An Efficient Bayesian Algorithm for Localizing Contaminants in Nuclear Waste: Application on 3D Imaging of Waste Drums

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Outline

1. Temporal Imaging CeBr3 Compton camera as a 3D imager
2. 3D image reconstruction: Maximum A Posteriori (MAP) algorithm
3. Numerical results
4. Conclusions & Application on the Dream Scanner project

3D imaging:
A promising concept for waste characterization

a 3D map of major isotopes contamination is an attractive solution as it allows:

- To optimise storage costs (no overkill assumptions on contamination distribution)
- To communicate & store for future operators an easy to interpret initial situation

But today this is not realistic economically as 3D scanning systems, based on collimated Germanium are both expensive and slow.

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3D imaging: Cost & speed of scanning are the issue today

- The cost of a 3D scan is a function of:
  - The number of views needed for 3D reconstruction. This number depends on:
    - Camera Field Of View FOV (nb of views to 2D image an object)
    - How many photons are needed by voxel/by view
  - The sensitivity of the camera (how long should we wait to reach a given detection limit?)
  - How fast the reconstruction algorithms converges with a limited number of photons & views

Why are Compton cameras uniquely suited for 3D scans?

Compton camera has a wide Field of View (90°x90° here)

→ A limited number of views should fully cover an object

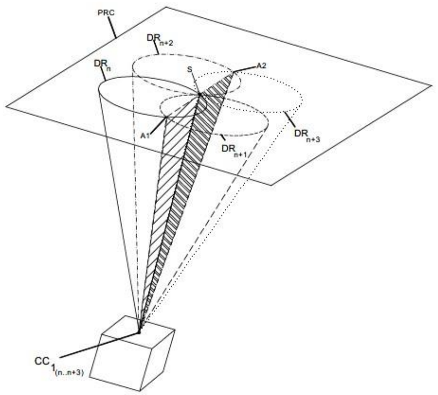
Compton events generate large thick cones : « fuzzy objects »

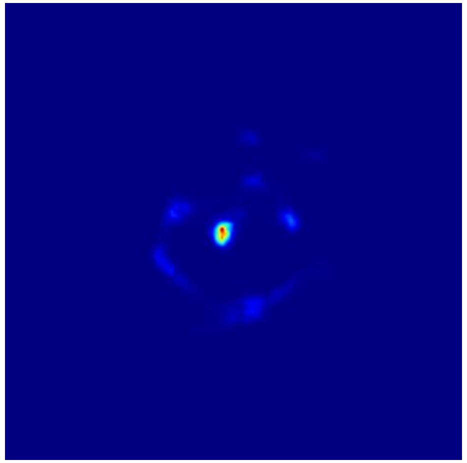
→ In 2D reconstructions High statistics are needed to avoid false positive

→ In 3D the volume of intersection between cone shrinks by an order of magnitude

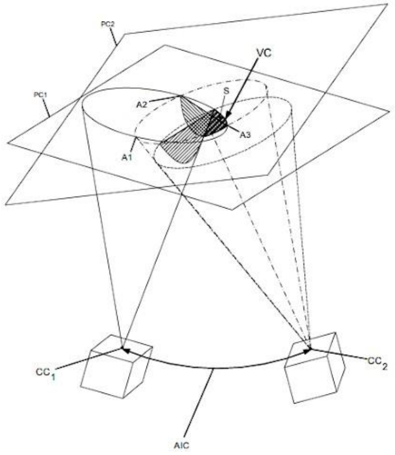
Compton image reconstruction works much better in 3D than in 2D

