# Deep learning-based material decomposition for spectral CT

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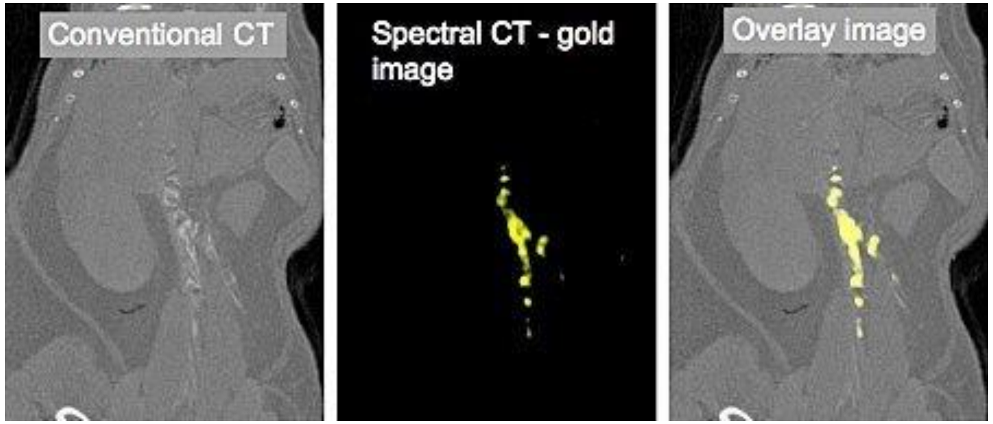
# Motivation

- Spectral CT, "color CT", counts every photon (energy) → adds a new molecular dimension to standard CT
- Improves standard CT and allows for material decomposition [1]




D Cormode *et al*, Radiology, 2010

- Few challenges (nonlinear and ill-posed problem, energy response)
  → Deep learning for Inverse Problems [2]?

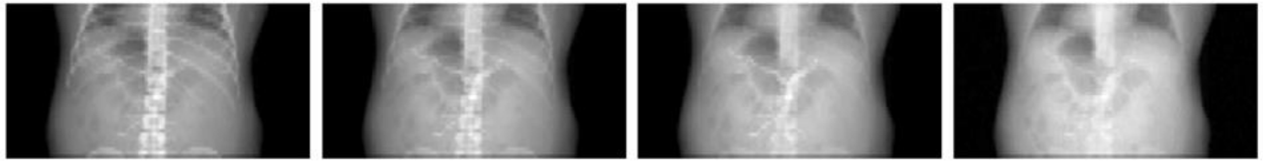

[1] E Roessl and R Proksa. *Med Phys*, 2007
[2] M T McCann et al, *IEEE Signal Processing Magazine*, 34, 2017

# Introduction – Spectral CT imaging

- Imaging in spectral CT involves two steps:

**1st Material decomposition**

Spectral photon counting data (4 energy bins)



Projected mass density (soft tissue, bone, Gadolinium)

- Nonlinear, ill-posed
- Projection-by-projection

**2nd Tomographic reconstruction**

Mass density (soft tissue, bone, Gadolinium)

- Requires all projections
- Computationally expensive

# Introduction - Goal

- Goal:
  - Solve material decomposition using deep learning approach (U-Net)
  - Compare it to a regularized Gauss-Newton (RGN) method [2]

- Methods:
  - Material decomposition using U-Net and RGN
  - Perform tomographic reconstruction using FBP
  - Methods assessed on a realistic thorax phantom (soft tissue, bone and portal vein marked with Gd) [2]

