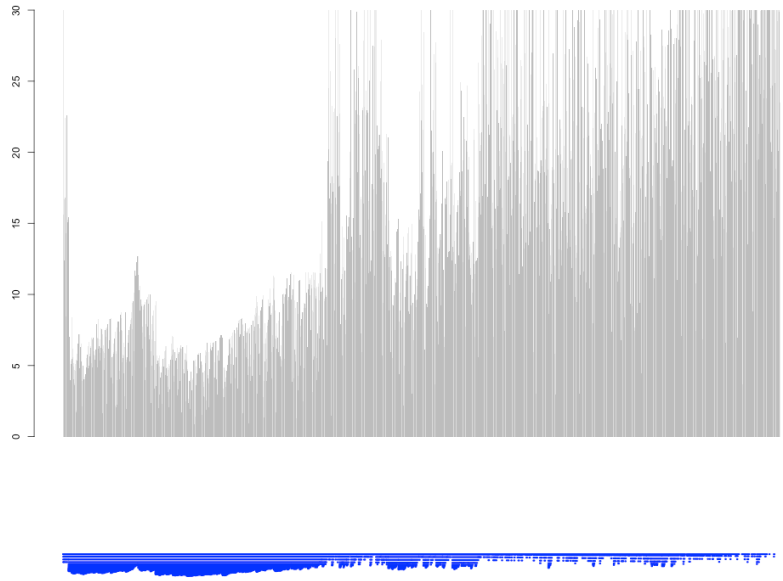
Scan1

Scan2

Cut Theta>2°

Optics - MuonAtCenterScenario



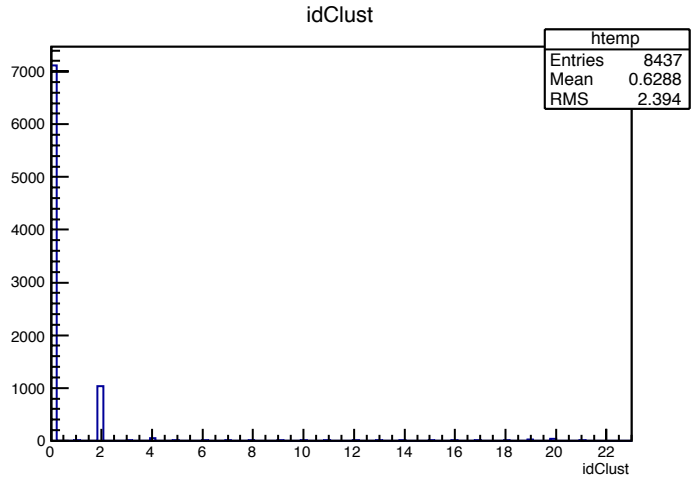


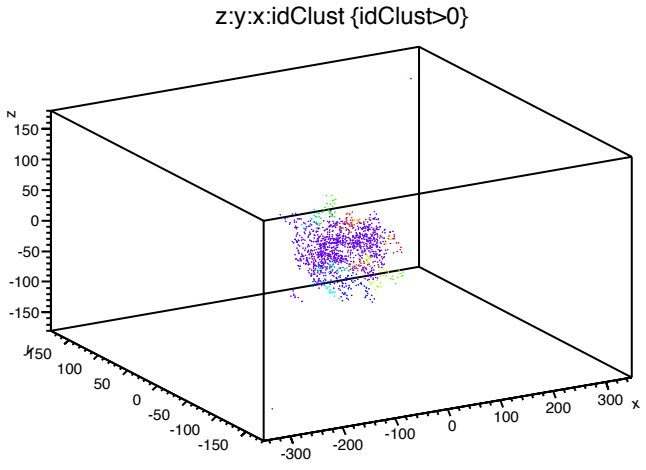
Scan3

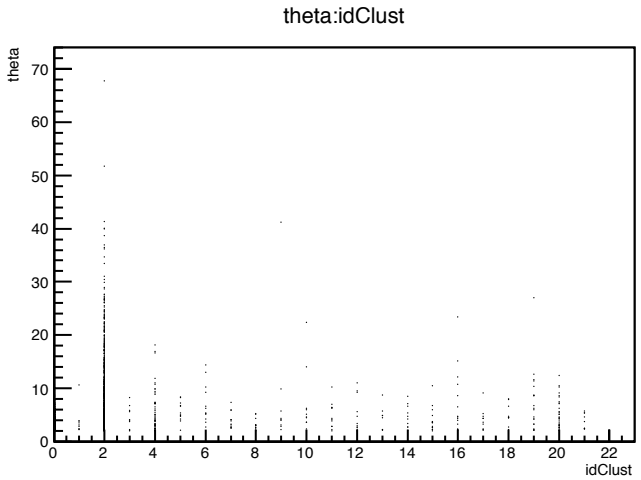
Scan4

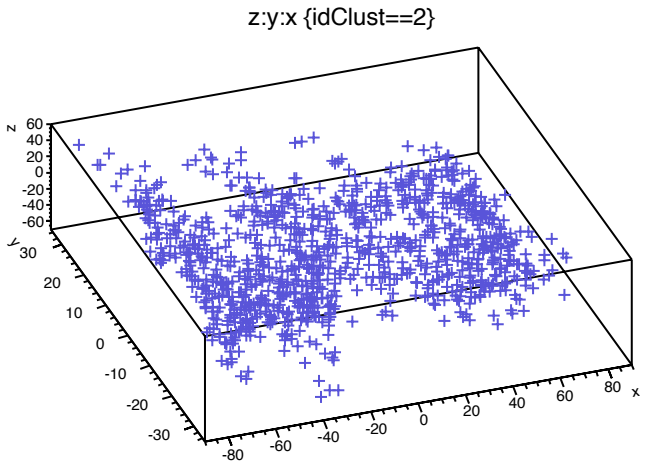
