

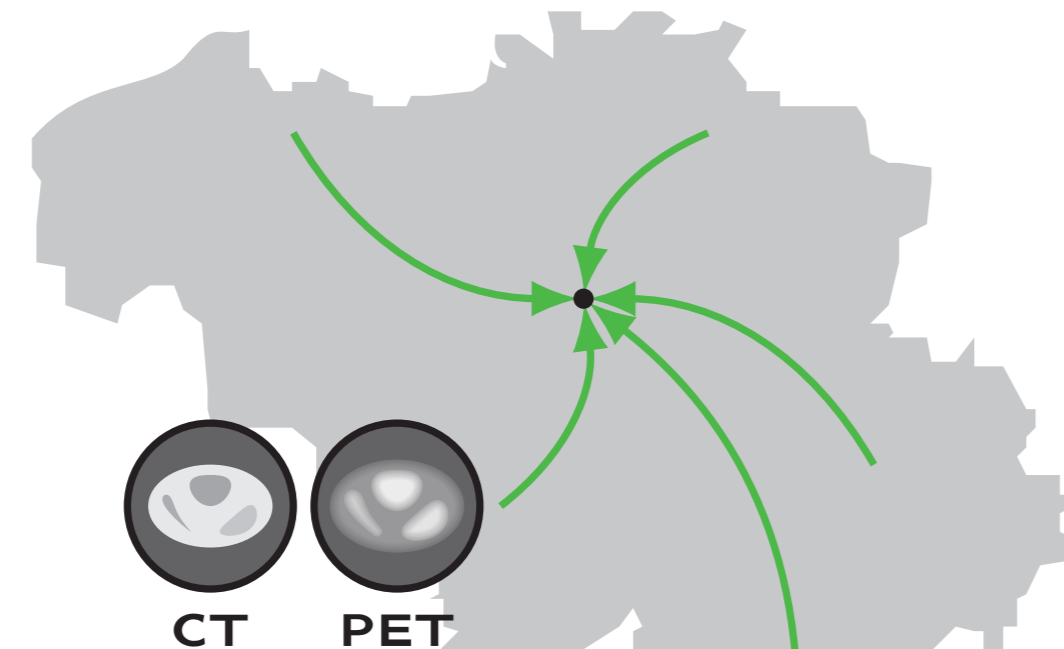
Blind Deconvolution of PET Images using Anatomical Priors

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Goal. Improvement of the quality of positron emission tomography (PET) images for a better delineation of tumor volumes.