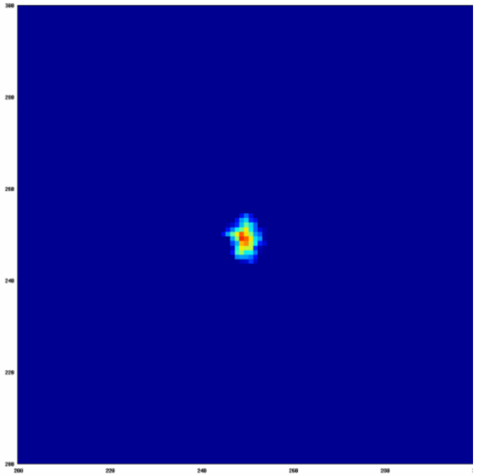
One view



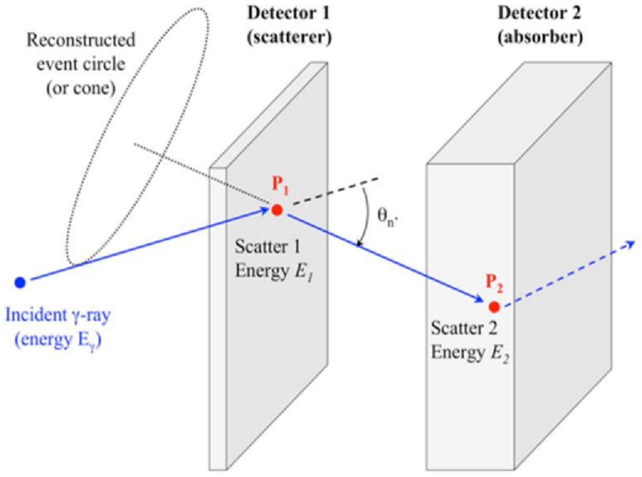


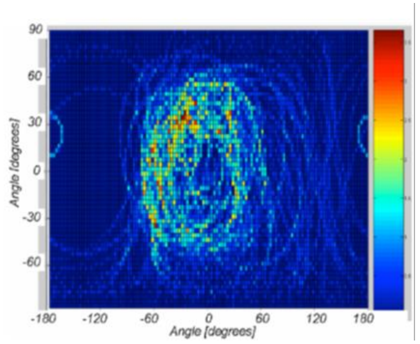
2 or more views





Temporal imaging Compton camera $CeBr_3$:
A technology well suited for 3D imaging





Low noise level

- Two fast CeBr3 scintillating crystals plates
- Low natural background
- <500 ps Coïncidence veto on Compton events

High angular resolution

- <8° vs < 20° for CZT cameras

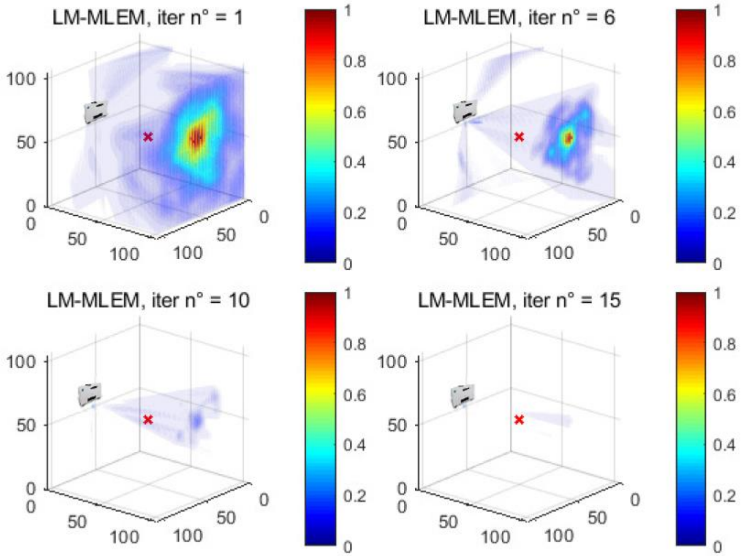
Large Field of View

- 90° x 90°

3D Compton image reconstruction: *Problem statement*

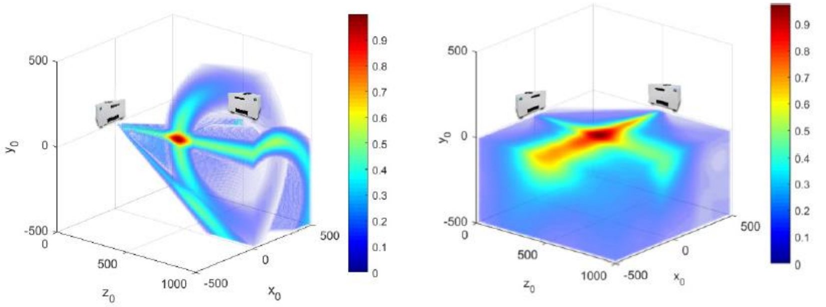
Single-view **reconstruction**

- 2 approaches: analytical, iterative
- 2 classes of models: deterministic, probabilistic
- Reconstruction is marginal if parallax is sufficient (large detector, near field)
- 3D reconstruction Fails if parallax is low (compact camera, far field)