Cut Theta>2°

FOF - MuonAtCenterScenario (scan1)

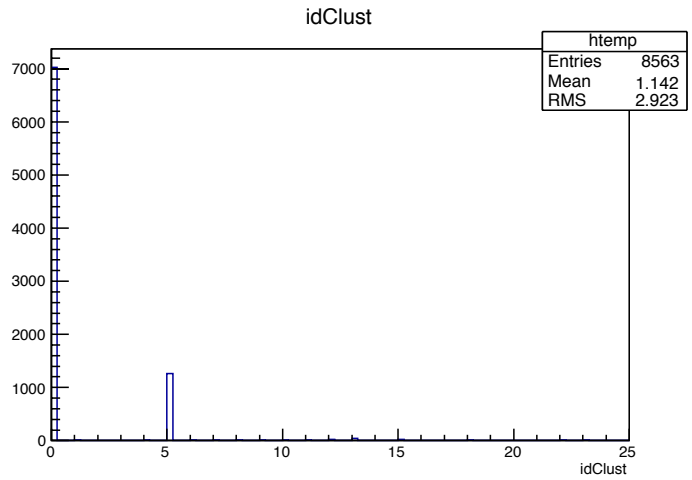


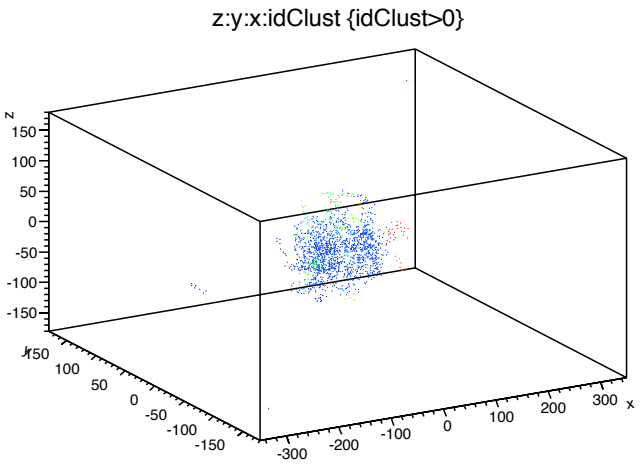


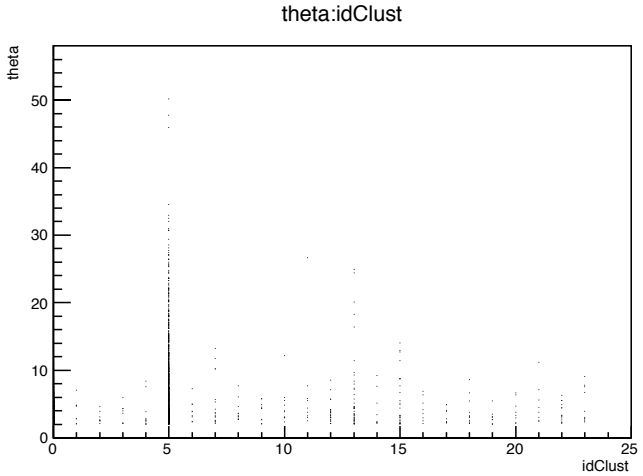


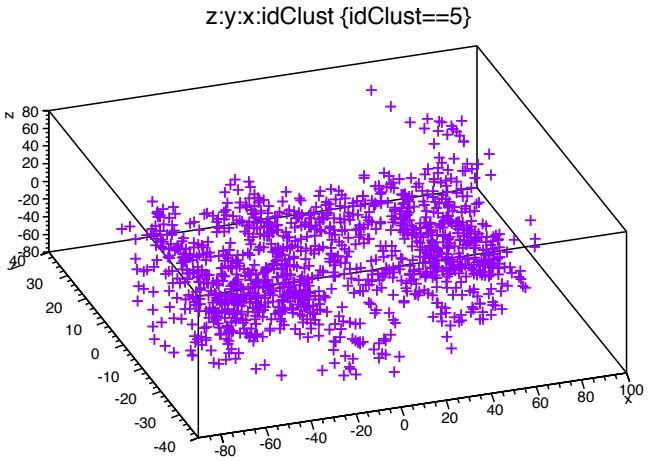


FOF - MuonAtCenterScenario (scan2)