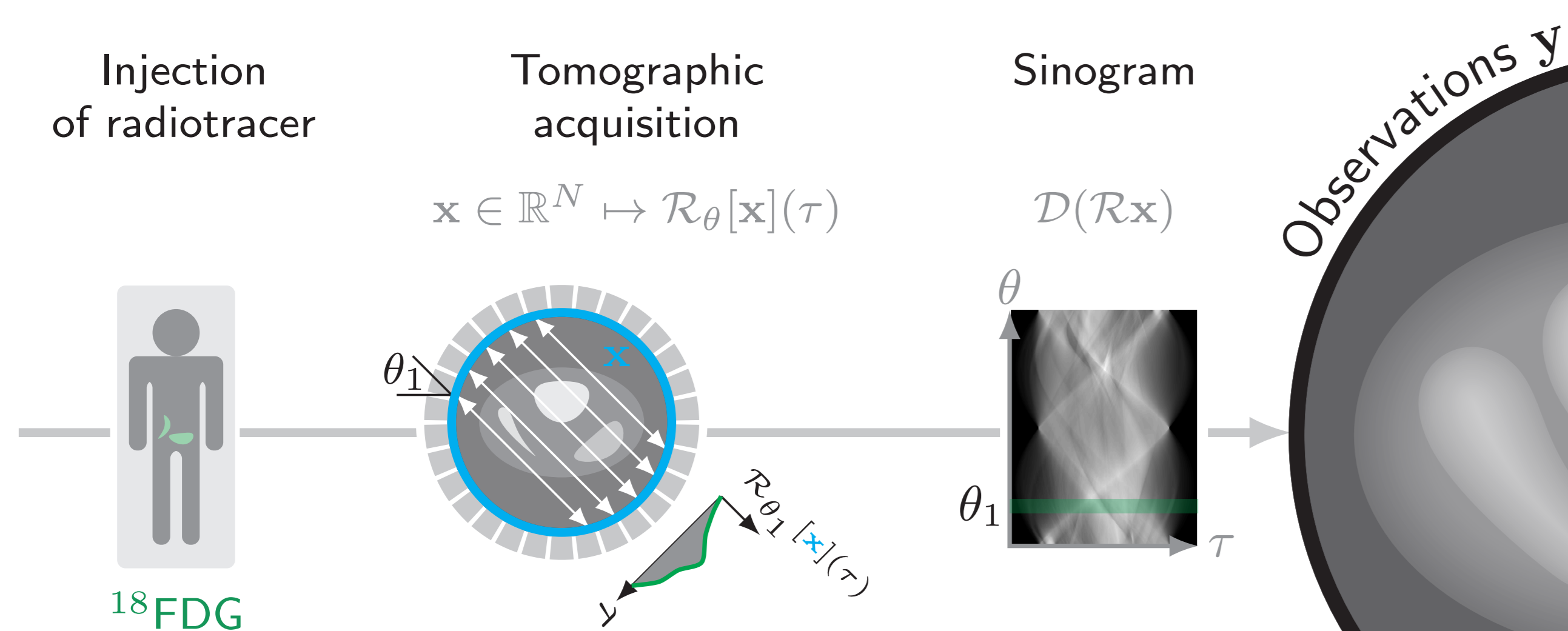
Context. Access to reconstructed images from different clinical centres and raw anatomical images from combined PET/CT scanners.



Challenge. No access to scanners properties (e.g., the point spread function) and raw PET data.

Acquisition process

External and internal factors degrade the image resolution.



Forward model

$$y = h \otimes x + \eta$$

Assumptions

- $h \in \mathbb{R}^N$: unknown convolution operator (linear and uniform)
- $\eta \in \mathbb{R}^N$: additive, white and Gaussian noise