Multi-view **reconstruction**

- Improve the parallax of detected events
- Methods to be developed



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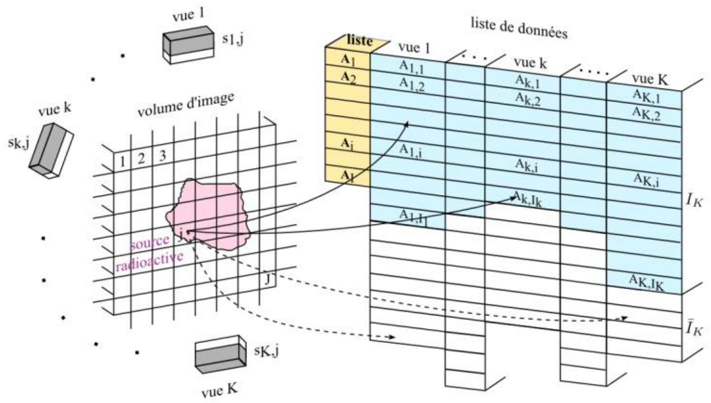
Reconstruction 3D – Extended LMMLEM algorithm

Ordinary LMMLEM

$$\hat{f}_j^{(t+1)} = \frac{\hat{f}_j^{(t)}}{s_j} \sum_{i=1}^{I} \frac{t_{ij}}{\sum_{l=1}^{J} t_{il} \hat{f}_l^{(t)}}$$

(failed due to lack of parallax)

new list-mode data

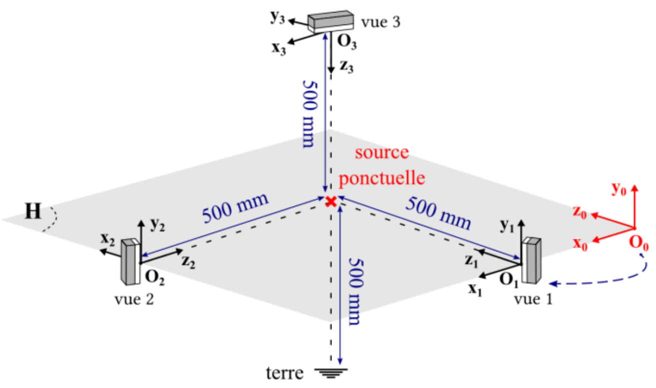


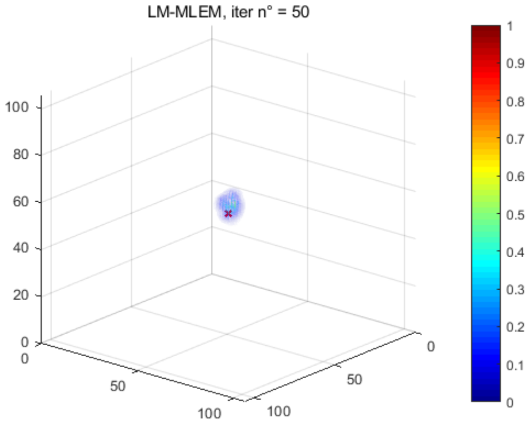
extended LMMLEM

$$\hat{f}_j^{(t+1)} = \frac{\hat{f}_j^{(t)}}{\sum_{k=1}^{K} s_{jk}} \sum_{i=1}^{I} \frac{\sum_{k=1}^{K} t_{ijk}}{\sum_{l=1}^{J} t_{il} \hat{f}_l^{(t)}}$$

(improved parallax)