[2] N Ducros *et al*. *Med Physics*, 2017

# Methods – Material decomposition with UNet

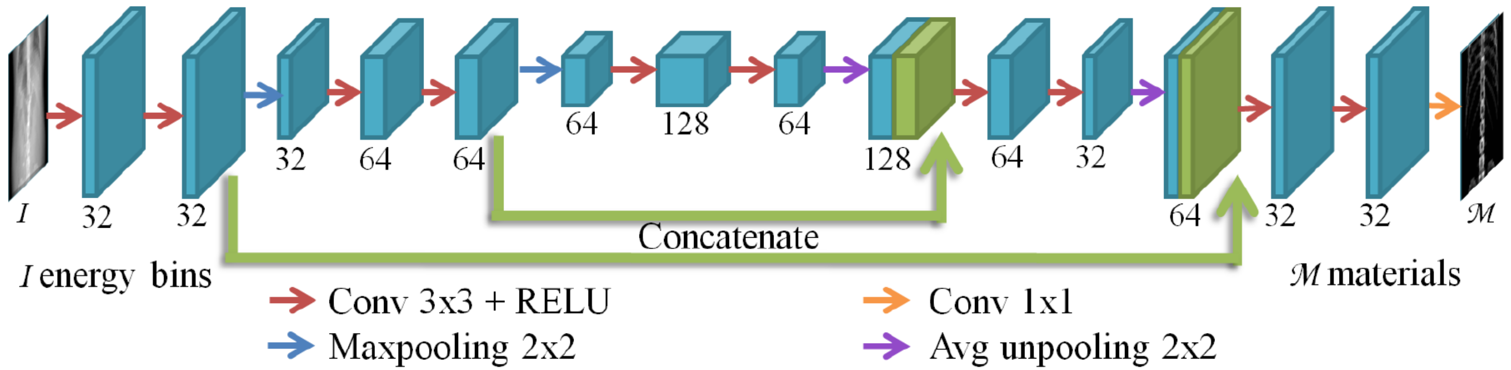
- Learning approach

$$L(\beta) = \sum_{n=1}^{N} \|\boldsymbol{h}(\boldsymbol{s}^n;\beta) - \boldsymbol{a}^n\|^2 = \sum_{n=1}^{N}\sum_{m=1}^{M} \|\boldsymbol{h}_m(\boldsymbol{s}^n;\beta) - \boldsymbol{a}_m^n\|^2,$$

where $(\boldsymbol{s}^n, \boldsymbol{a}^n)$ are input-output vector pairs array pairs of size $(P_x \times P_y \times I, P_x \times P_y \times M)$,

***s*** = PCD data
***a*** =decomposed data
*F*= Forward operator
*R*=Regularization

- Unet (333k parameters) [3], [4]



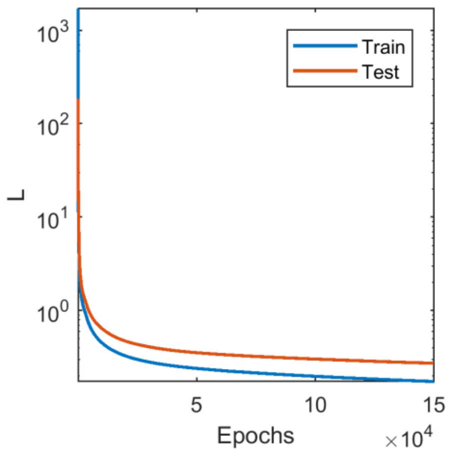


[3] O Ronneberger *et al*, *MICCAI*, 2015
[4] K H Jin *et al*, *IEEE Trans Imag Process*, 2017

# Methods – Data and training

- Training data:
  - Data augmentation: 11-270 phantoms (generalization) → 2k-50k projections
  - Projection image = 155 x 40 (downsampled by x4)
  - Input *I* and output *M* normalization
  - Data divided in files of 1GB
- Training:
  - Batch size = 45, learning rate=$10^{-3}$,
  - Adaptive gradient descent under Tensorflow

