Evaluation of different image regularization techniques on simulated phantoms with the TRIMAGE brain PET scanner

Luigi Masturzo[1,2], Pietro Carra[1,2], Paola Anna Erba[3], Matteo Morrocchi[1,2], Alessandro Pilleri[2], Giancarlo Sportelli[1,2], Nicola Belcari[1,2]

[1] National Institute of Nuclear Physics (INFN), Pisa Section, Pisa, Italy

[2] Department of Physics “E.Fermi”, University of Pisa, Pisa, Italy

[3] Department of Translational Research and New Technology in Medicine and Surgery, Regional Center of Nuclear Medicine, Azienda Ospedaliero Universitaria Pisana, University of Pisa, Pisa, Italy

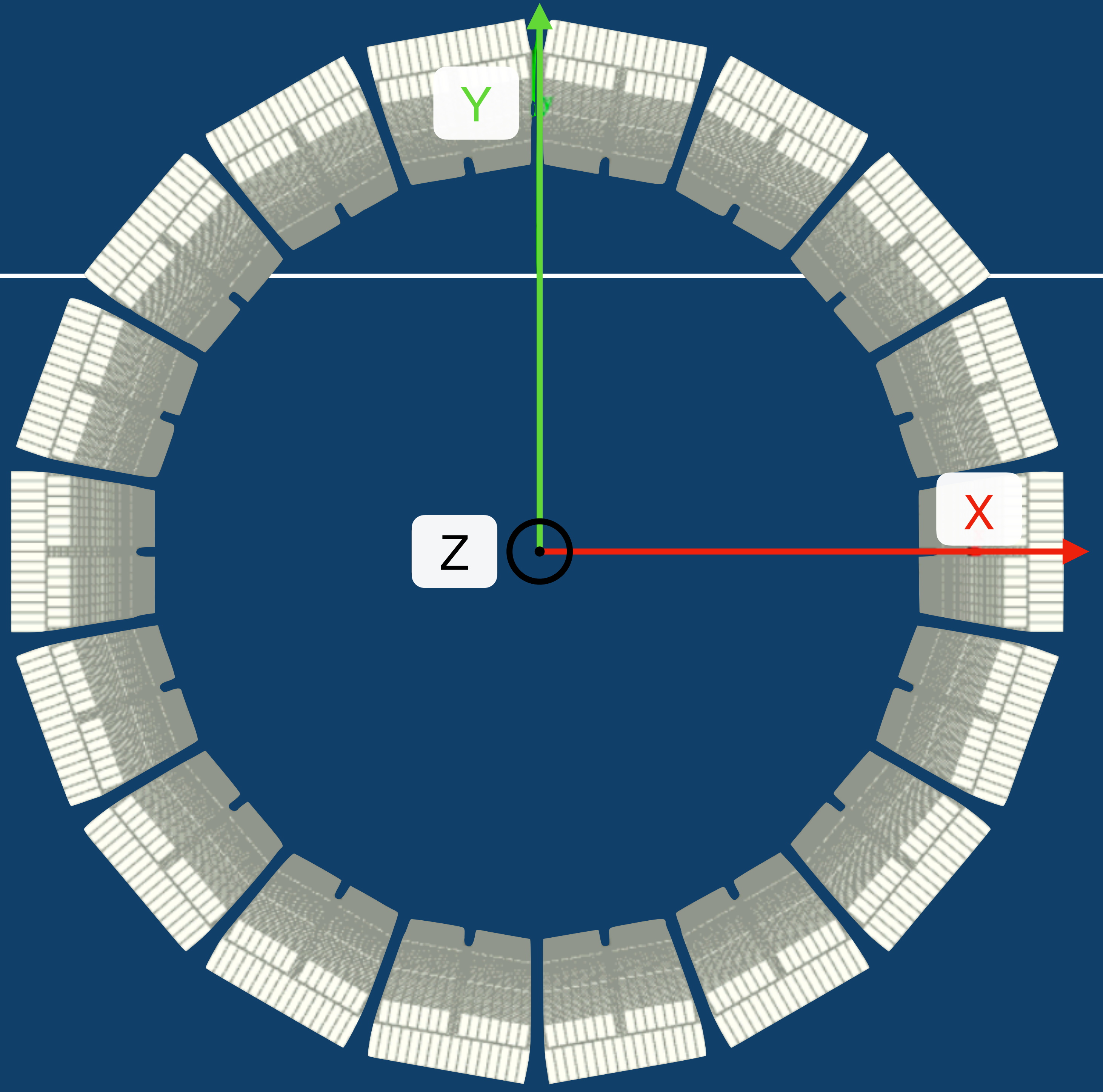
PET MR EEG TRImage

Università di Pisa

PSMR2022
9TH CONFERENCE ON PET/MR AND SPECT/MR
& TOTAL-BODY PET WORKSHOP

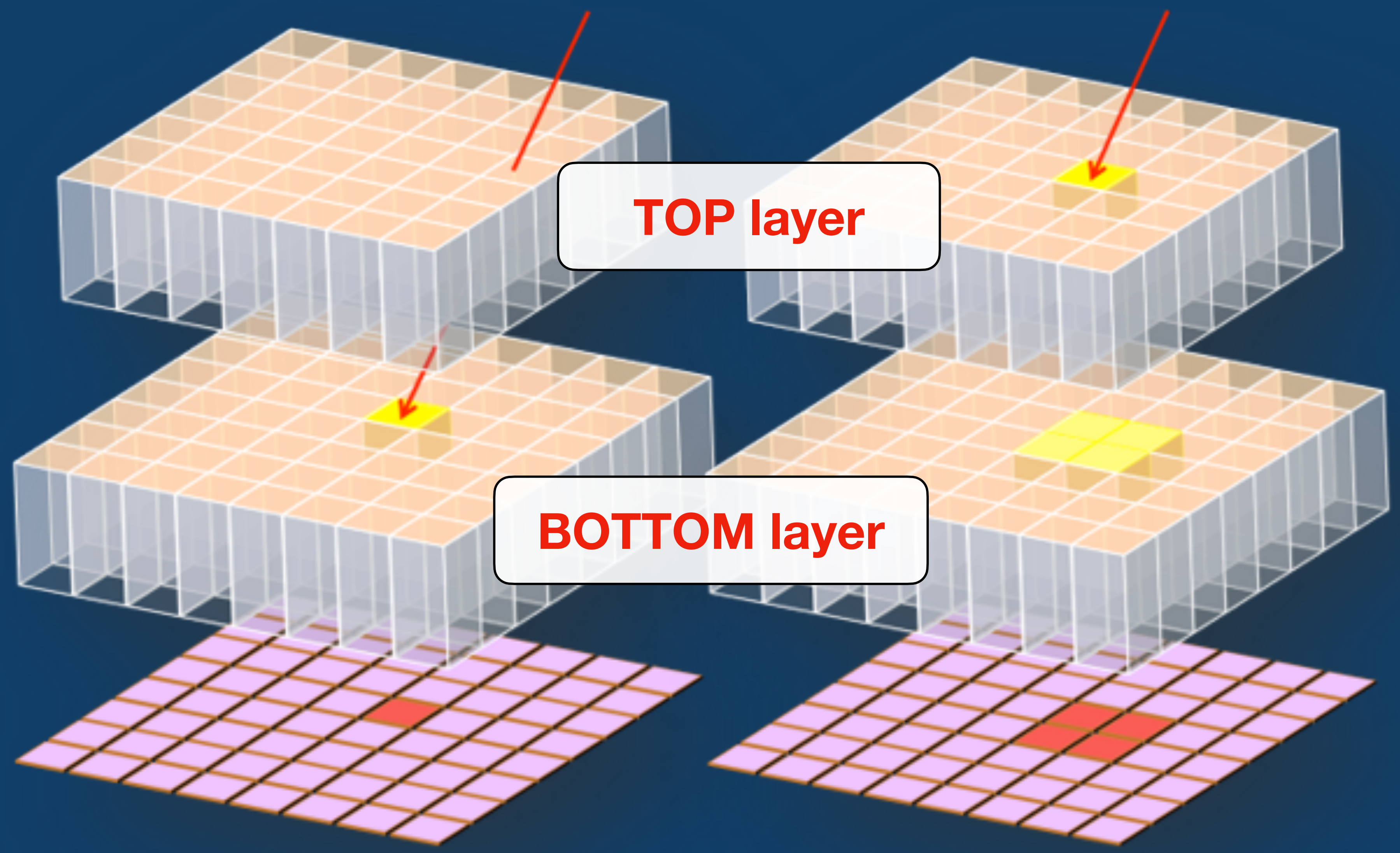
The TRIMAGE PET system

- Fully integrated PET/MRI brain system
- LYSO:Ce crystal staggered layers
- Crystal dimensions: 3.3 x 3.3 x (8-12) mm^3



Sectors	18	**Crystals**	24408
Modules	54	**Axial FOV**	164 mm
Tiles	216	**Transaxial FOV**	260 mm

Layer interactions



N. Belcari et al. “**Design and Detector Performance of the PET Component of the TRIMAGE PET/MR/EEG Scanner**”. In: *IEEE Transactions on Radiation and Plasma Medical Sciences* 3.3 (2019), pp. 292–301.