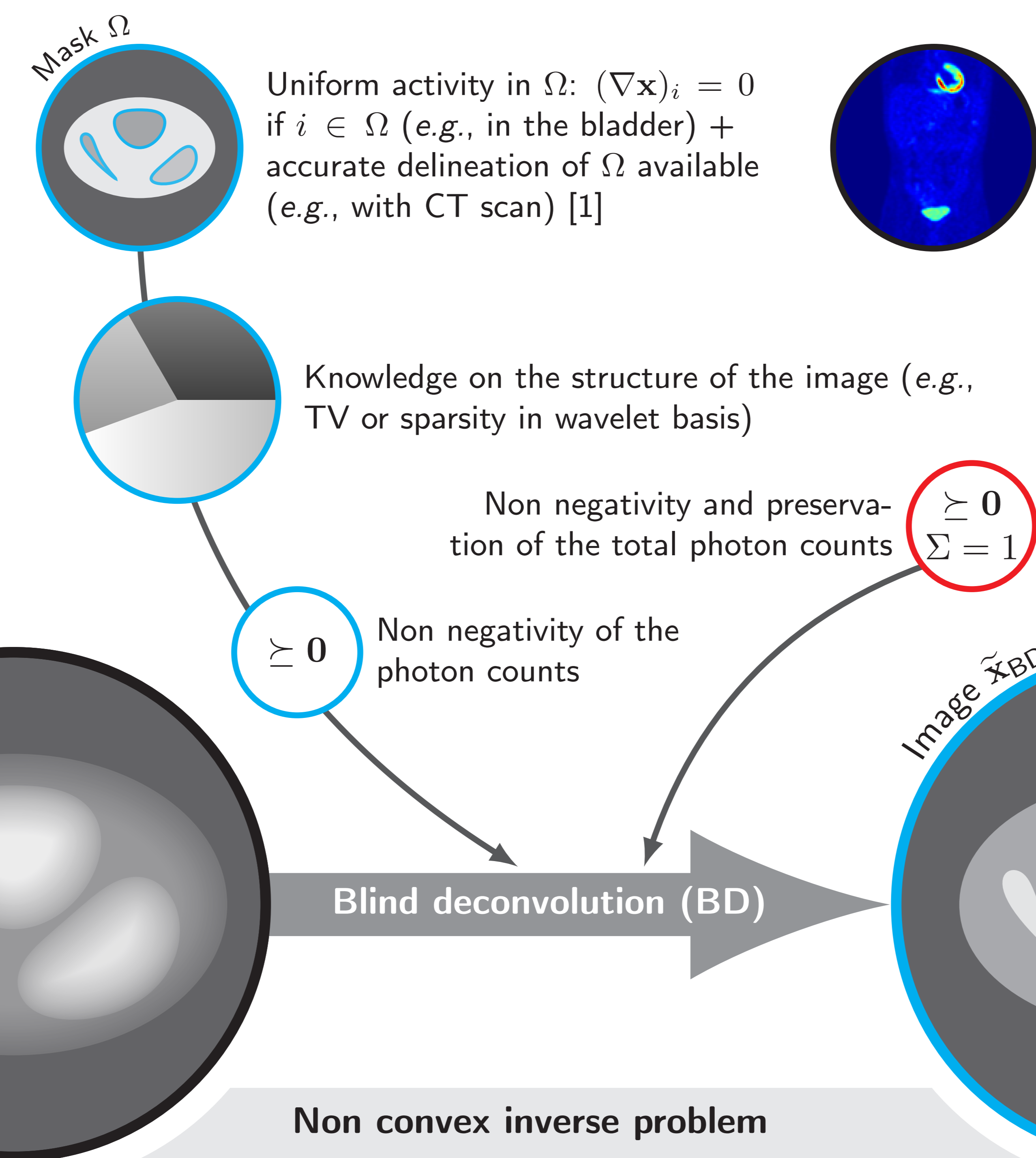
How to simultaneously estimate h and restore image x from y ?

Main references

- [1] A. González, V. Delouille and L. Jacques, "Non-parametric PSF estimation from celestial transit solar images using blind deconvolution," *J. SpaceWeather Space Clim.*, 6(A1), 2016.
 [2] A. Chambolle and T. Pock, "A First-Order Primal-Dual Algorithm for Convex Problems with Applications to Imaging," *Journal of Mathematical Imaging and Vision*, 40(1):120-145, 2010.
 [3] H. Attouch, J. Bolte, P. Redont and A. Soubeyran, "Proximal Alternating Minimization and Projection Methods for Nonconvex Problems: An Approach Based on the Kurdyka-Łojasiewicz Inequality," *Math. Oper. Res.*, 35(2):438-457, 2010.



Prior knowledge on the image and the PSF



Blind deconvolution (BD)

Non convex inverse problem

$$\begin{aligned} & \underset{x, h}{\text{minimize}} && \frac{\rho}{2} \|h \otimes x - y\|_2^2 + \text{TV}(x) \\ & \text{subject to} && (\nabla x)_i = 0 \quad \text{if } i \in \Omega_1, \Omega_2, \dots, \\ & && x \succeq 0, \quad h \succeq 0, \quad \sum_{i=1}^N |h_i| = 1. \end{aligned}$$