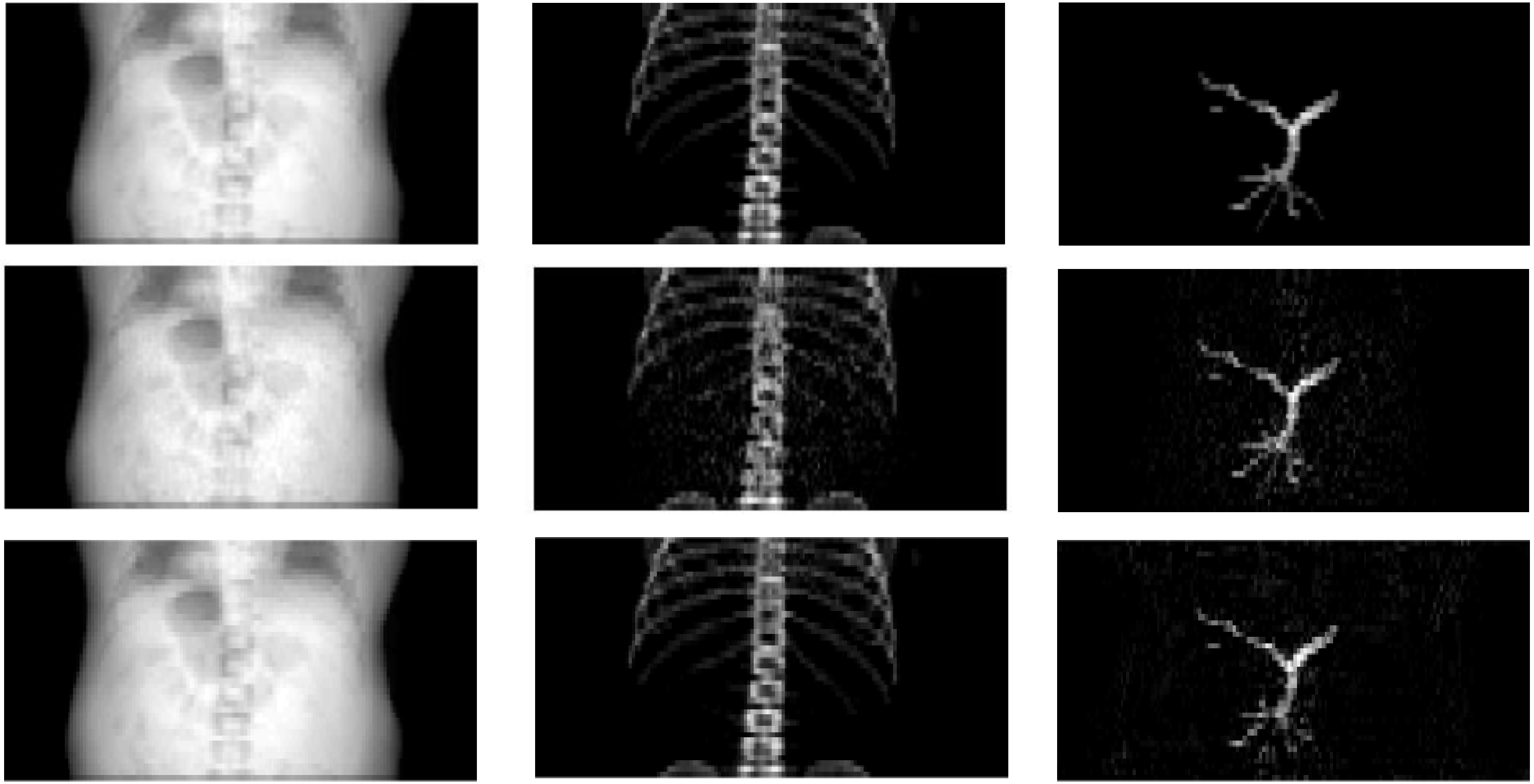
# Results



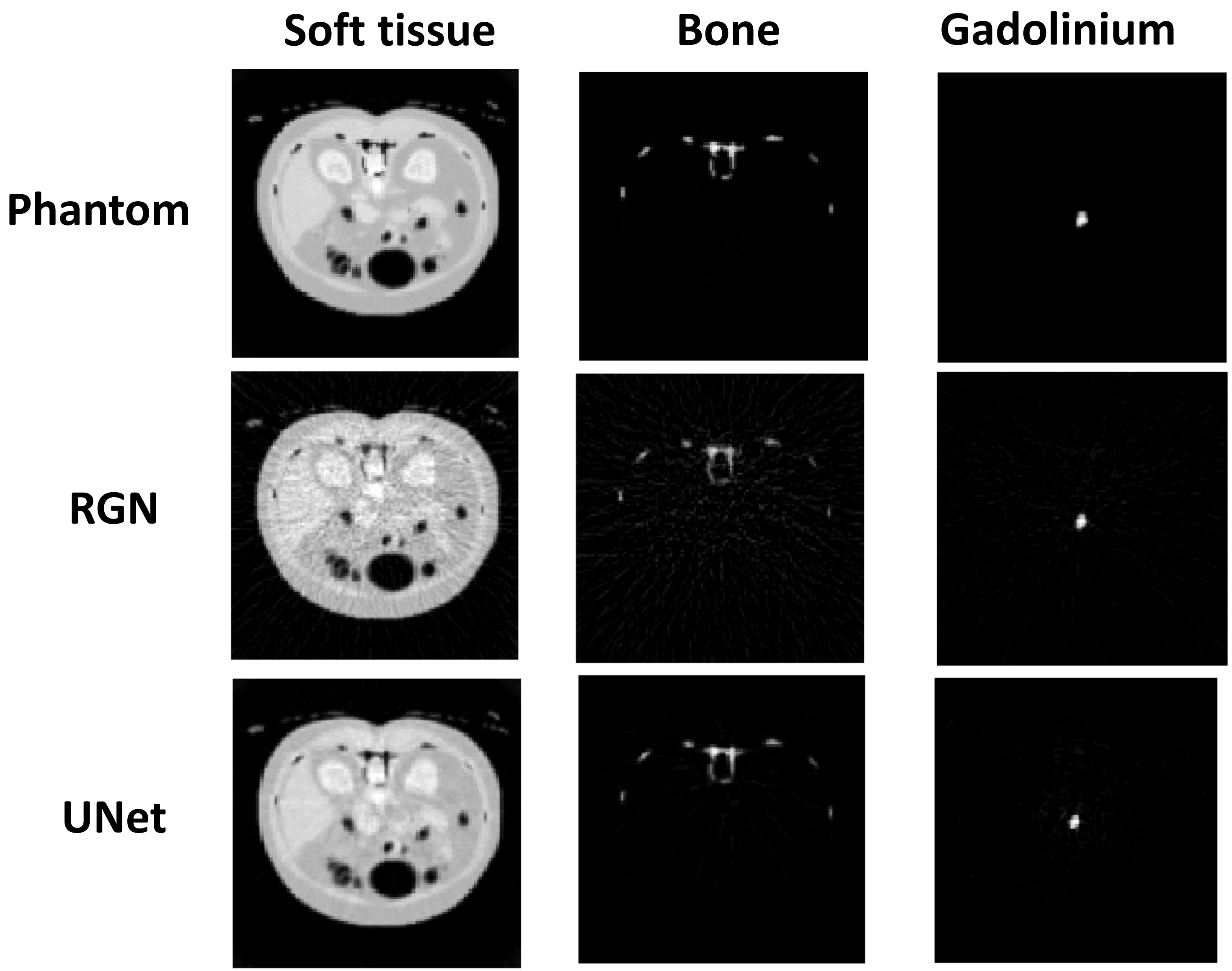

- Training time (GPU):
  - 1.6s/epoch (2k data), <u>3 days for 150k epochs</u>
  - > 1 week training (more data)
- Prediction times (155x42x180 images):
  - Decomposition U-Net: 4 s for 180 projections (CPU)
  - Decomposition GN: 115 s, 43 s with parallelization (4 cores, CPU)
  - Tomographic reconstruction (Matlab FBP): 0.8 s
- Prediction times (634x286x720 images):
  - Decomposition GN: 10 h (without parallelization)
  - Tomographic reconstruction: 20 min (GPU)