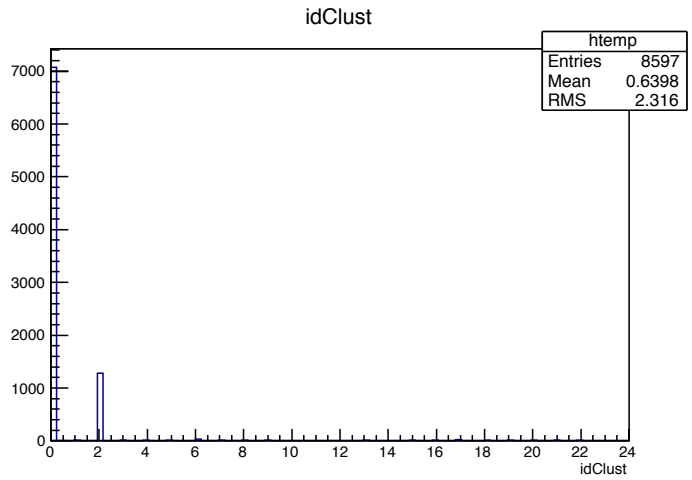


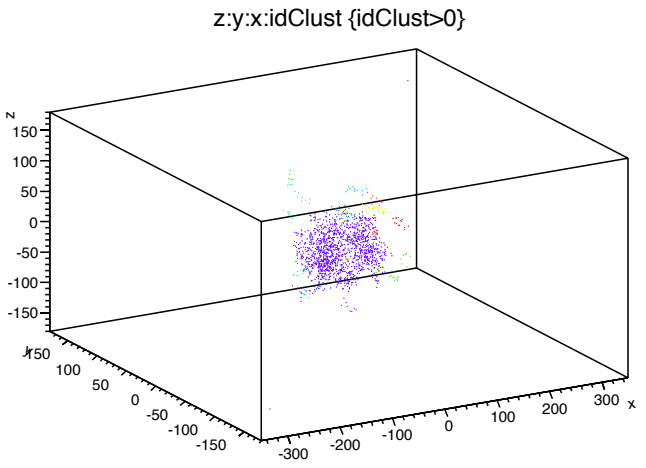


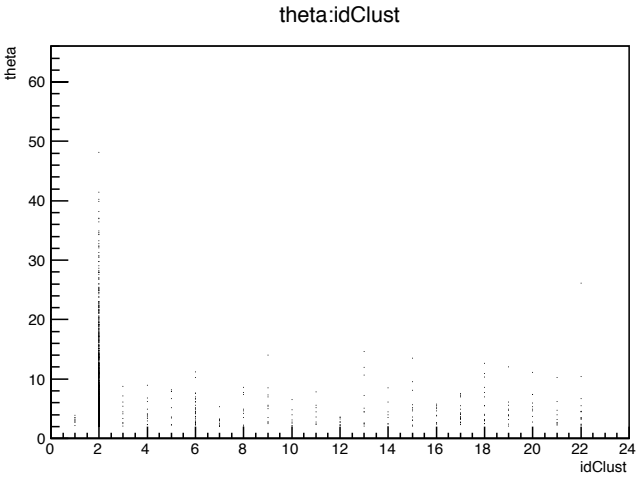


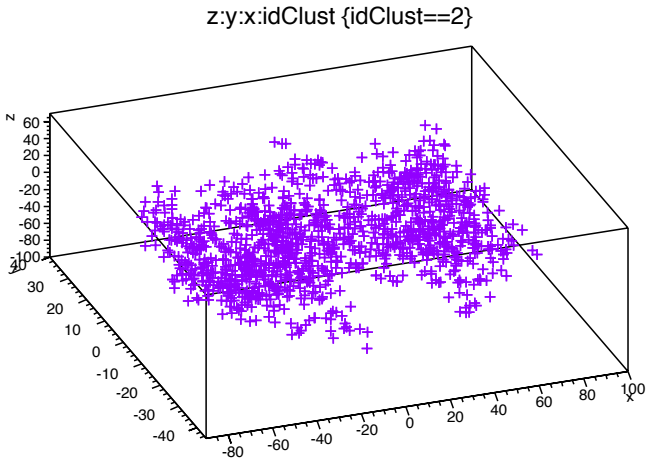


FOF - MuonAtCenterScenario (scan3)