Result given by extended LMMLEM algorithm





Problem

- ➢ Convergence is slow
- ➢ Large number of data is needed

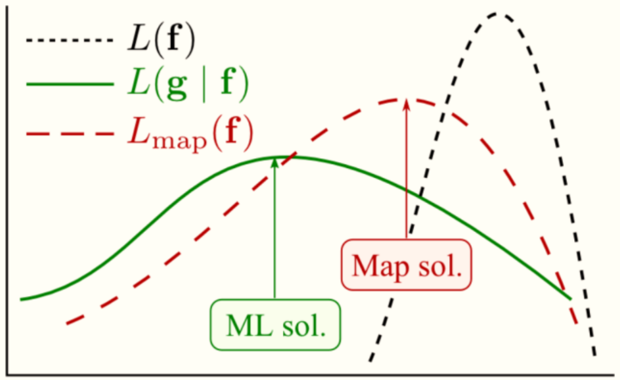
Solutions

- ➢ Using a priori knowledge of source
- ➢ Bayésian reconstruction
- ➢ Optimisation algorithm

Markov Random Field MAP algorithm (LM-MRFMaP)

Bayesian approach: maximum a posteriori (MAP) estimate

$$\hat{\boldsymbol{f}} = \arg\max_{\boldsymbol{f}\geq 0}\{p(\boldsymbol{f} \mid \boldsymbol{g})\} = \arg\max_{\boldsymbol{f}\geq 0}\{L(\boldsymbol{g} \mid \boldsymbol{f}) + L(\boldsymbol{f})\}$$



MAP with Markov random field (MRF) prior

$$\hat{\boldsymbol{f}} = \arg\max_{\boldsymbol{f}\geq 0}\left\{\underbrace{\sum_{i=1}^{I}\sum_{j=1}^{J}\left(\frac{t_{ij}f_j'}{\sum_{s=1}^{J} t_{is}f_s'} - t_{ij}f_j\right)}_{\text{surrogate of Poisson log-likelihood}} - \underbrace{\sum_{j=1}^{J}\sum_{\{j,l\}\in C}\beta_{jl}\rho(f_j - f_l)}_{\text{enery of MRF prior}}\right\} = \arg\max_{\boldsymbol{f}\geq 0}\{L_{\mathrm{map}}(\boldsymbol{f})\}$$

Iterative maximization scheme for a concave $L_{\mathrm{map}}(\boldsymbol{f})$

$$\hat{\boldsymbol{f}}^{(k+1)} \leftarrow \hat{\boldsymbol{f}}^{(k)} + \sum_{j=1}^{J} a_j^{(k)}\boldsymbol{e}_j^{(k)} \qquad \text{with} \qquad a_j^{(k)} \leftarrow \arg\max_{a_j \geq -f_j^{(k)}}\left\{L_{\mathrm{map}}\left(\hat{\boldsymbol{f}}^{(k)} + a_j\boldsymbol{e}_j^{(k)}\right)\right\}$$

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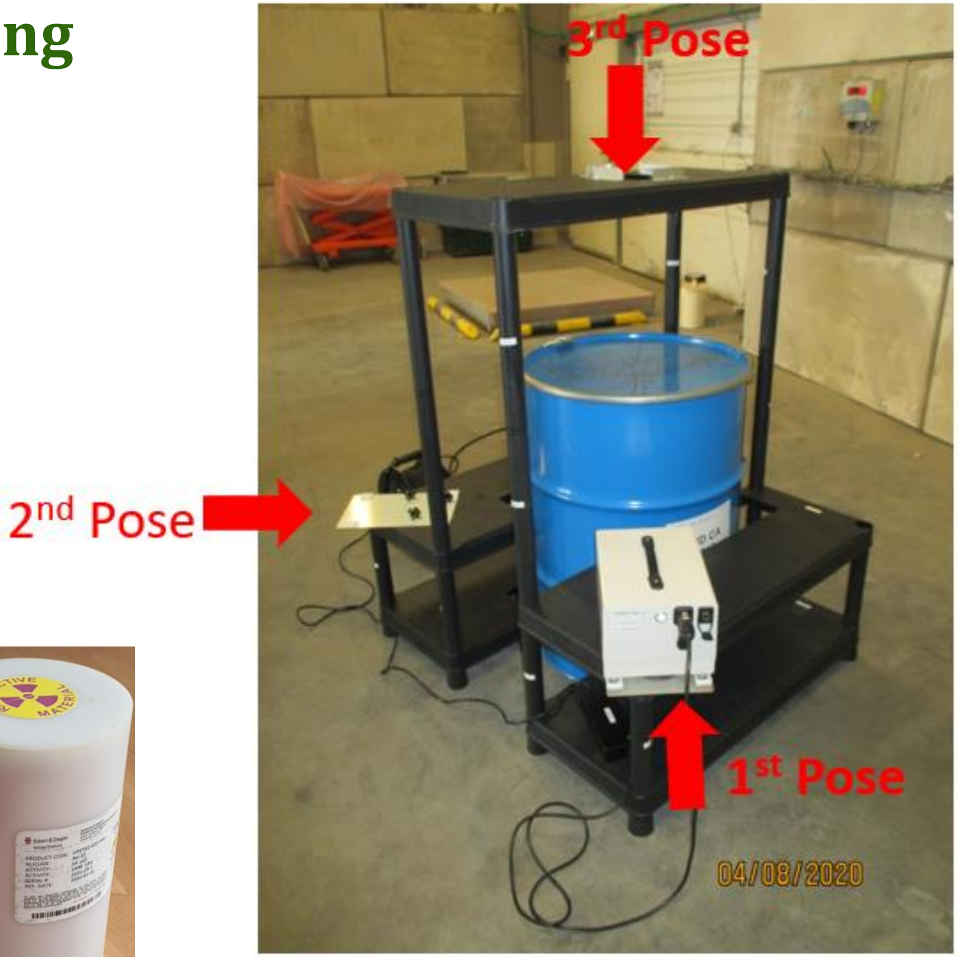
Numerical experiments on real data