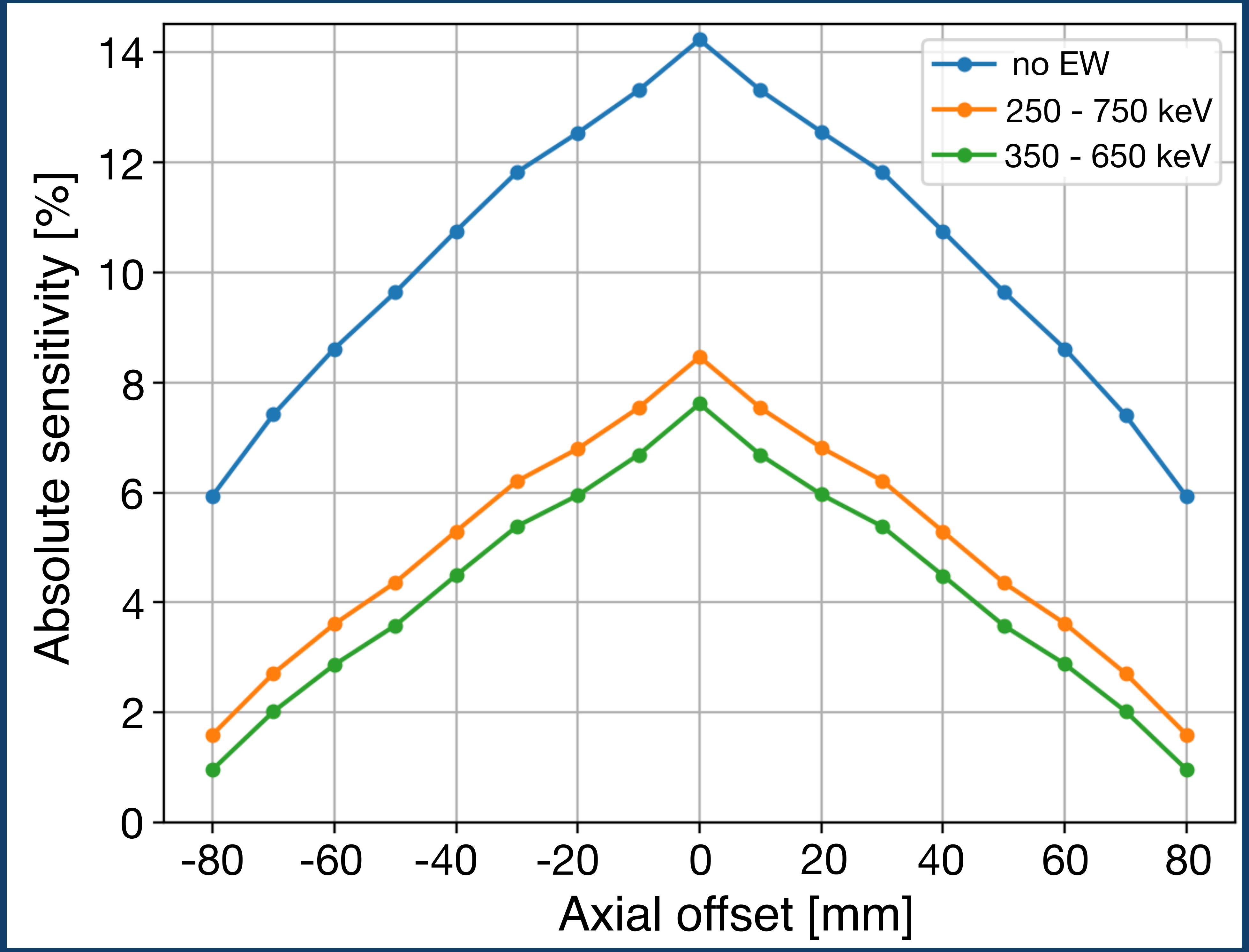
PET system performance

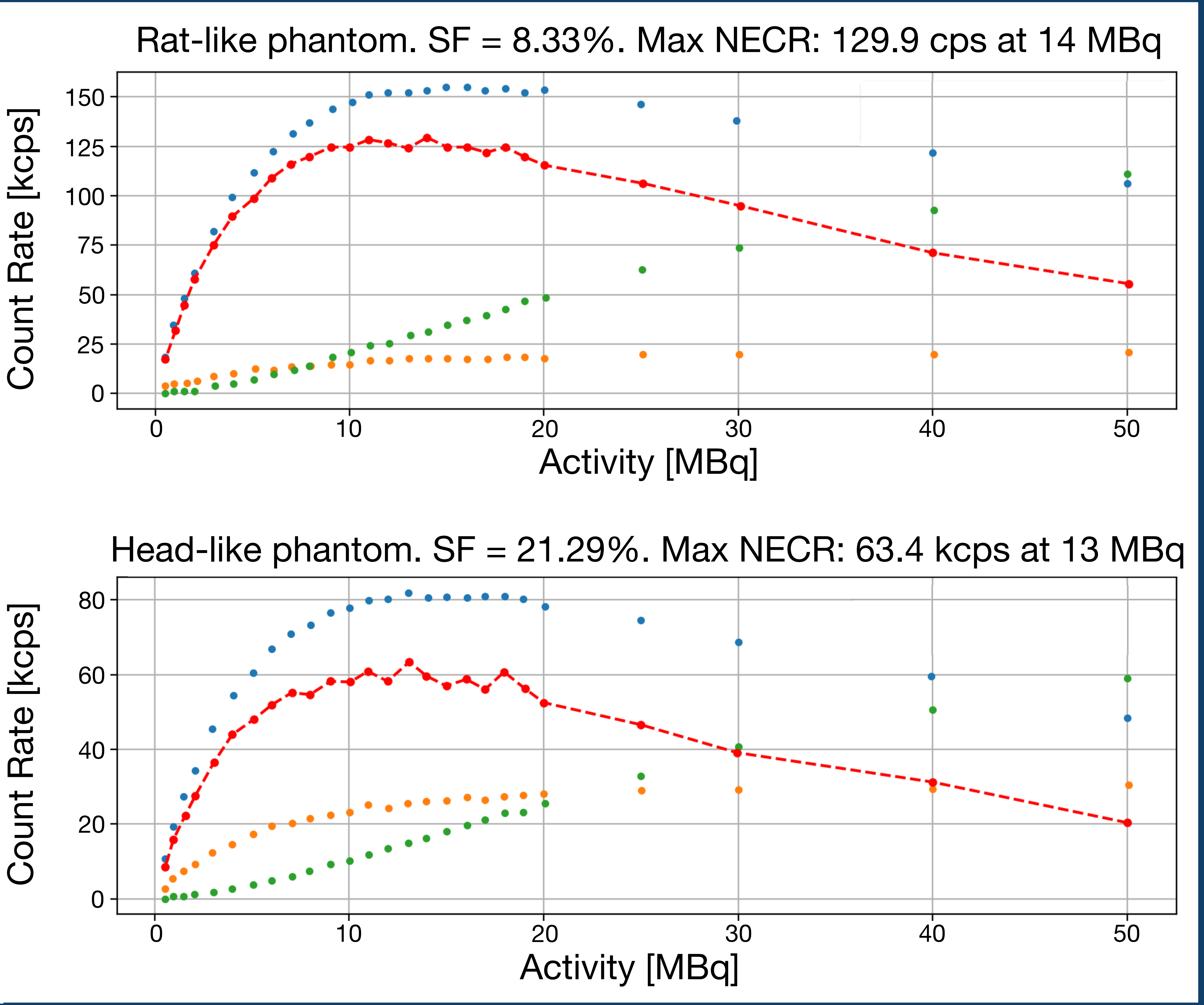
Energy resolution — 17.8%

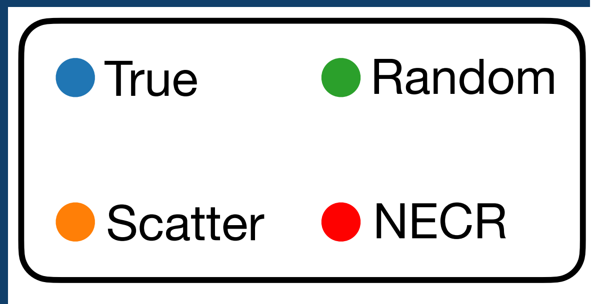
Coincidence window — 5 ns

Sensitivity (CFOV) — 7.61% [350-650 keV]

	Rat-like	Head-like
Diameter [cm]	5	20
Height [cm]	15	15







Reconstruction software

In-house reconstruction software - Histogram mode **-** MLEM/OSEM - image space resolution modelling - Two step reconstruction

System matrix factorization

- **N** - Normalization
- **D** - Detector
- **A** - Attenuation
- **G** - Geometry
- **R** - Blurring

$$S = N \times D \times A \times G \times R$$

A. Pilleri. "**Efficient projection-space resolution modelling for image reconstruction in Positron Emission Tomography**". PhD thesis. University of Pisa, 2021.

D is computationally intensive $\rightarrow$ Excluded from **S** $\rightarrow$ Noise increases

Regularization

- **Noise reduction**
- **Improvement of image quality**

- Two possible ways:
  - Limit the number of iterations → Worse image quality
  - Modify the object function → Regularization

Object function — Energy function

$$\Omega(\rho, n) = \log L(\rho, n) - \beta U(\rho)$$

Penalty function

$$U(\rho) = \frac{1}{4} \sum_{j=1}^{N} \sum_{k \in N_j} \omega_{jk} \cdot \psi(\rho_j - \rho_k)$$

- Compromise between spatial resolution and noise

Image Quality procedures

- **Specific NEMA procedures for brain imaging do not exist**
- NEMA-like phantom ⟶ NEMA NU4 2008 procedures

NEMA NU 4-2008. ***Performance measurements of Small Animal Positron Emission Tomographs***; National Electrical Manufacturers Association, Rosslyn, VA, 2008.

L. Moliner et al. **NEMA Performance Evaluation of CareMiBrain dedicated brain PET and Comparison with the whole-body and dedicated brain PET systems**. Sci. Rep. 2019, 9, 15484.

Image quality parameters:

- Spatial resolution
- Uniformity
- **R**ecovery **C**oefficient (**RC**)
- **S**pill **O**ver **R**atio (**SOR**)

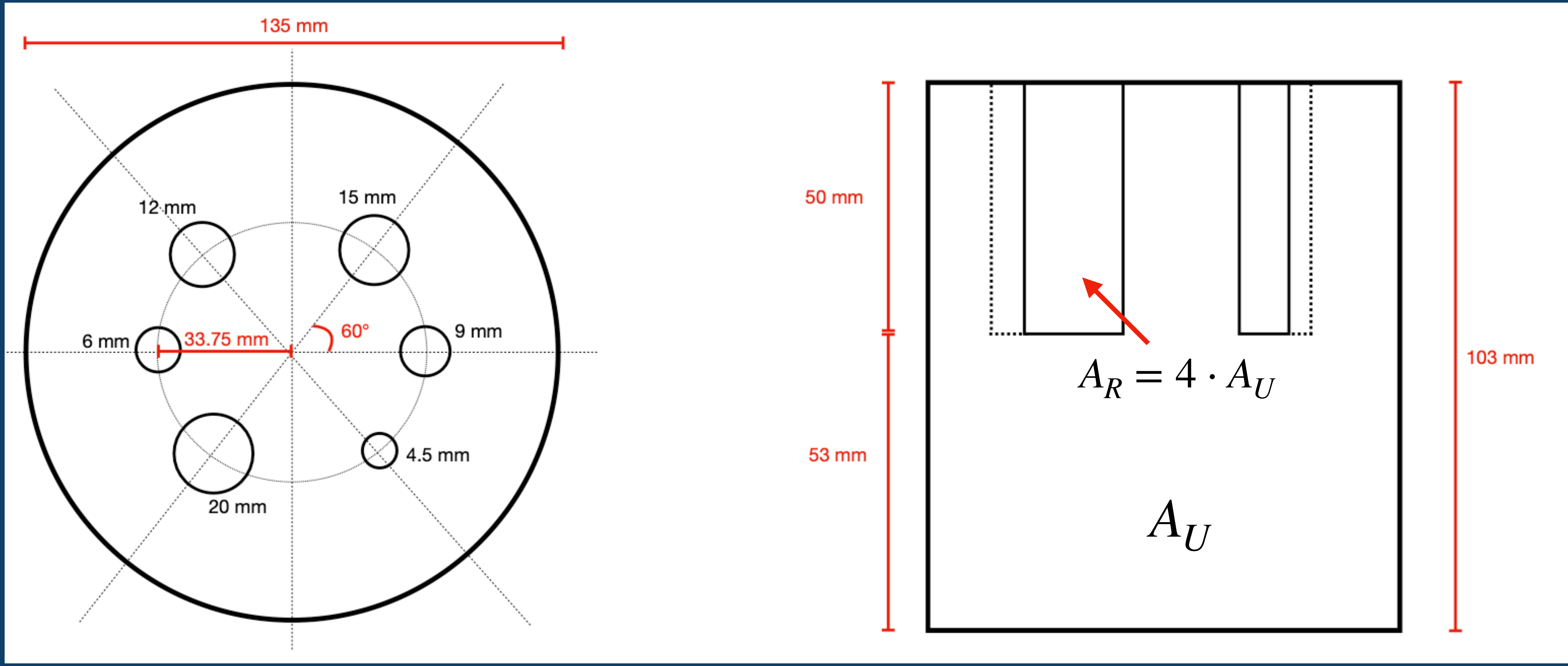
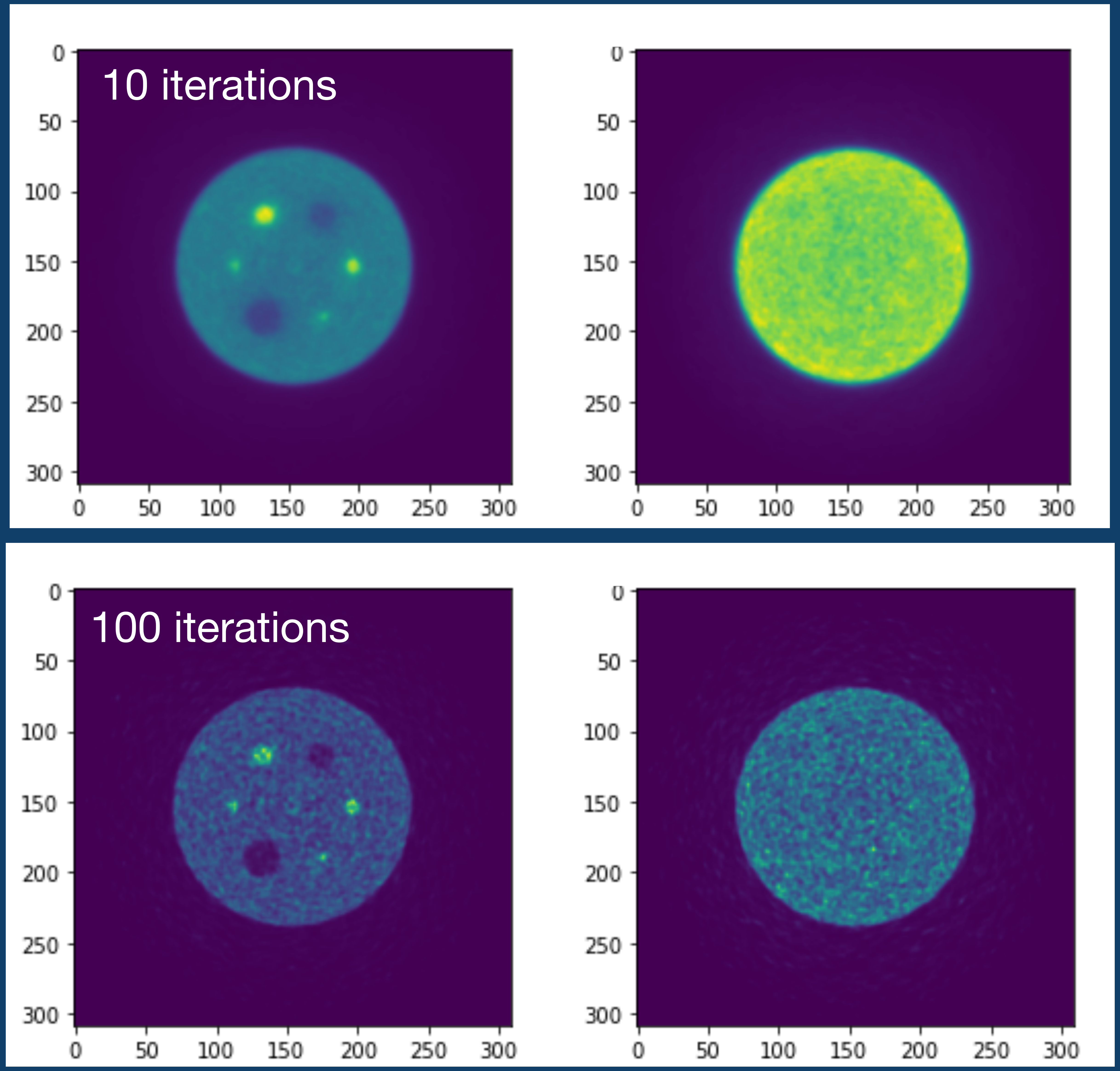