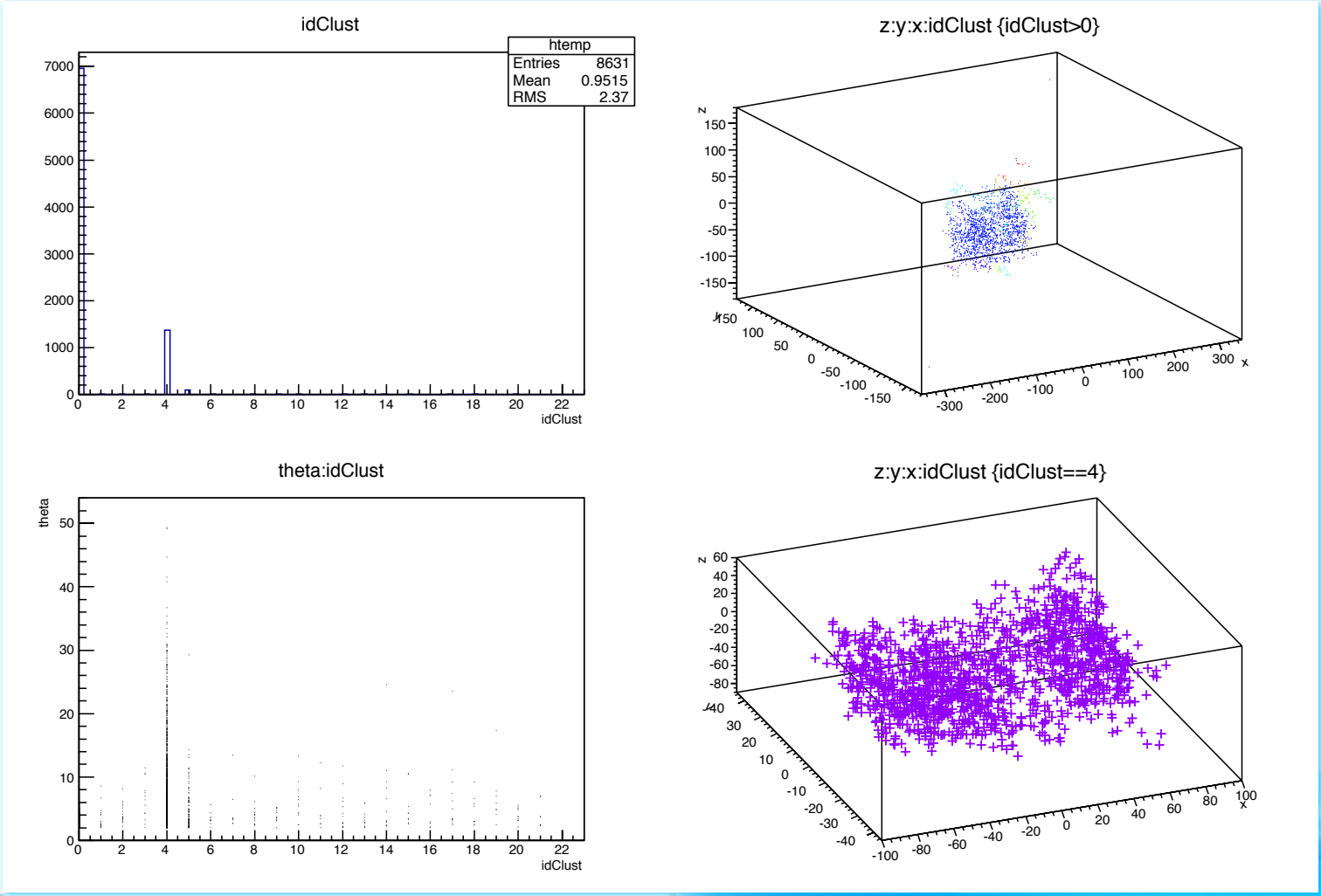




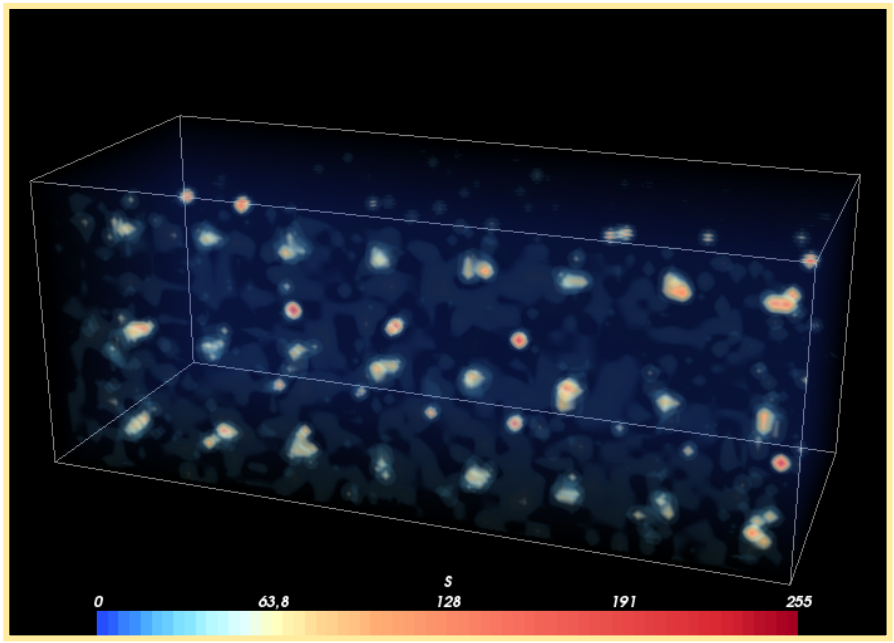




FOF - MuonAtCenterScenario (scan4)