Temporal Imaging Compton camera V3 developped by Damavan Imaging

Radioactive sources :

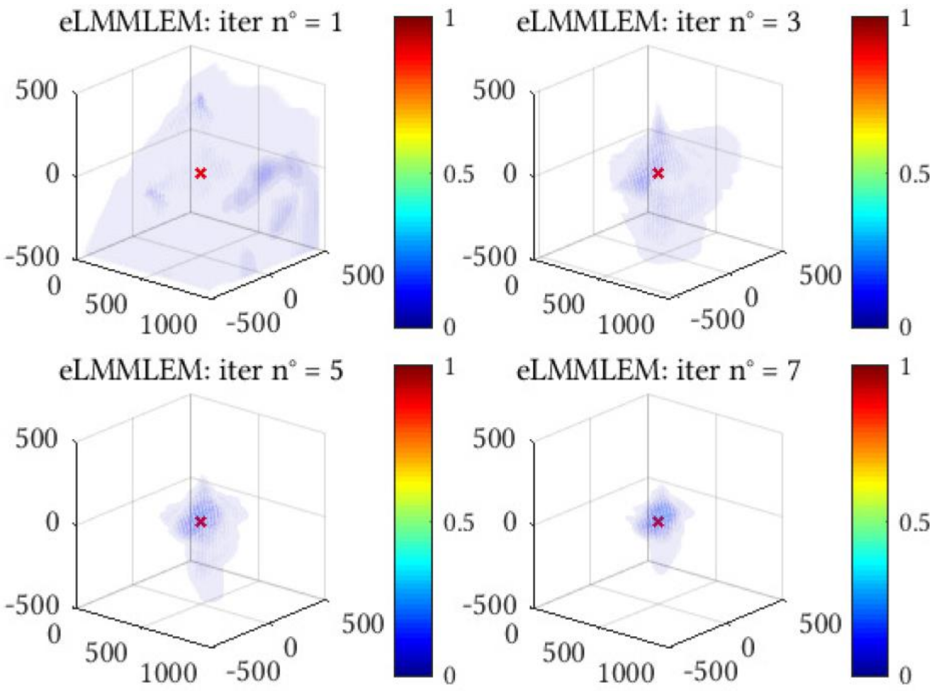
- Homogeneous cylinder
- Sodium ^{22}Na
- 0,7 MBq of total activity
- Acquisition times: 10mn/view