Image Quality procedures



RC and SOR

Ratio between full (RC) and empty (SOR) rods activity and background activity

Uniformity

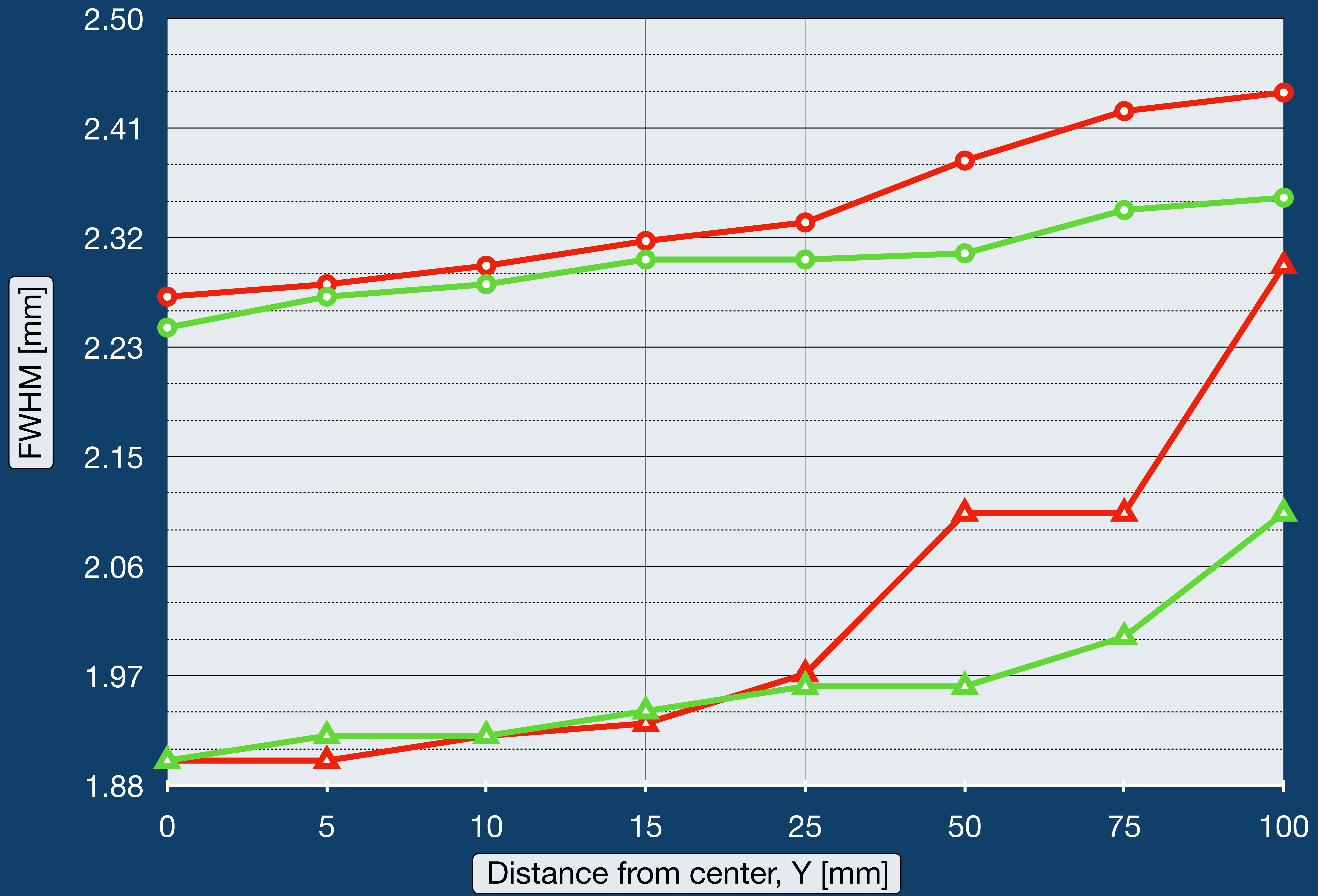
%STD of background region

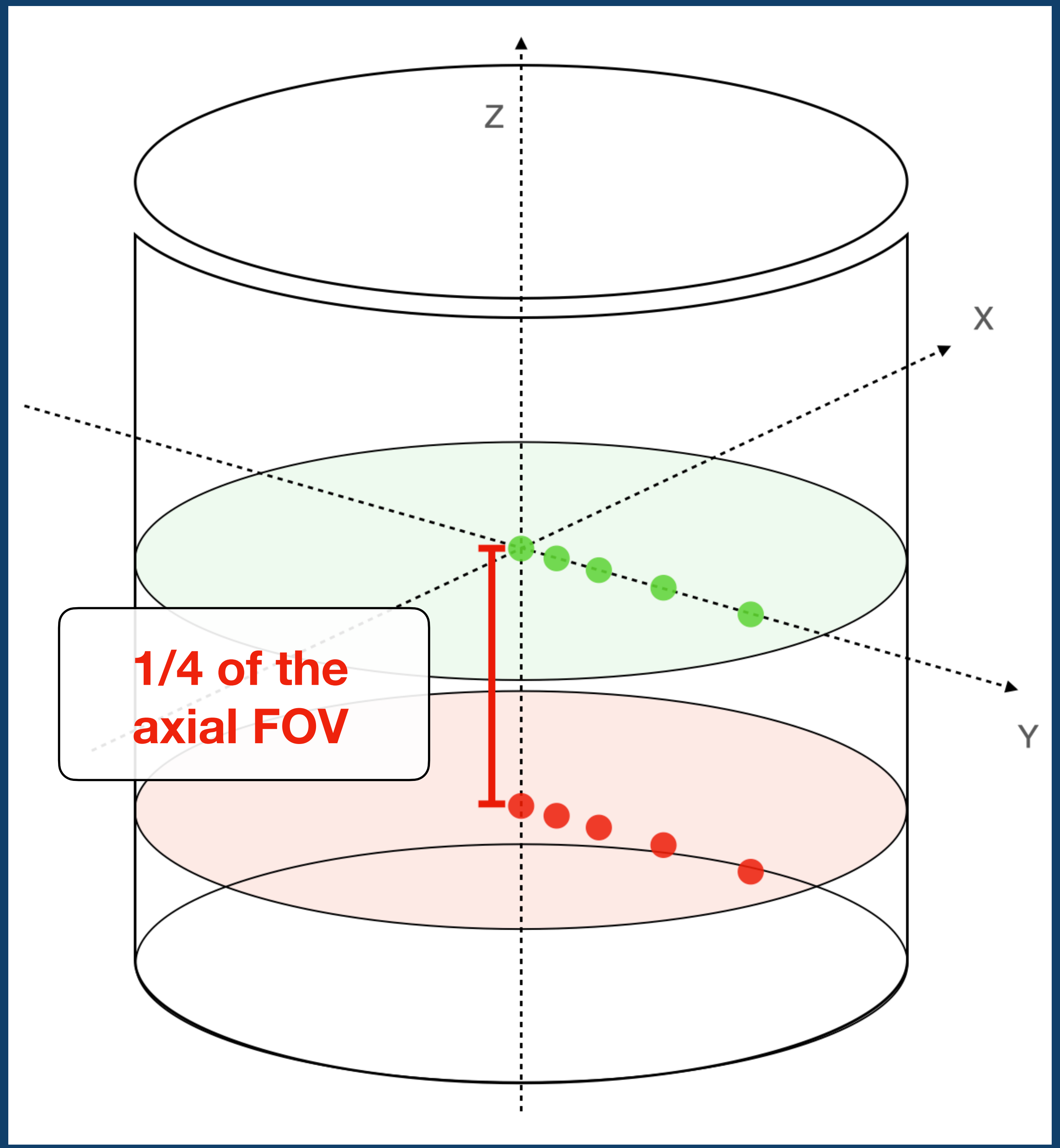
Spatial resolution

FWHM of point sources in predetermined positions in a warm background

K. Gong, S. Cherry and J. Qi. "**On the Assessment of Spatial Resolution of PET Systems with Iterative Image Reconstruction**". In: *Physics in Medicine and Biology* 61 (Feb. 2016), N193.