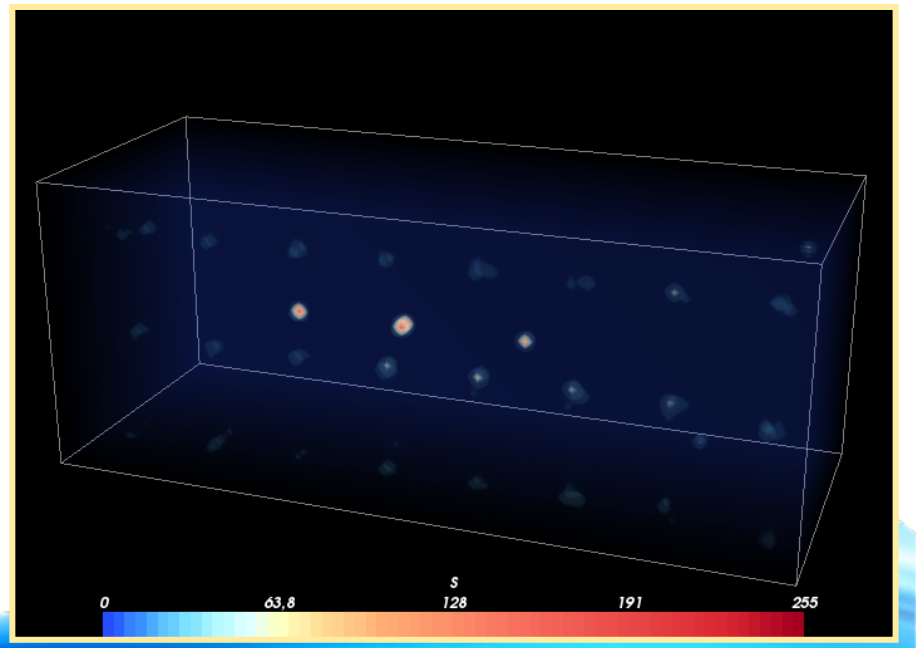


Momentum filter



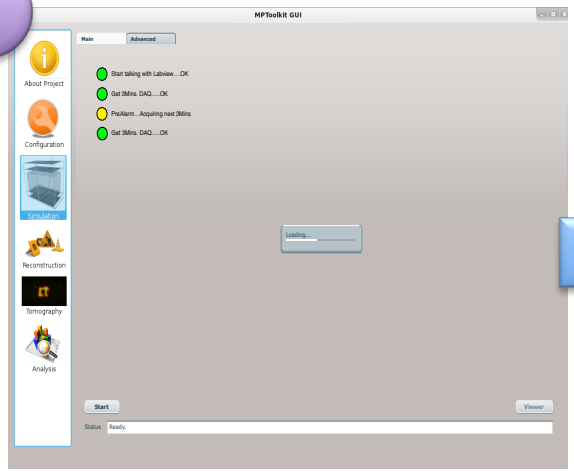
Additional prototype detector
to reject low momentum muons
being tested

After cutting low momenta
(< 1 GeV/c) muons



Tomographic images elaboration, visualization and monitoring UI

1



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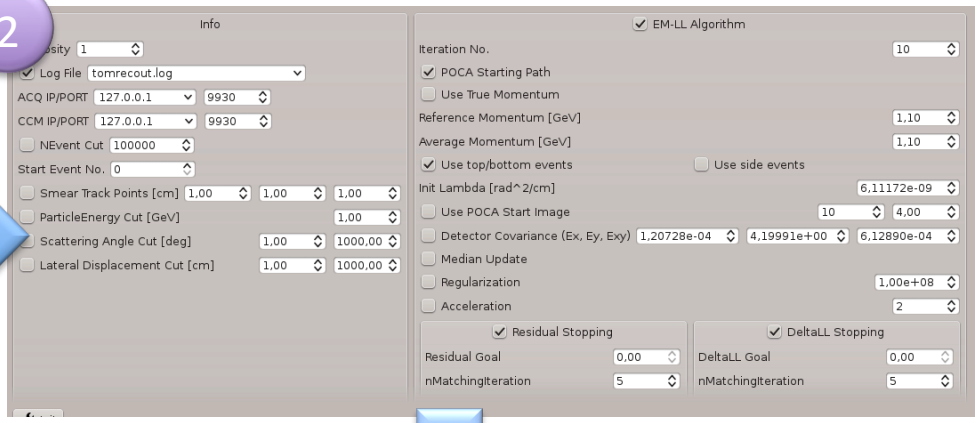