# Results – Material decomposition

| | Soft tissue | Bone | Gadolinium |
|---|---|---|---|
| Phantom | | | |
| RGN | | | |
| UNet | | | |



# Results – Tomographic reconstruction




- U-Net decreases noise and MSE for bone and soft tissue
- Both RGN and U-Net lead to low quantification error but RGN achieves lower error

# Conclusions and future work

- U-Net
  - Reduces noise and improves image quality
  - U-Net can learn the image prior
  - Does not require knowledge of scanner energy response
- Future work will focus on learning generalization
  - Different noise levels, concentration of Gd
  - Experimental data
  - Use transfer learning to decrease training time
- CC IN2P3 is very important for us
  - 2 months, 1-3 tests per week (more tests in future + PhD student)
  - mc_gpu_long, mc_gpu_longlasting (100 % only once)

# Acknowledgements – Funding bodies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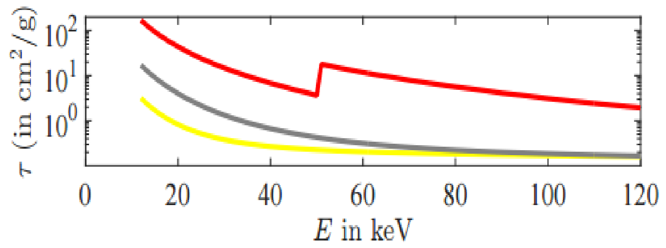
- LabEx PRIMES (ANR-11-LABX-0063) of University de Lyon
- France Life Imaging, FLI

# Extra slides

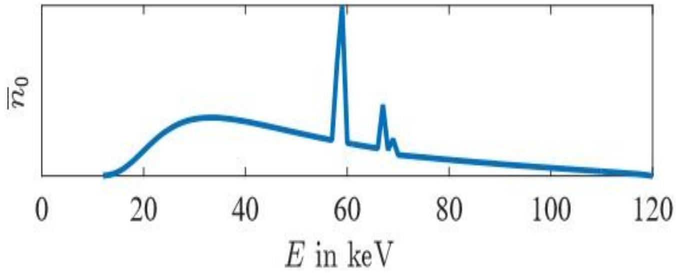
# Introduction – Spectral CT

- Spectral CT is nonlinear
- Current methods rely on prior knowledge of scanner energy response function:
  - X-ray attenuation is **material and energy dependent**
  - X-ray source is **polychromatic**
  - **Photon-counting detectors** simultaneously count photons and resolve their energy [1]

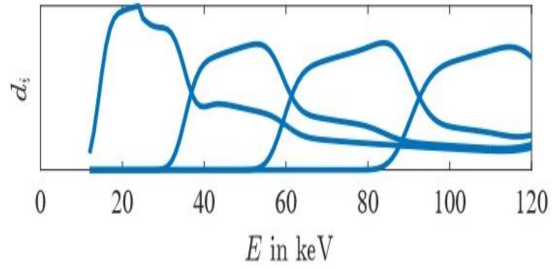
**Mass attenuation** for three materials (soft tissue, bone, Gd)