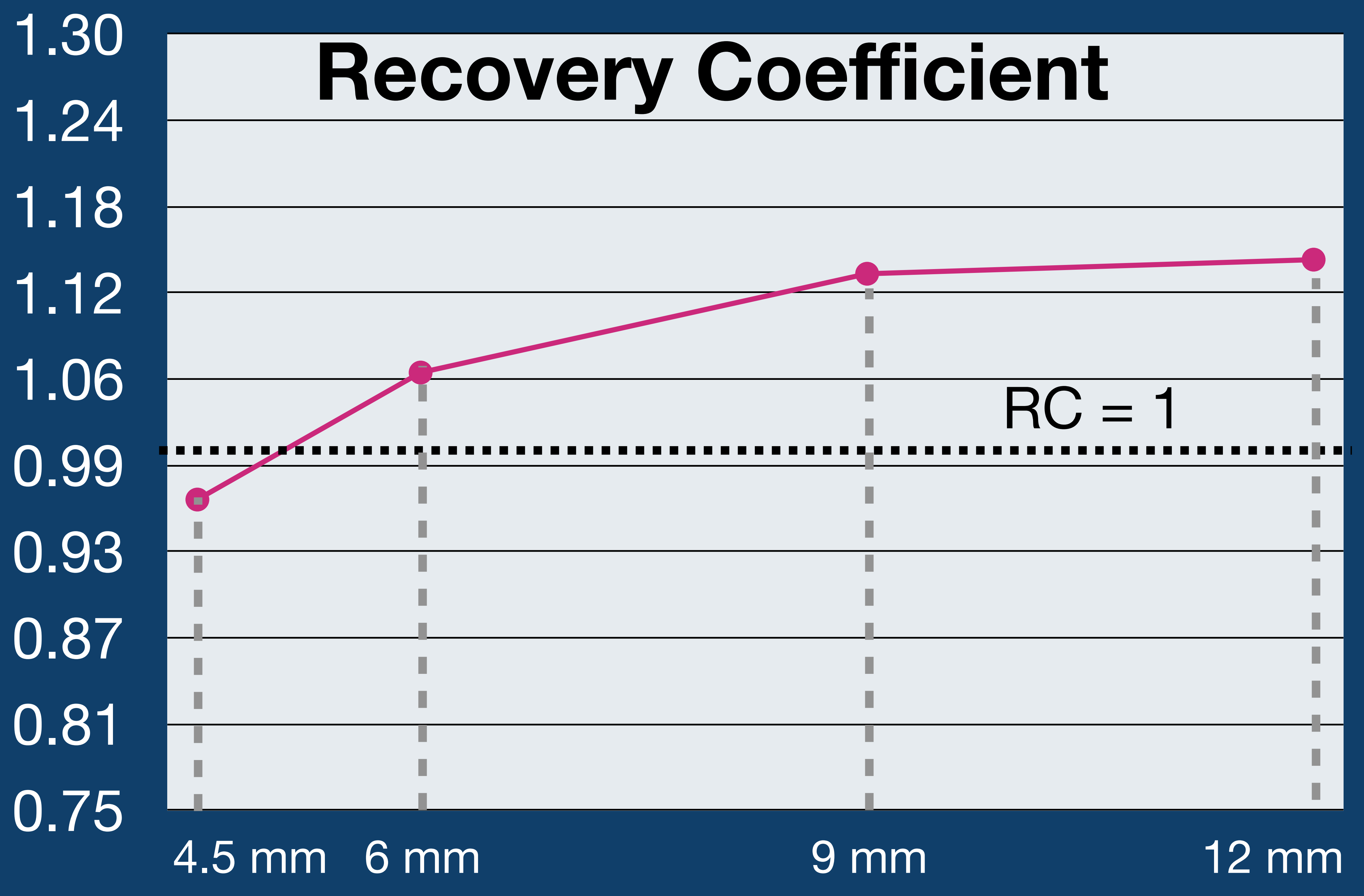
Spatial resolution

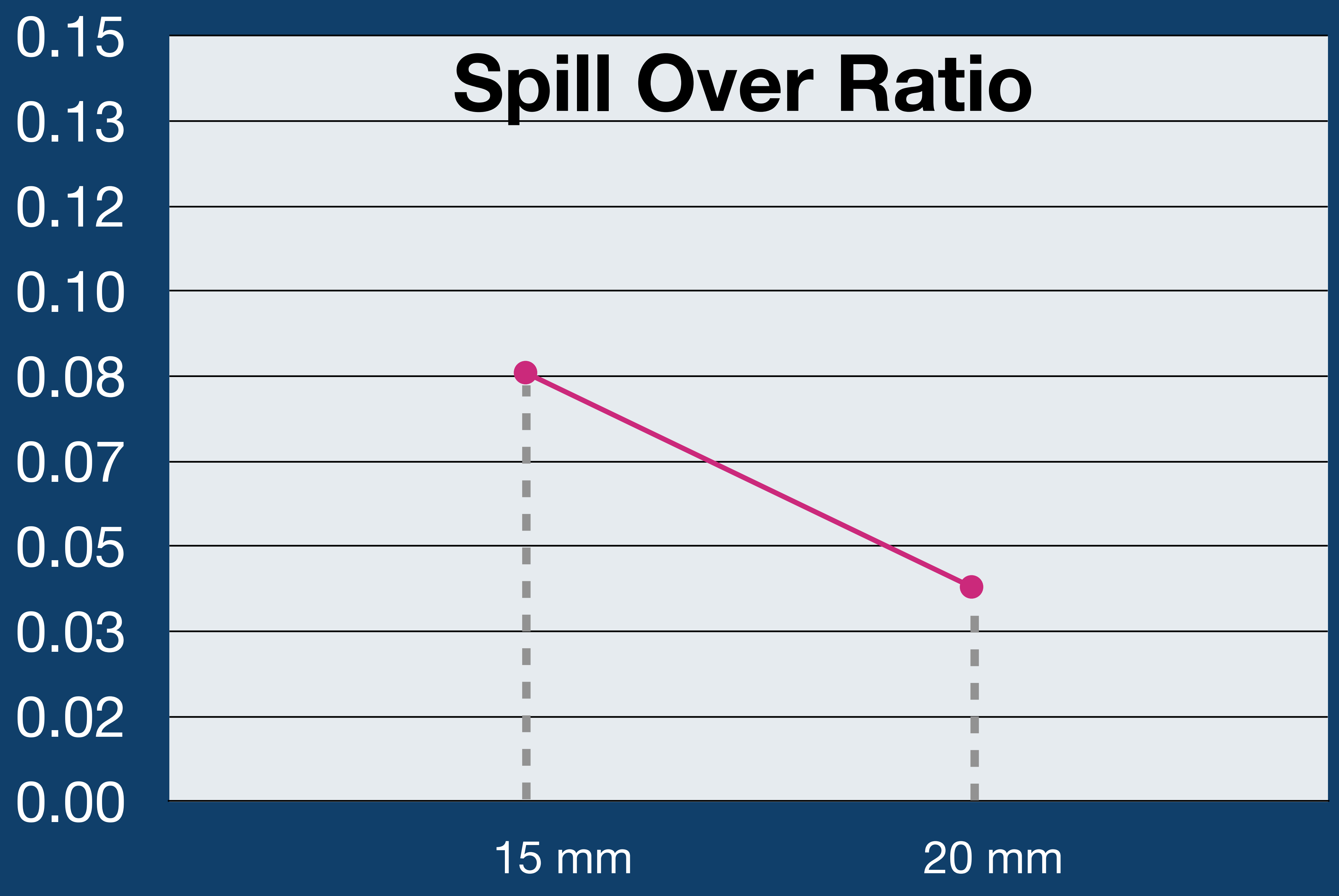




Uniformity, RC and SOR

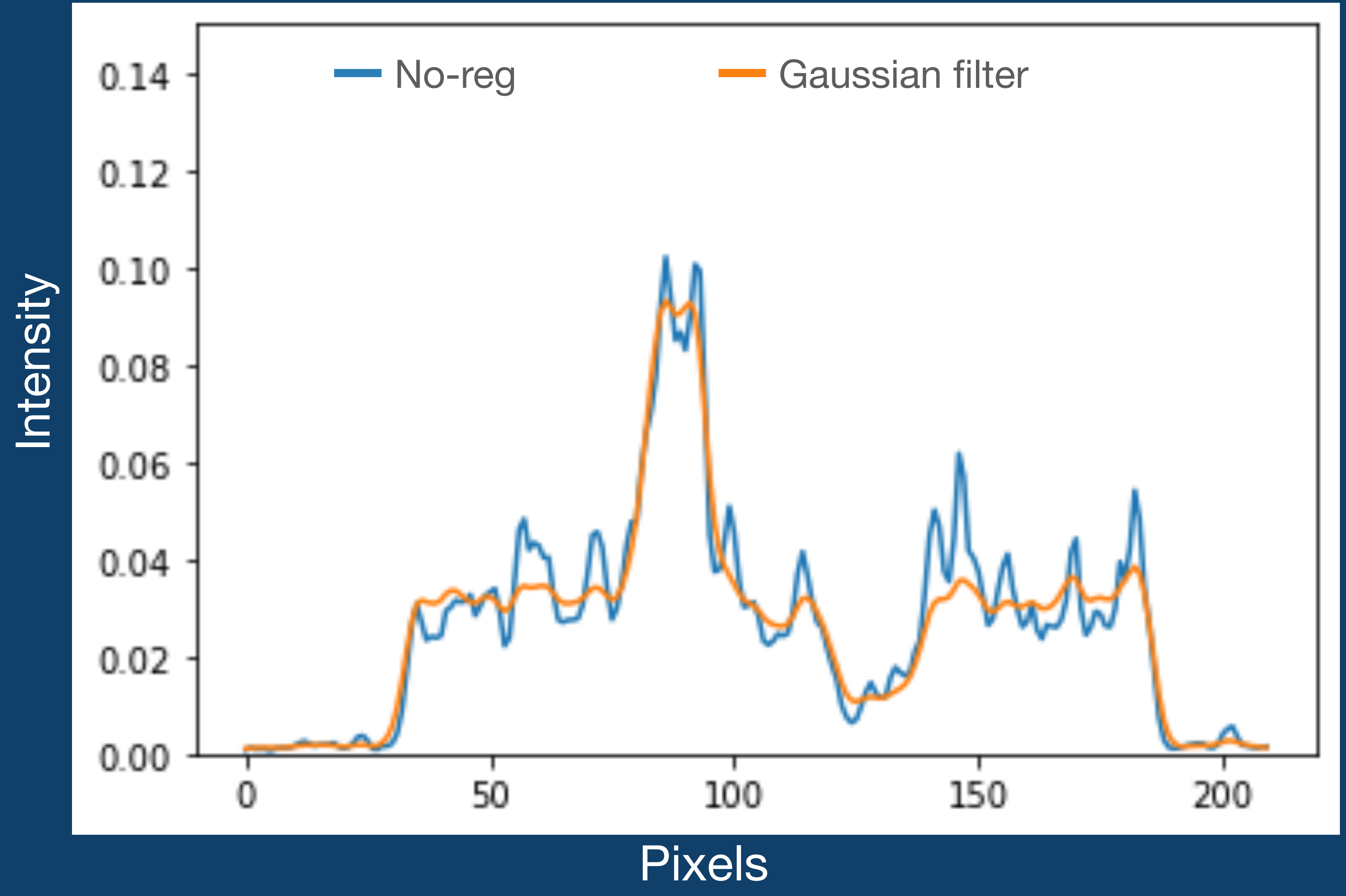
Iteration number	10	20	30	40	50	60	70	80	90	100
Uniformity [%]	4.19	7.01	9.58	11.82	13.96	15.84	17.55	19.13	20.56	21.88