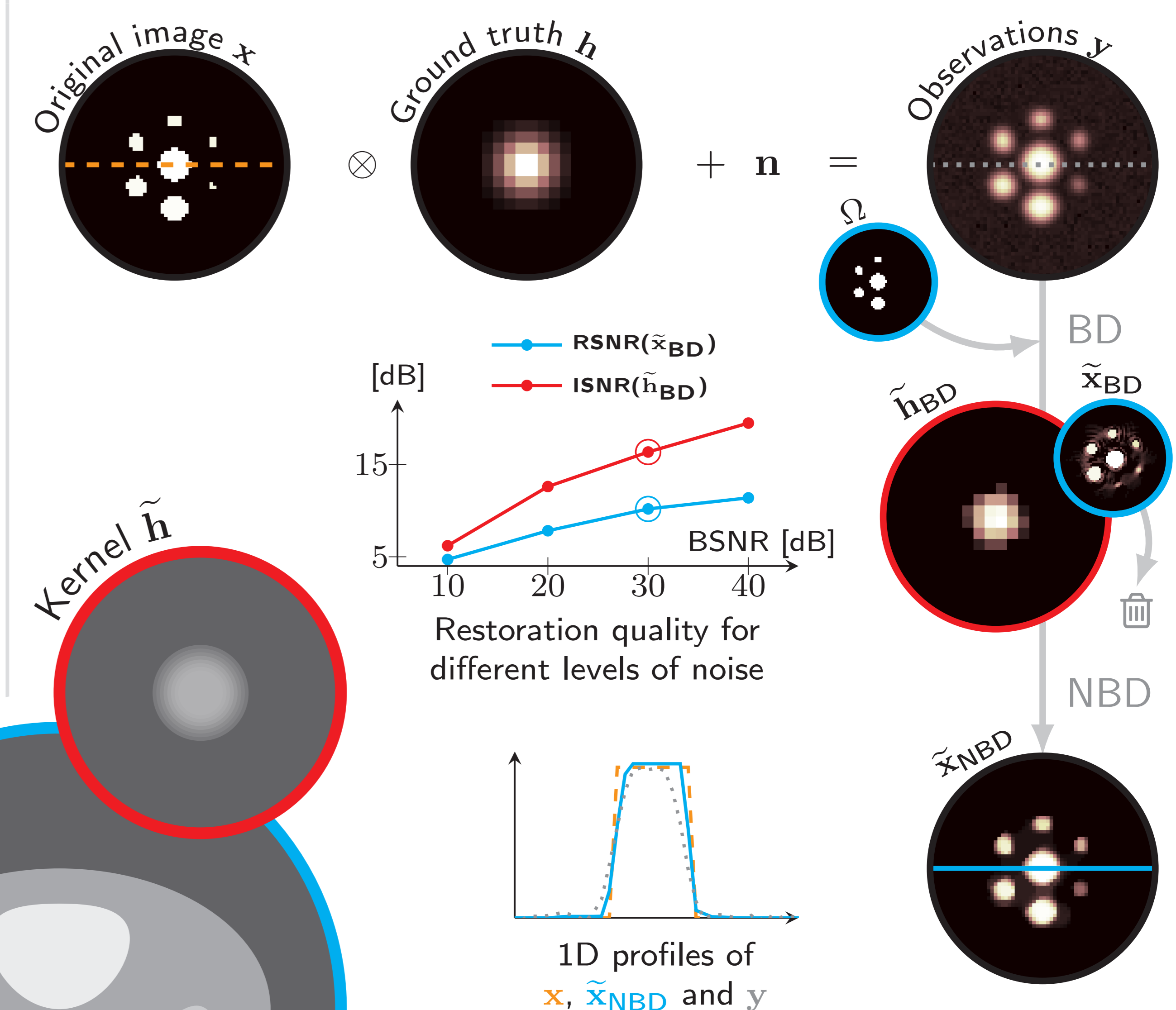
Solved through an alternated minimization [2,3]:

$$(x^{(k)}, h^{(k)}) \rightarrow (x^{(k+1)}, h^{(k)}) \rightarrow (x^{(k+1)}, h^{(k+1)})$$

$$\begin{cases} x^{(k+1)} = \underset{x}{\text{argmin}} L(x, h^{(k)}) + \frac{\lambda_x^{(k)}}{2} \|x - x^{(k)}\|_2^2 \\ h^{(k+1)} = \underset{h}{\text{argmin}} L(x^{(k+1)}, h) + \frac{\lambda_h^{(k)}}{2} \|h - h^{(k)}\|_2^2 \end{cases}$$