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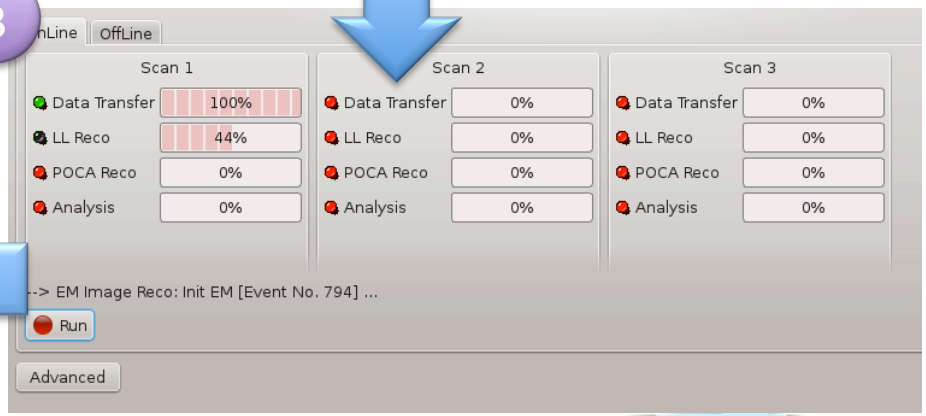

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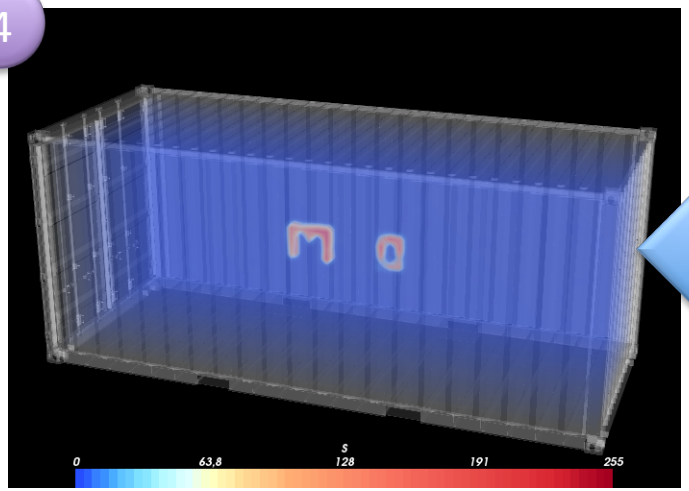
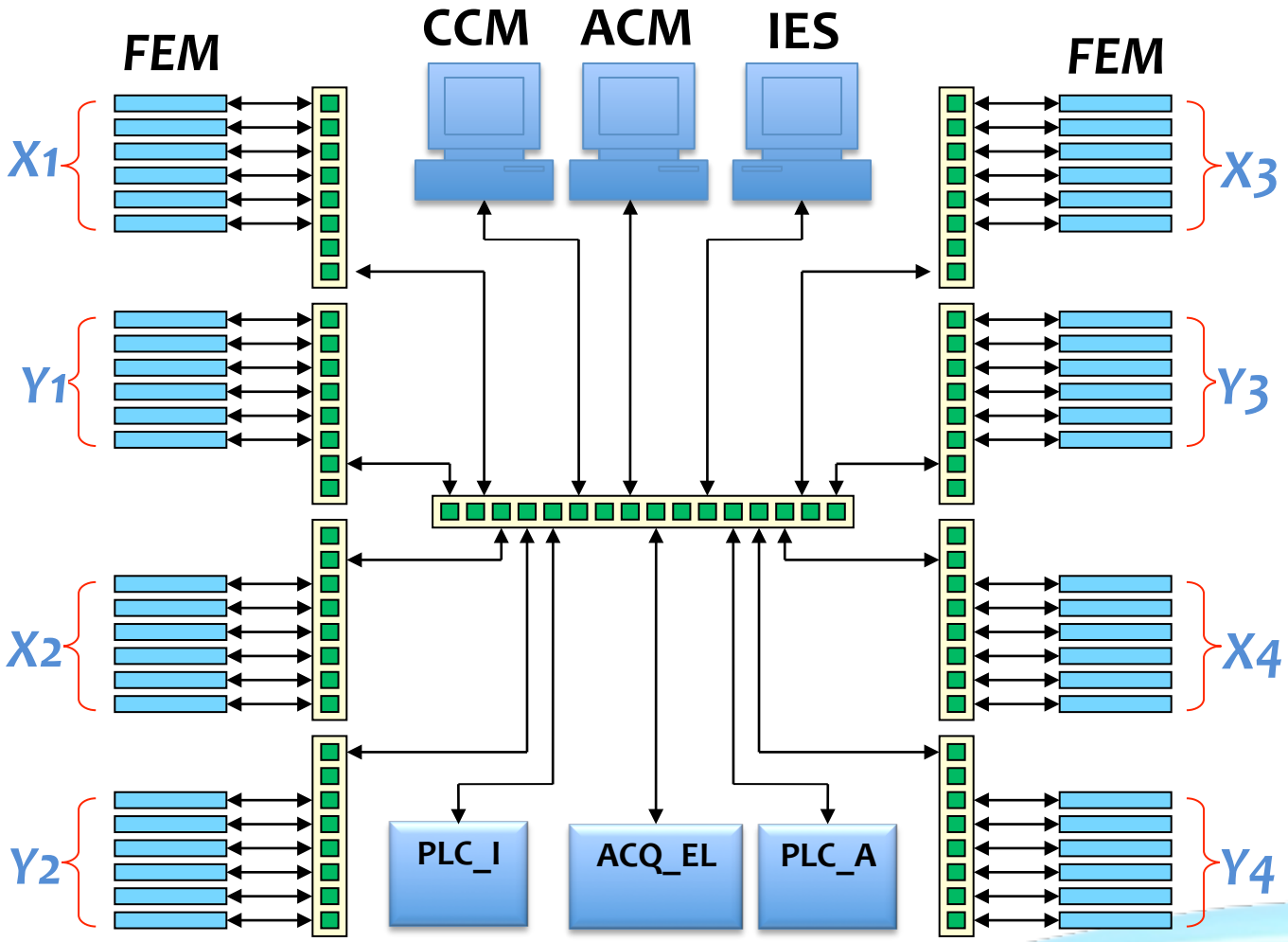