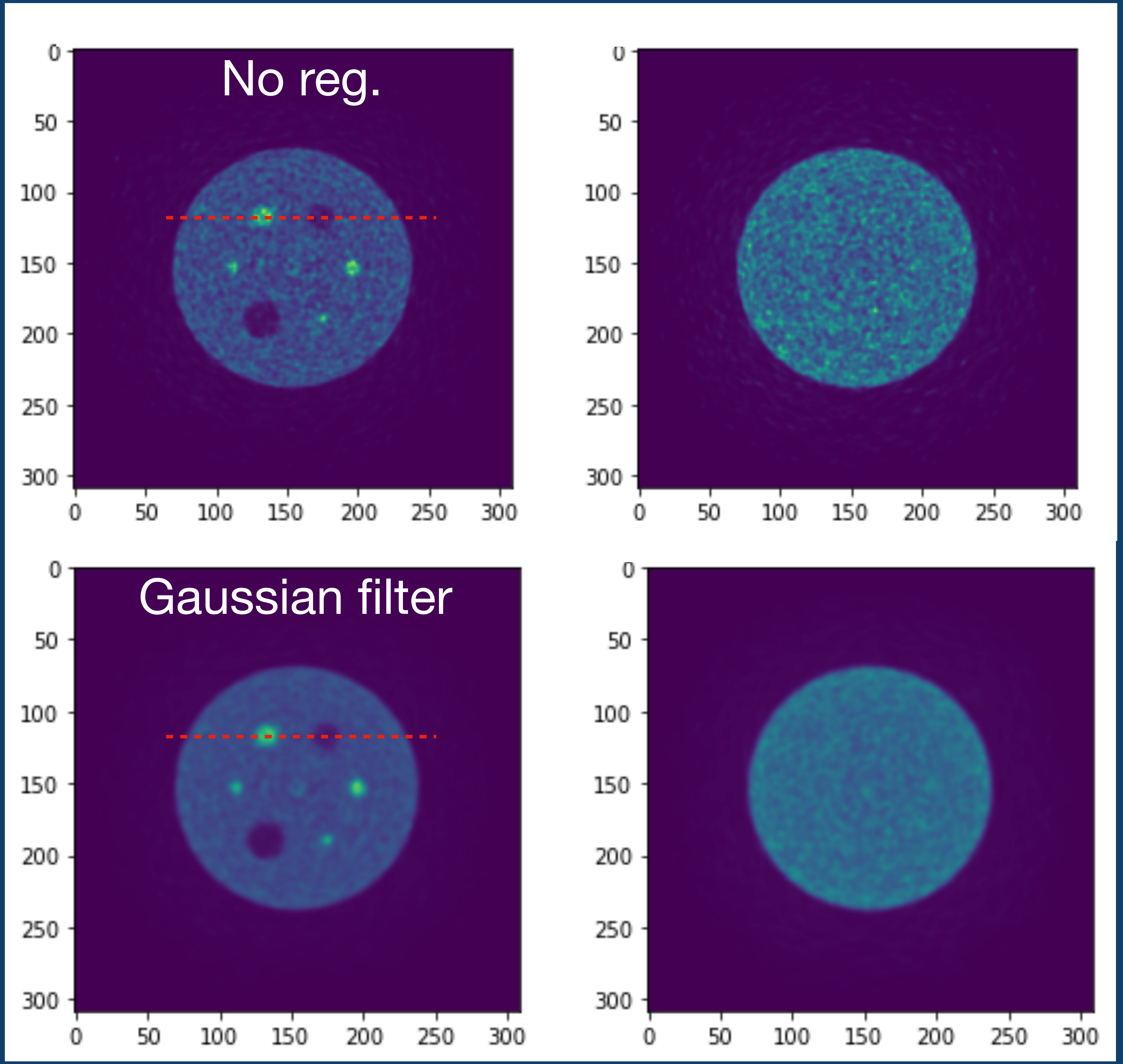




Gaussian filter

- Post smoothing operation
- Easy to implement
- Fastest method

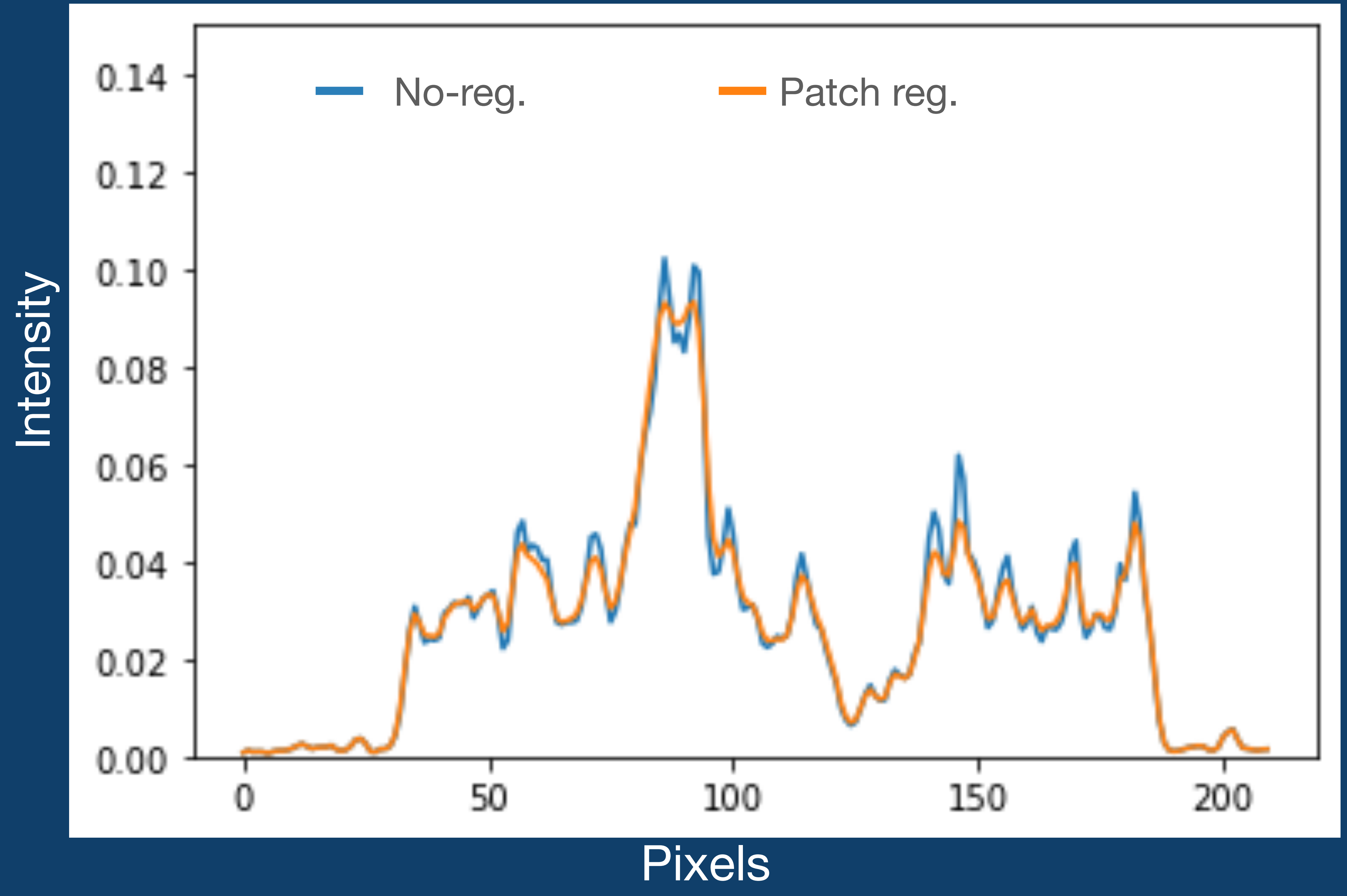


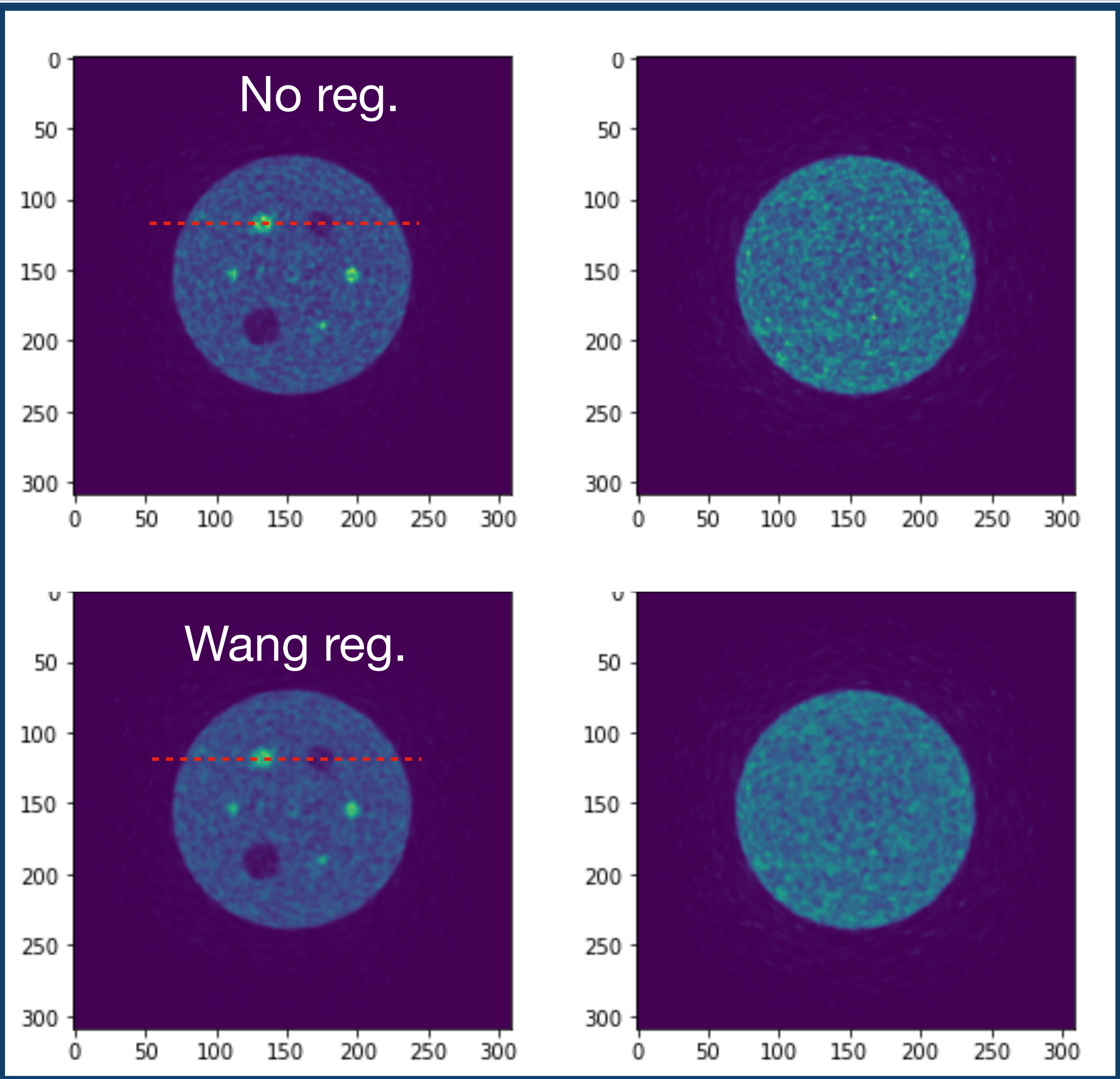


Patch-based regularization

G. Wang, J. Qi **Penalized likelihood PET image reconstruction using patch-based edge-preserving regularization**. *IEEE Trans. Med. Imaging 2012*, *31*, 2194–2204.

Good edge preserving and noise control



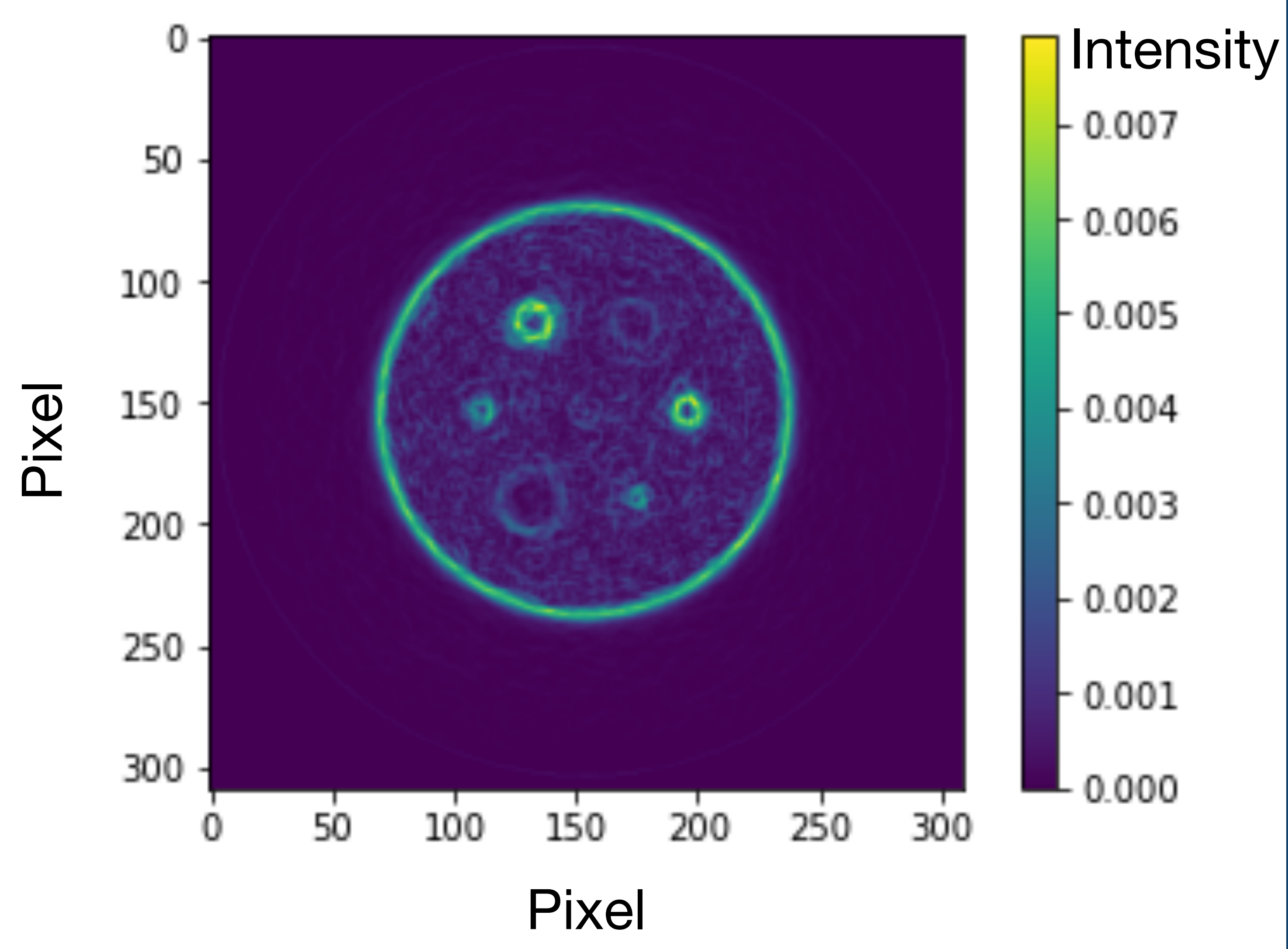


Gradient-based regularization

- Two steps
  - Noise reduction
  - Feature restoration

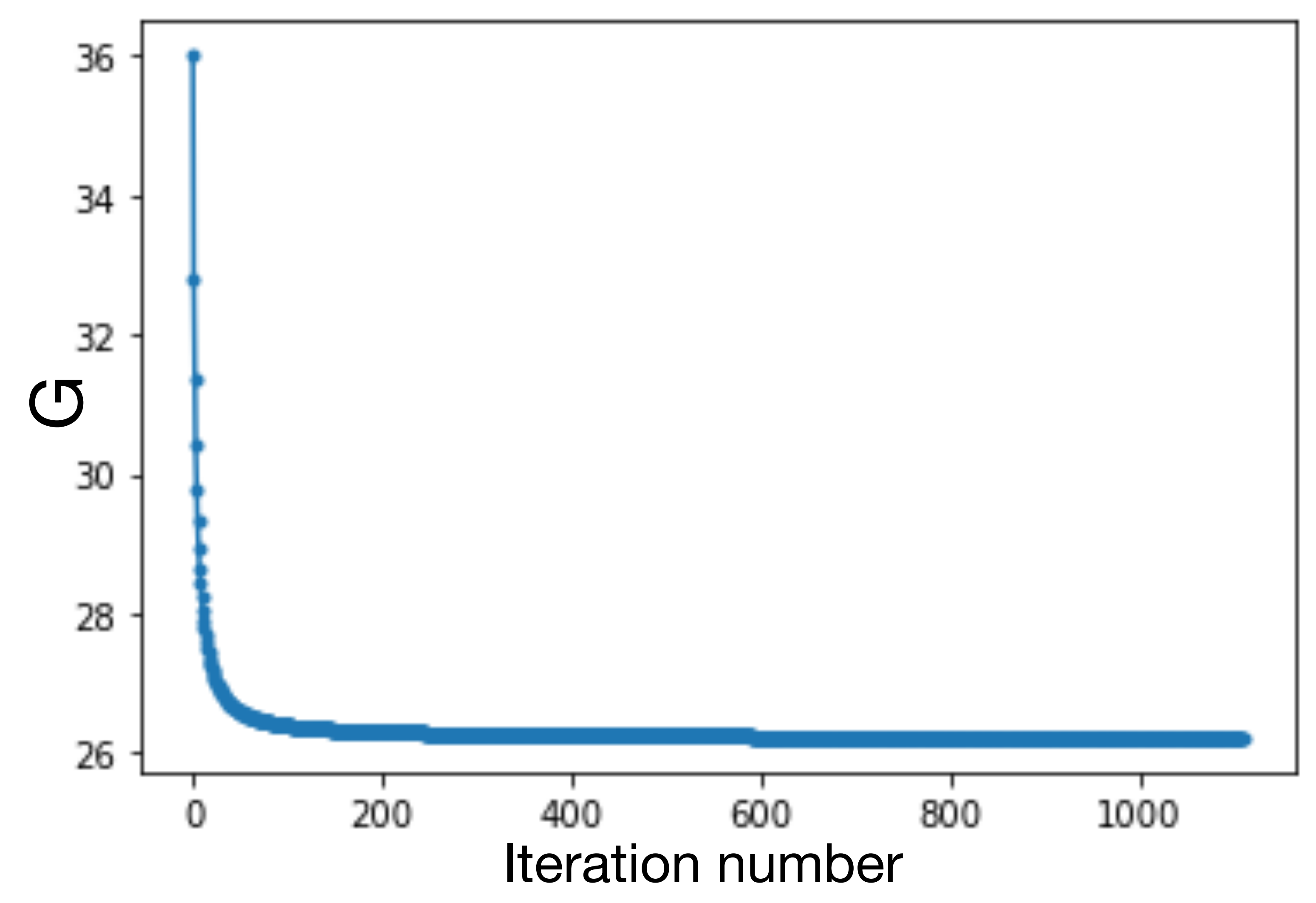
$$\rho' = \frac{\boxed{\rho - \alpha \cdot V}}{\boxed{\beta \cdot N + 1}}$$