Real experiment setting

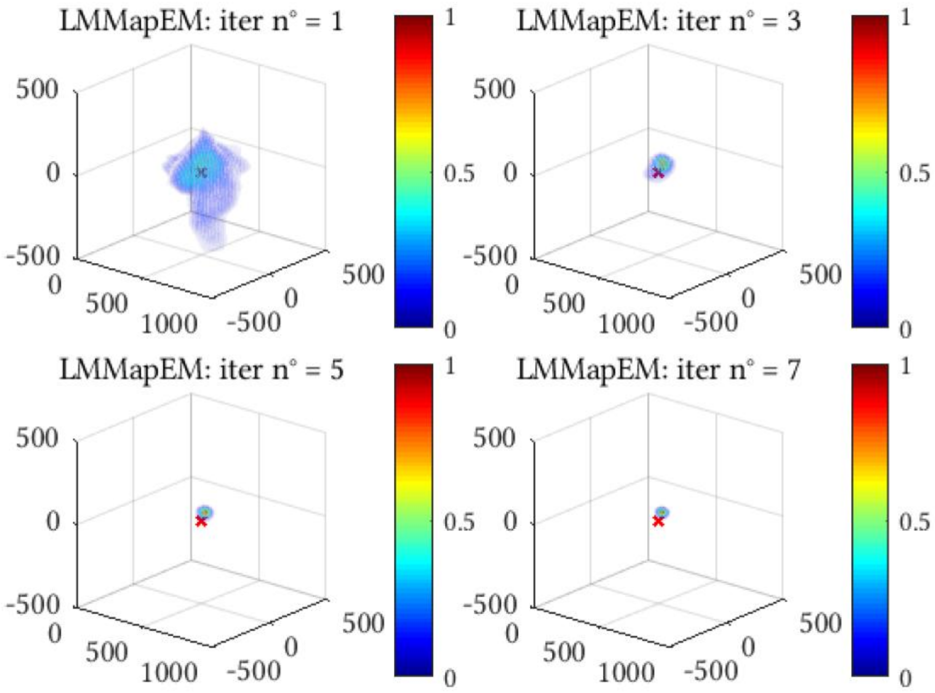


Reconstruction results - LM-MRFMaP algorithm

eLMMLEM algorithm

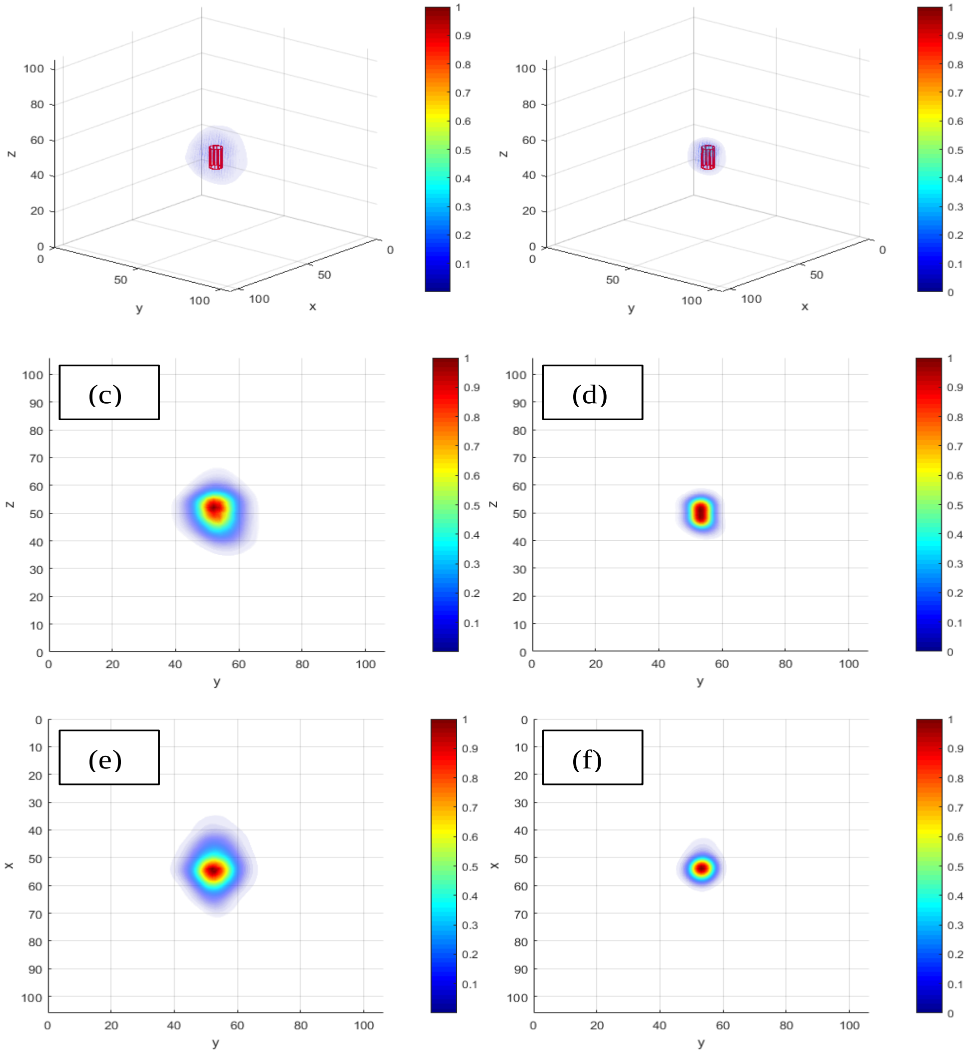


LM-MRFMaP algorithm



- LM-MRFMaP algorithm converges much faster than the extended eLMMLEM algorithm

Reconstruction results - LM-MRFMaP algorithm
Image Quality is also much better



Reconstruction results at 20th iteration using the LM-MLEM algorithm:

- (a) 3D image
- (c) y-z projection
- (e) x-y projection, and the proposed MAP algorithm:
- (b) 3D image
- (d) y-z projection
- (f) x-y projection

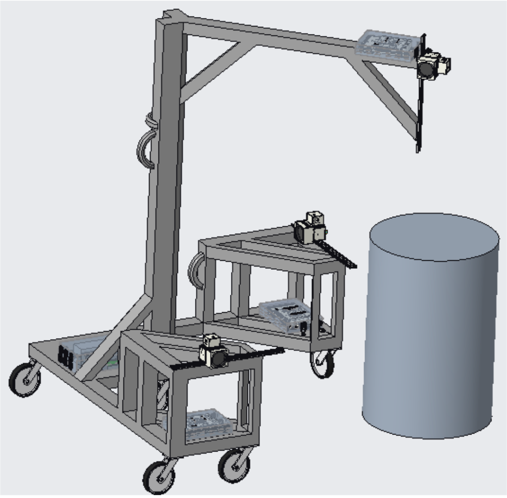
Conclusion

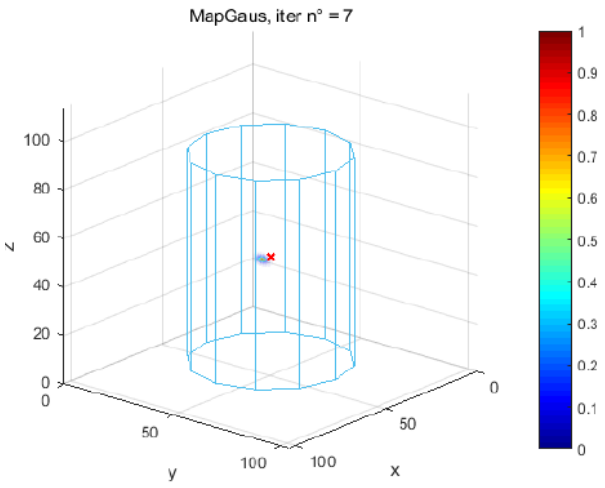
Conclusions	Large scale 3D mapping our drums prior to storage would allow storage costs reductions and better safety on the long term
	High angular resolution comton imaging is uniquely suited for this task thanks to it's sensitivity & wide angular acceptance
	But existing reconstruction algorithms like ML/MLEM were ill suited to the « diffuse nature » of Compton reconstruction objects (fuzzy cones)
	Here we propose a new bayesian algorithm MAP-SCA-EM that has obtained very promising results on an extended source

Perspectives:
Application to the Dream Scanner project

This reconstruction technology will be implemented on Dream scanner prototype

This scanner is a joint project with Orano DS





- 3 Compton camera heads
- The scanner moves, not the drum
- Will implement the new algorithm
- Our target is to reach 10 minutes for a 3D scan of a low density 225 l drum

Thank you for your attention!

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