Data acquisition system



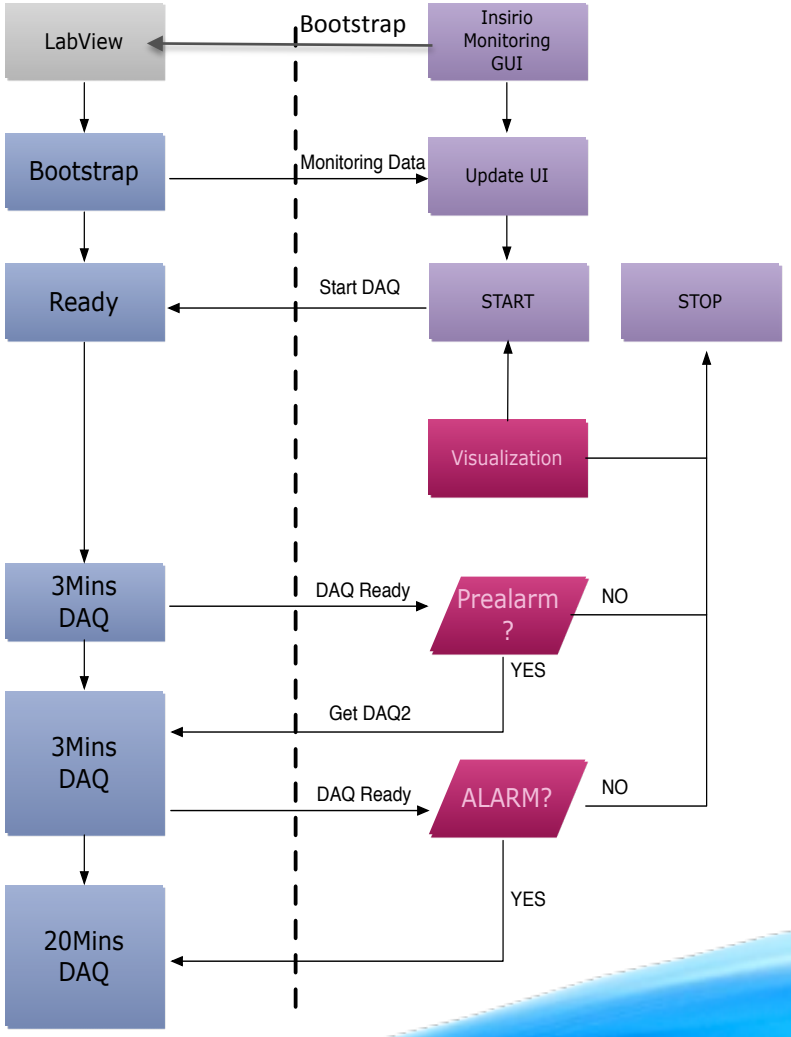
Communication workflow

Rt controller

FPGA board

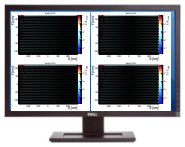
Chassis

DAQ MODULE



CCM – Monitoring

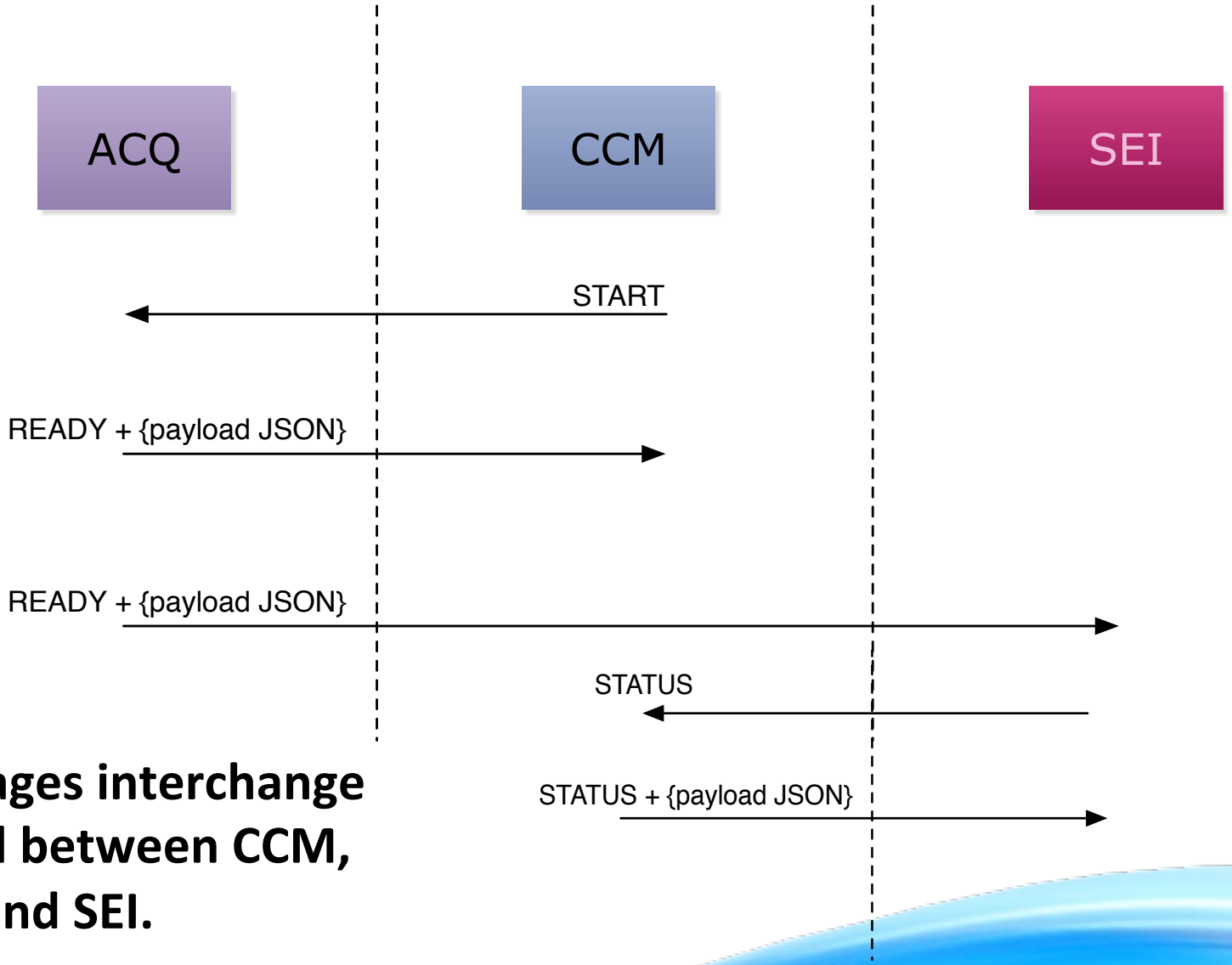
IES – Visualization



ACM - Calibration

Tomographic Images EMV SYSTEM

Interprocess communication over HTTP



Messages interchange model between CCM, ACQ and SEI.

EM-likelihood Algorithm

- Assume the container volume divided into:

  Nx ×Ny ×Nz 3D voxels

  → Each voxel has a scattering density

$$\lambda_j = \left(\frac{15}{p_0}\right)^2 \frac{1}{L_{rad}}, \; j=1,\ldots N_{voxels}, \; L_{rad}=\text{rad. length}$$

$$\rightarrow \mathcal{L}=\frac{1}{2}\sum_i^N (\log|\Sigma_i^{-1}| - y_i^T \Sigma_i^{-1} y_i)$$

- Model the scattering and displacement data yi=(Δθi ,ΔXi) with a bivariate normal distribution:

$$\text{covariance } \Sigma_i = E_i + p_{r,i}^2 \sum_{j=1}^{N_{voxels}} W_{ij}\lambda_j$$

$$\rightarrow \lambda_j^{(k+1)} = \frac{1}{M_j}\sum_i S_{ij}^{(k)} \qquad S_{ij} = 2\lambda_j^{(k)} +$$

$$p_{r,i}^2 [\lambda_j^{(k)}]^2 (y_i^T \Sigma_i^{-1} W_{ij} \Sigma_i^{-1} y_i - \text{Tr}(\Sigma_i^{-1} W_{ij}))$$

Algorithm Steps:

1. Collect data $(\Delta\Theta_{x,y}, \Delta_{x,y})_i$
2. Compute muon path lenght through the voxel (L_{ij}, T_{ij})
3. Compute the weight matrix W_{ij}
4. Inizialize $\lambda j = \lambda j^{(o)}$
5. Iterate until convergence/stopping:
   - Find median correction term $\Delta\lambda j$
   - Update λj using previous iteration estimate
   - Return vector λ

***Use** the EM algorithm to maximize Λ and find an estimate of* λ_j