Differences



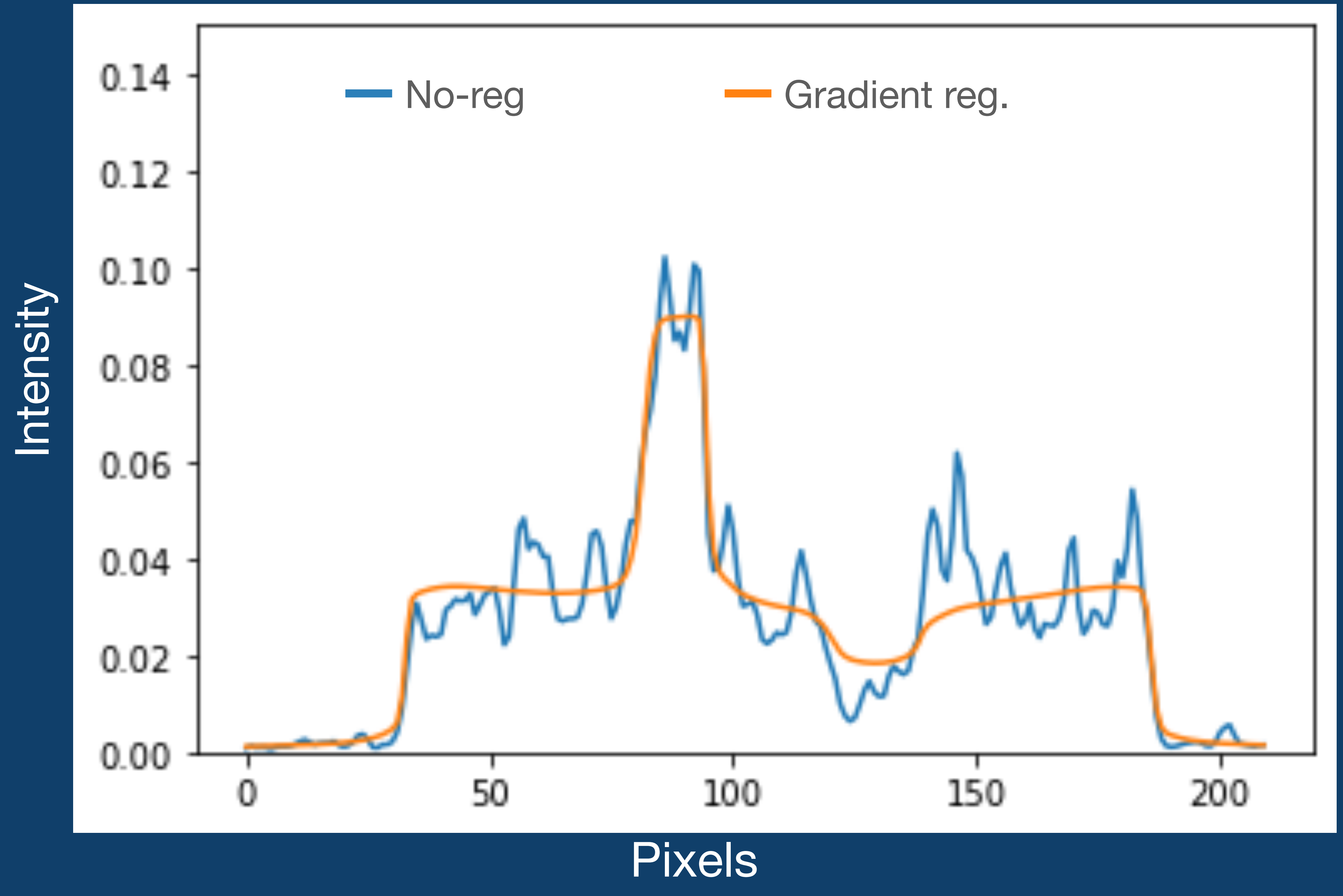
$$N = \sqrt{(\rho_{x+1,y} - \rho_{x,y})^2 + (\rho_{x,y+1} - \rho_{x,y})^2}$$

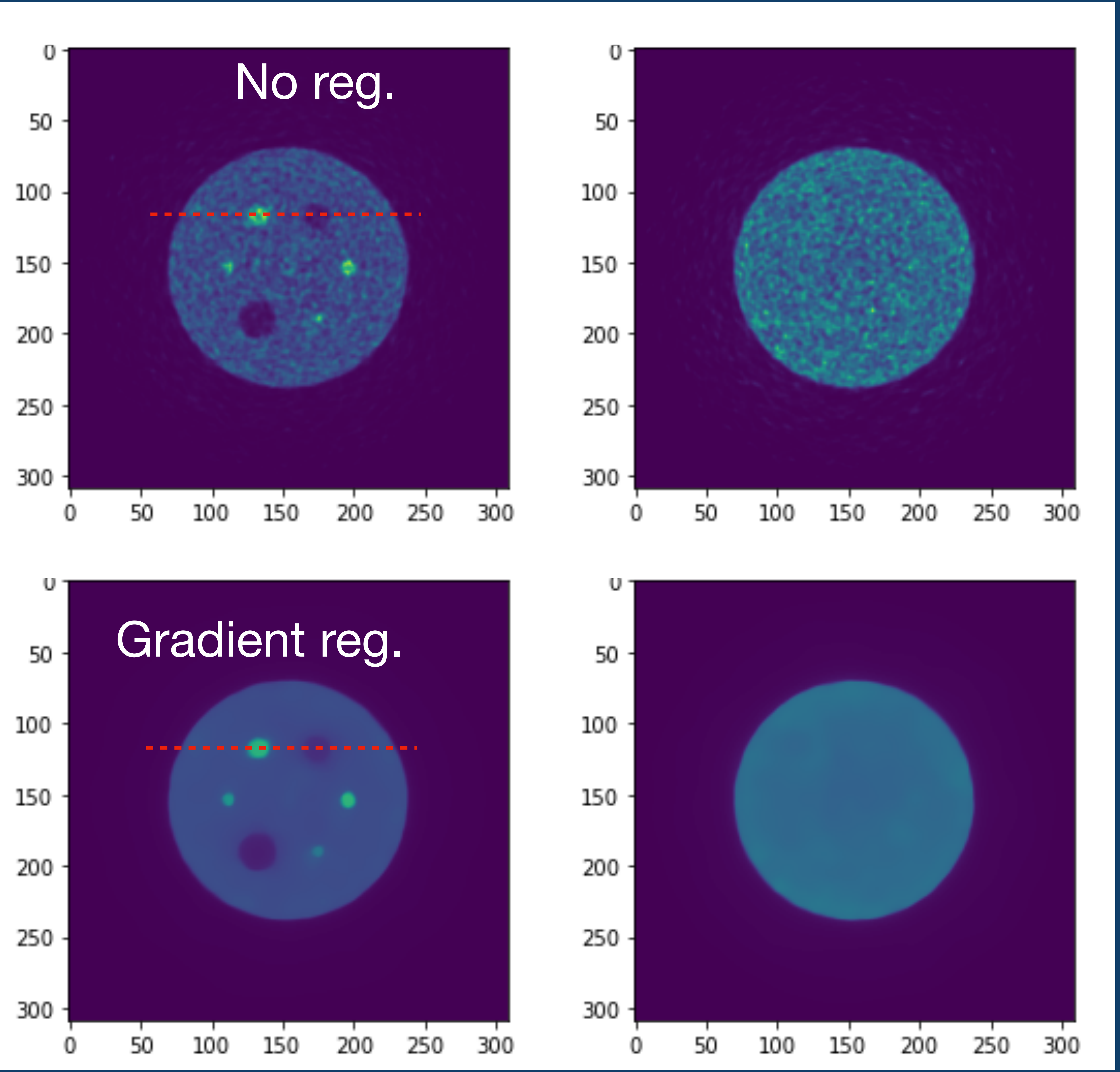
$$G = \frac{\sum_{x,y}(N)}{len(N)}$$



Gradient-based regularization

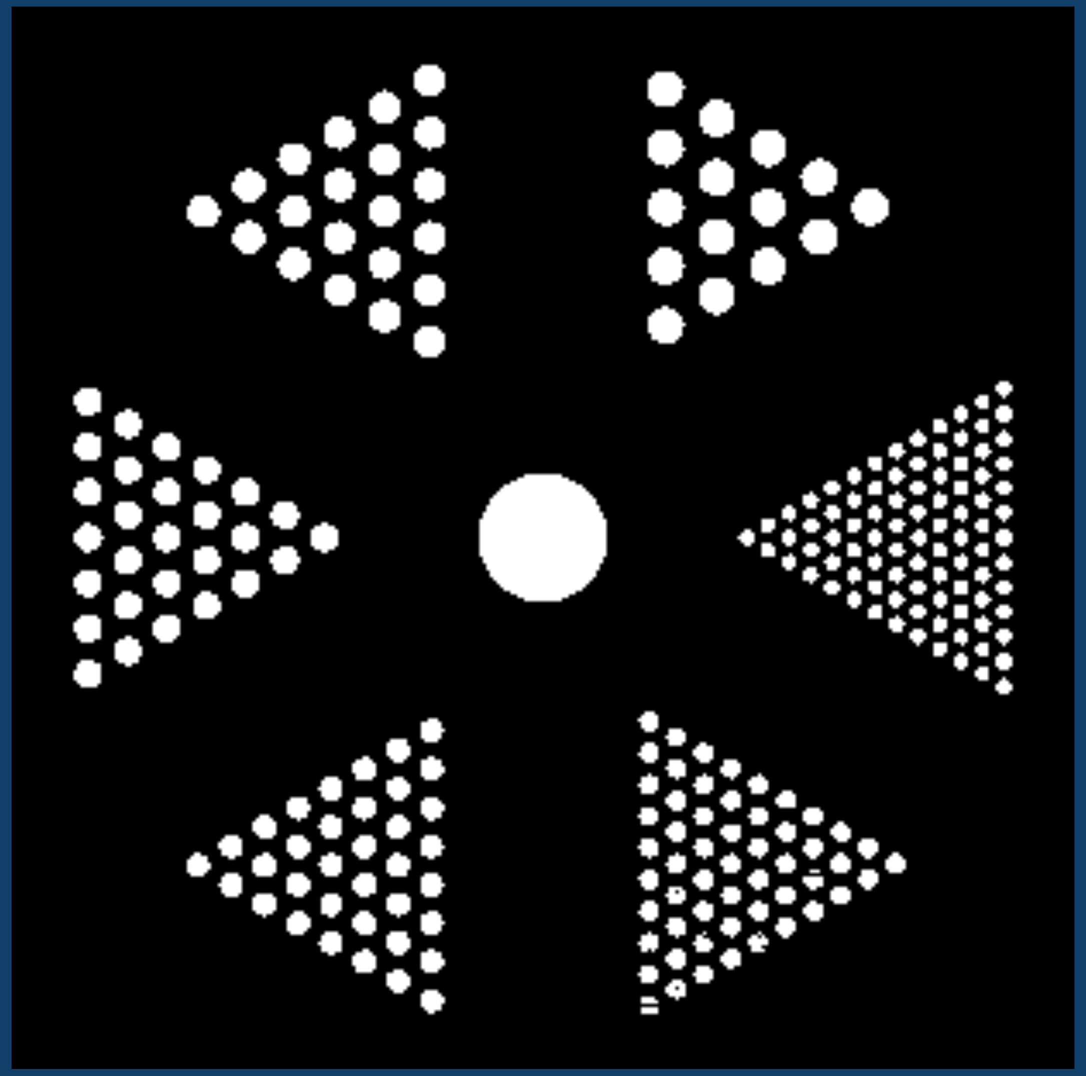
- Removes noise effectively
- Faster than Patch reg. algorithm
- Good edge preservation