- $L(x, h)$: objective function including cost function and constraints
- λ_x, λ_h : cost-to-move parameters

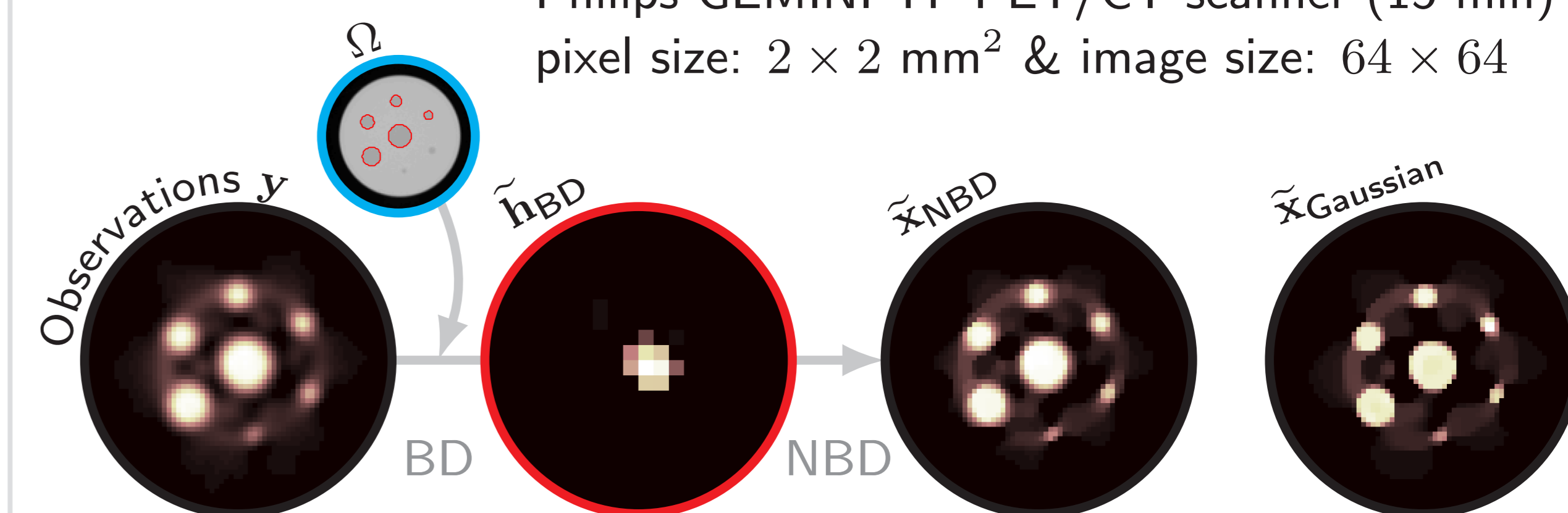
Validation and results on synthetic data



1. BD with priors on Ω : \tilde{h}_{BD} and \tilde{x}_{BD}
2. NBD of new y without prior on Ω : validation if \tilde{h}_{BD} leads to regions with vanishing gradient

Results on real data

Phantom properties: cylindrical holes filled with ^{18}F FDG
 Philips GEMINI-TF PET/CT scanner (15 min)
 pixel size: $2 \times 2 \text{ mm}^2$ & image size: 64×64



Future work

- Poisson noise and mixture Poisson/Gaussian noise
- 3D volume instead of 2D reconstruction per slice
- Extra constraints on the kernel (e.g., sparsity in wavelet basis)
- Work with patient data