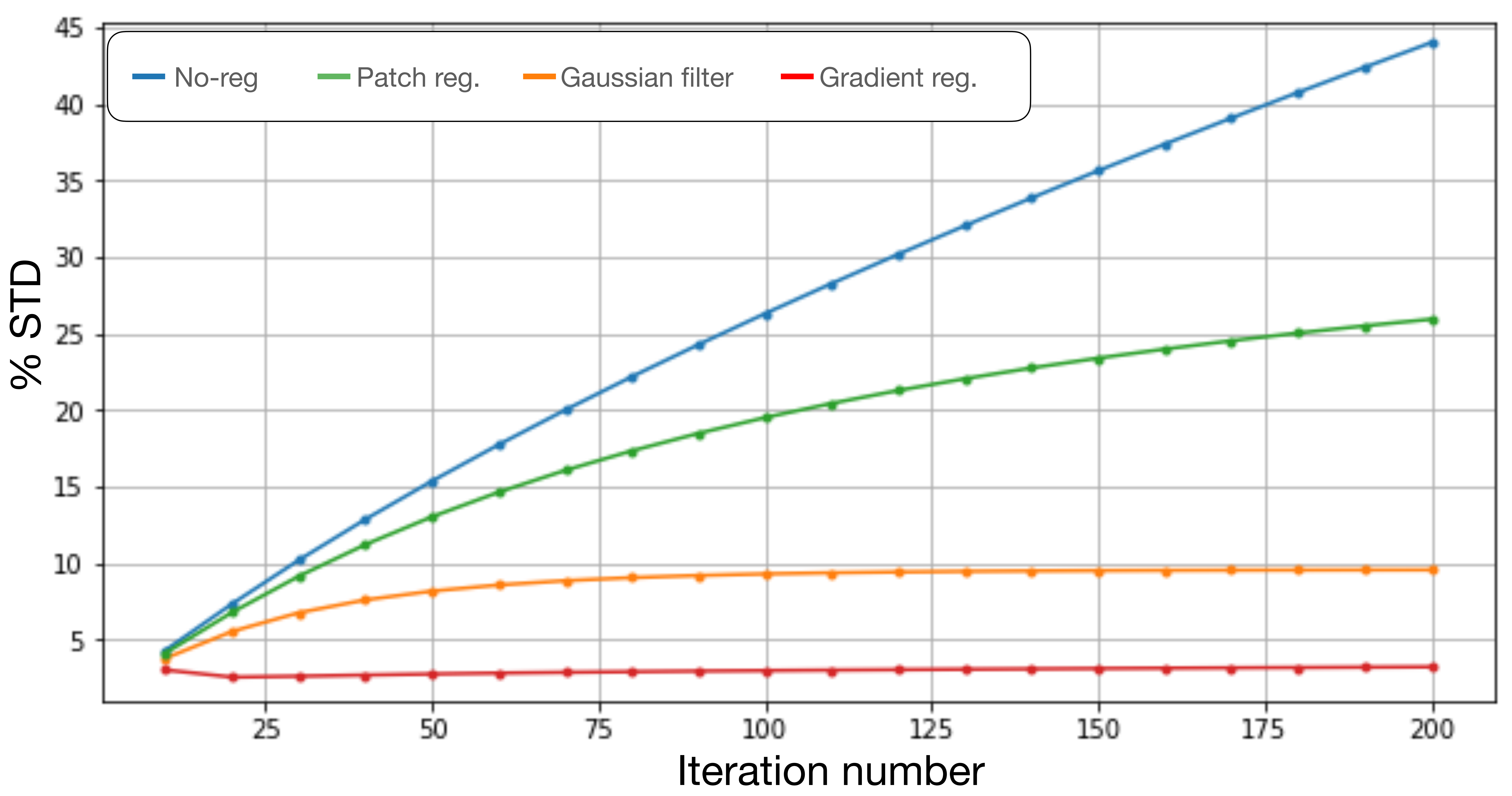


Spatial resolution

- Unable to perform the NEMA procedure
- Derenzo phantom with radius from 1.8 mm to 5.3 mm



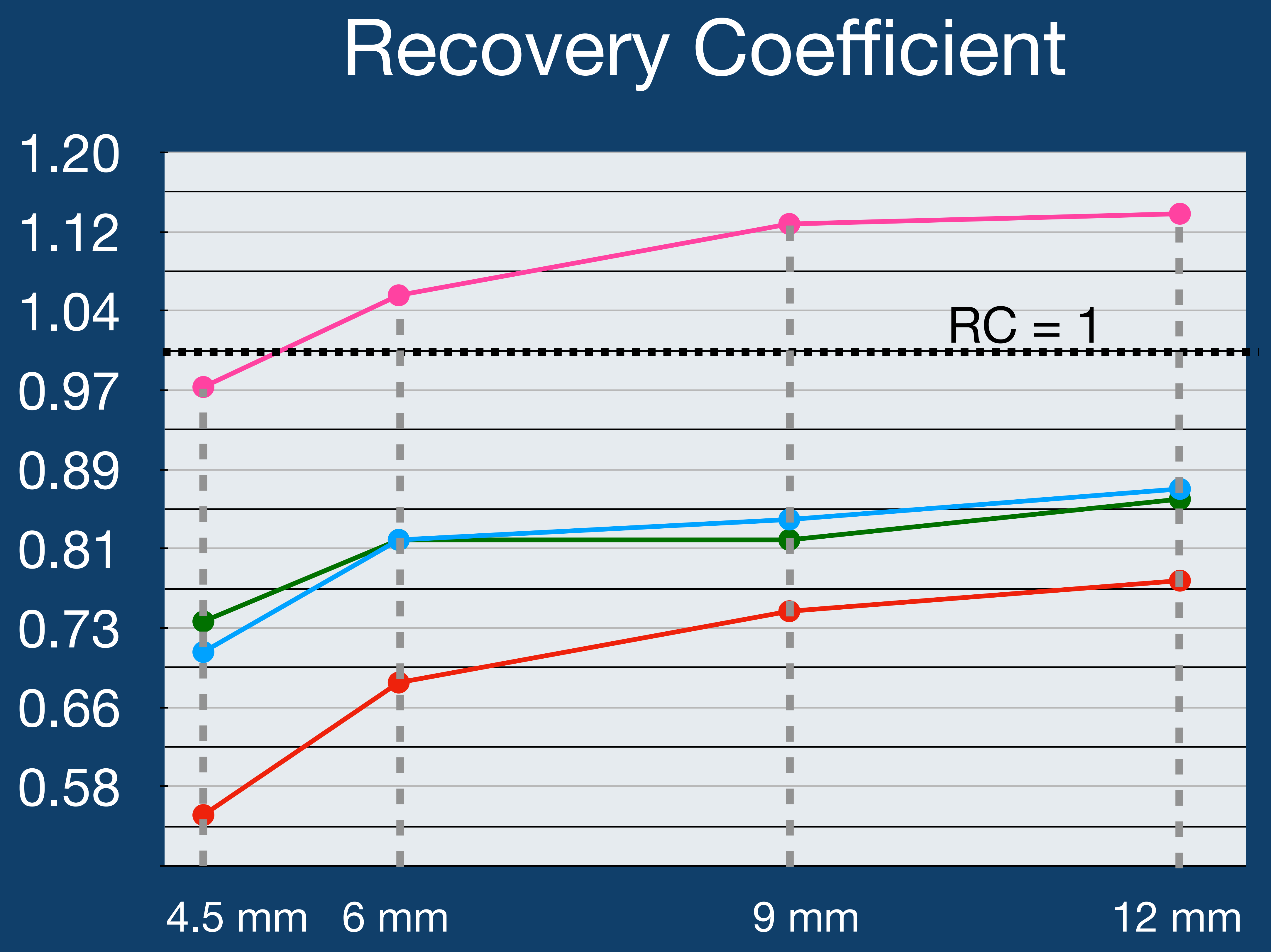
Uniformity

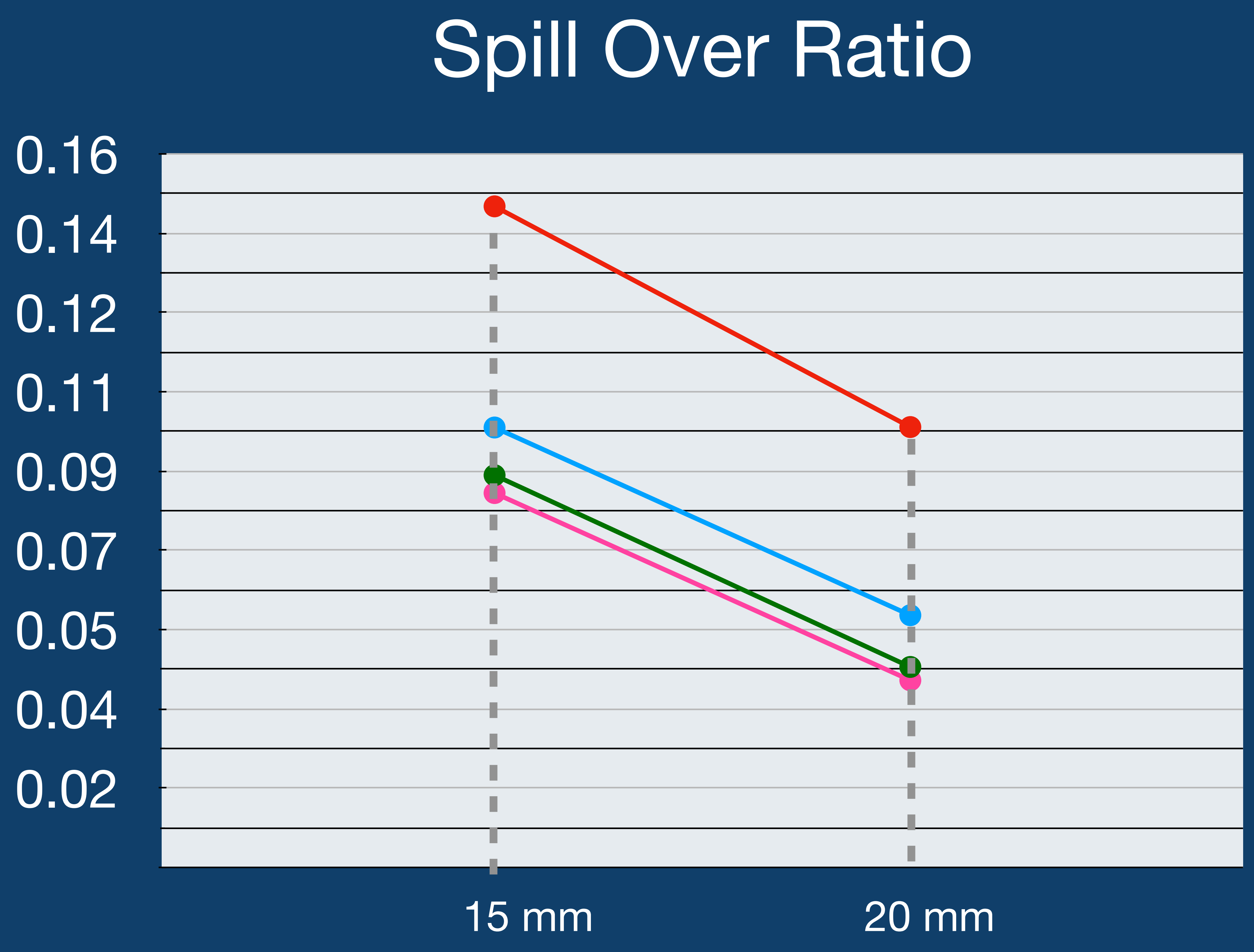


Increasing of noise

Convergence of noise

RC and SOR


Recovery Coefficient
1.20
1.12
1.04
0.97
0.89
0.81
0.73
0.66
0.58
RC = 1
4.5 mm
6 mm
9 mm
12 mm


Spill Over Ratio
0.16
0.14
0.12
0.11
0.09
0.07
0.05
0.04
0.02
15 mm
20 mm


Gaussian filter
Patch reg.
Gradient reg.
No reg.

Conclusions

- We obtained good results in terms of hardware system performance

Sensitivity	7.6% EW [350-650 keV]
MAX NECR curve	63.4 kcps @ 13 MBq
SF	21.29%

- The main IQ results needs some sort of regularization

Noise	21.88%
Spatial resolution	$\simeq$ 2.3 mm
RC	0.97 (smallest rod)
SOR	0.042 (air rod), 0.084 (water rod)

- Regularization is a compromise between noise and spatial resolution

The best available seems to be the **patch-based regularization** but the ability of reducing the noise makes the **gradient-based regularization** very auspicable for low activity dynamic imaging

Future work

◉ Improve the reconstruction software	The inclusion of Detector matrix **D** will improve the image quality
◉ Improve the gradient-based regularization	Changing the parameters in terms of iteration (not just fixed numbers), try different voxel sizes
◉ Need to perform Hoffman phantom simulations and reconstruction	Using a brain phantom to understand better the outcome of the regularising techniques
◉ Implementation of regularization by using AI	That's a good idea!

Thank you for your attention

Backup slides

Patch-based regularization

Energy function

$$U(\rho) = \frac{1}{4}\sum_{j=1}^{N}\sum_{k\in N_j}\omega_{jk}\cdot\psi(\rho_j-\rho_k)$$

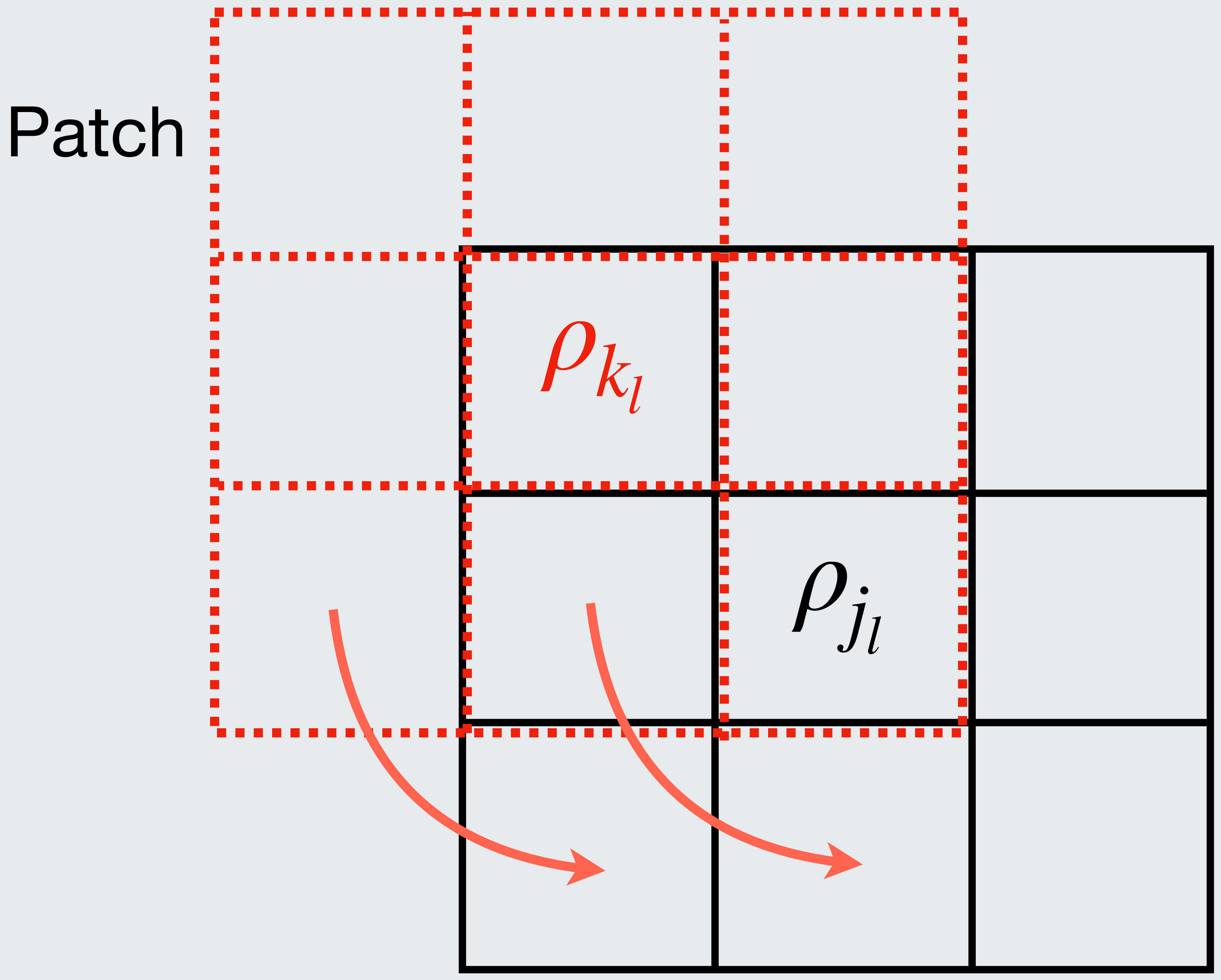
$$U(\rho) = \frac{1}{4}\sum_{j=1}^{N}\sum_{k\in N_j}\psi(||f_j(\rho)-f_k(\rho)||_h,\delta)$$

Patch-based distance

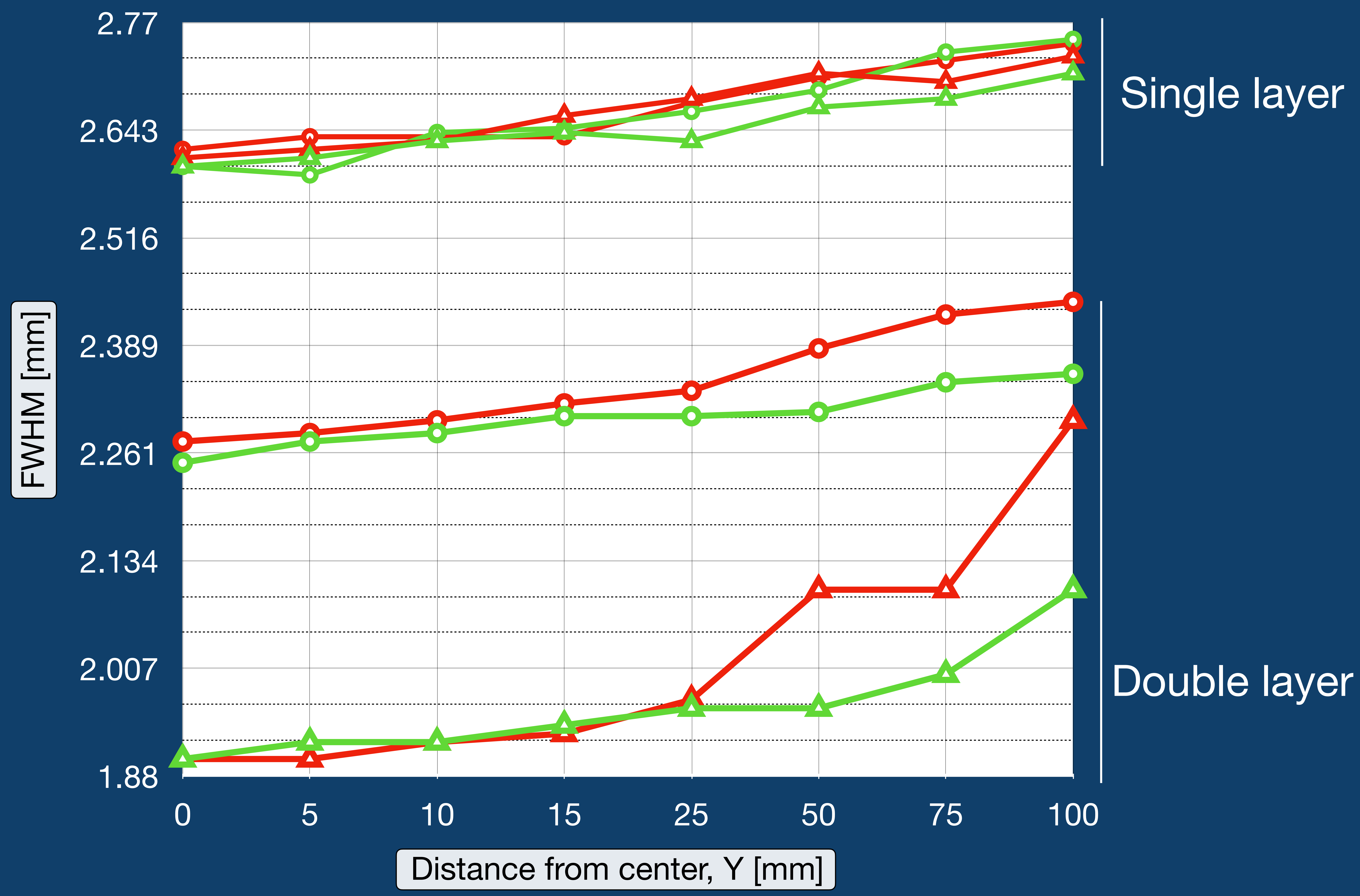
$$||f_j(\rho)-f_k(\rho)||_h = \sqrt{\sum_{l=1}^{n_l}h_l(\rho_{j_l}-\rho_{k_l})^2}$$

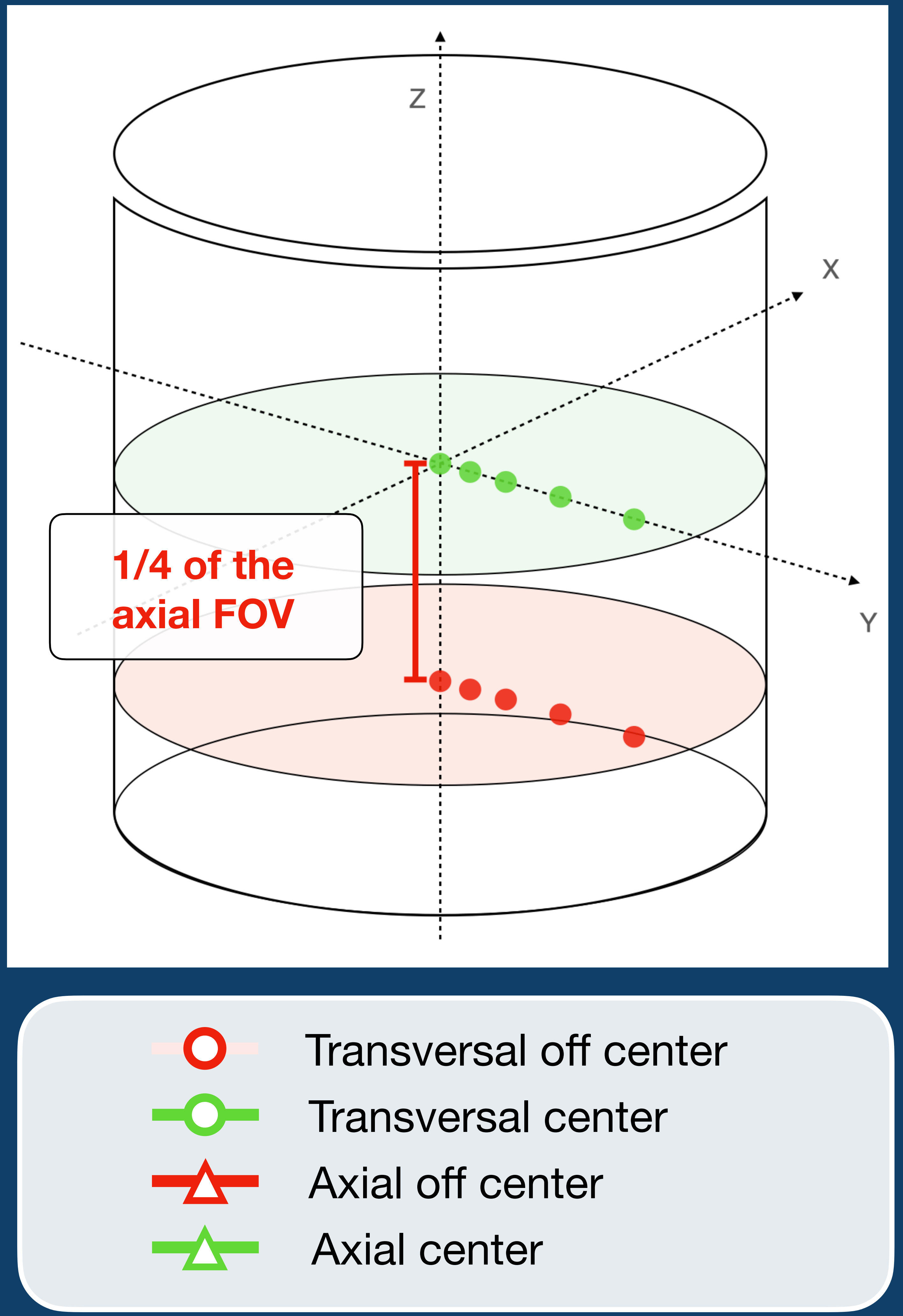
- Use of patches instead of single pixels

$$\Omega(\rho,n) = \log L(\rho,n) - \beta U(\rho)$$



Spatial resolution





PET reconstruction - iterative methods

Reconstruction process

Recover spatial distribution of radiotracer ρ starting from registered events n

$$n = S \times \rho$$

Iterative methods

- Model of the physics and the measurement uncertainty
- Set of basis function (voxel)
- Objective function (log-likelihood function)
- Numerical algorithm (EM)

MLEM (Maximun Likelihood Expectation Maximization)

$$\rho^{k+1} = \frac{\rho^k}{Sens} S^T \left(\frac{n}{S \times \rho^k} \right)$$

- Ratio (correction)
- Backprojection
- Normalization
- Apply correction