**Polychromatic source**



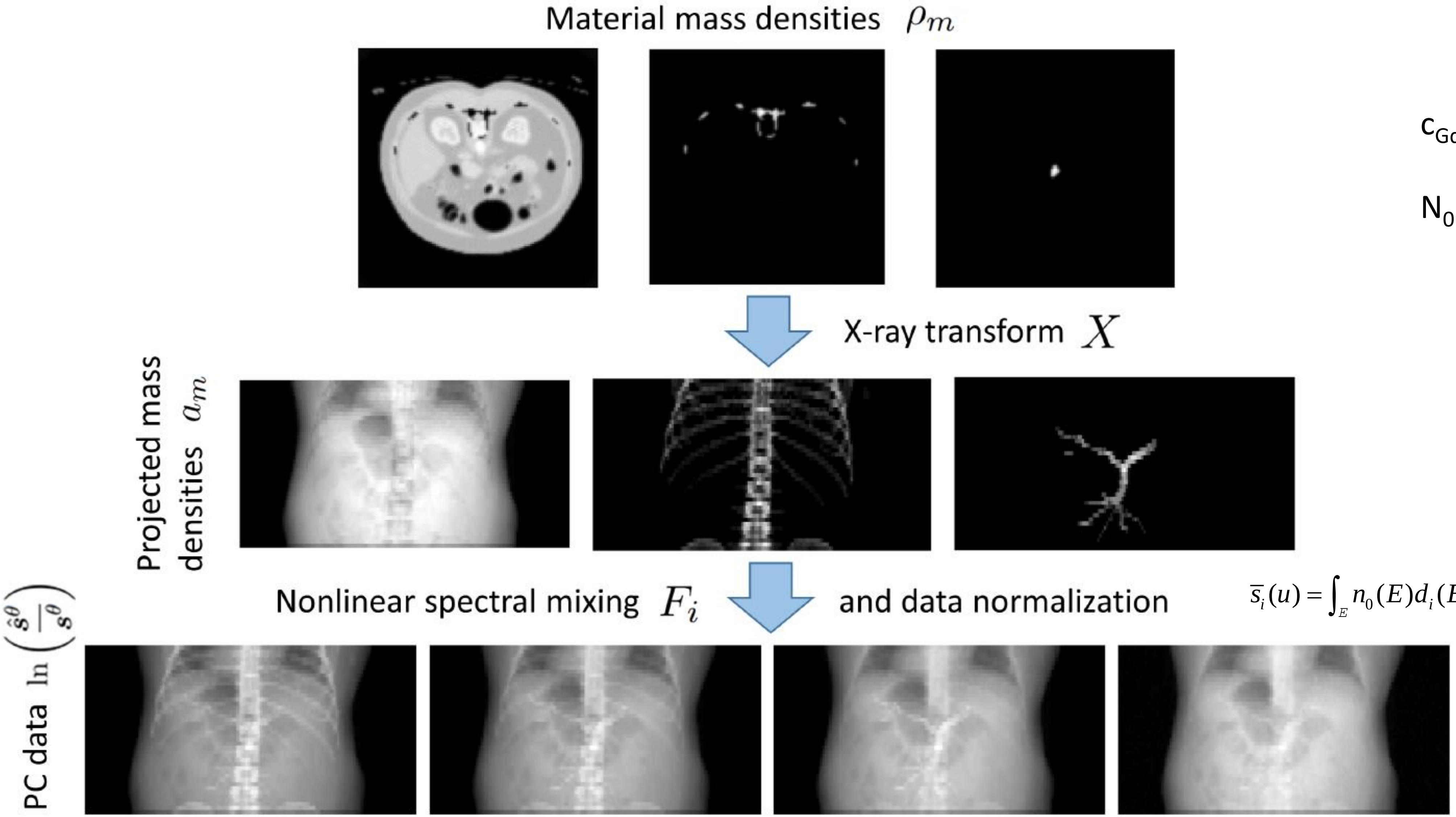

**Detector response**
(Photon counting detector)




[1] E Roessl and R Proksa. *Med Phys*, 2007

[2] N Ducros *et al*. *Med Physics*, 2017

# Methods – Data simulation




$c_{Gd}$=0.1gcm$^{-3}$

$N_0$=10$^7$ photons

$$R\rho_m = a_m$$

$$\overline{s}_i(u) = \int_E n_0(E) d_i(E) \exp\left[-\sum_{m=1}^{M} a_m(u)\tau_m(E)\right] \mathrm{d}E$$

# Methods – Material decomposition

- Variational approach (RGN) [1]

$$C(\boldsymbol{a}^\theta) = \frac{1}{2}\|\boldsymbol{s}^\theta - F(\boldsymbol{a}^\theta)\|^2_{W^\theta} + \alpha \sum_m R_m(\boldsymbol{a}^\theta), \quad 1 \leq \theta \leq \Theta$$

***s*** = PCD data
***a*** =decomposed data
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- Learning approach

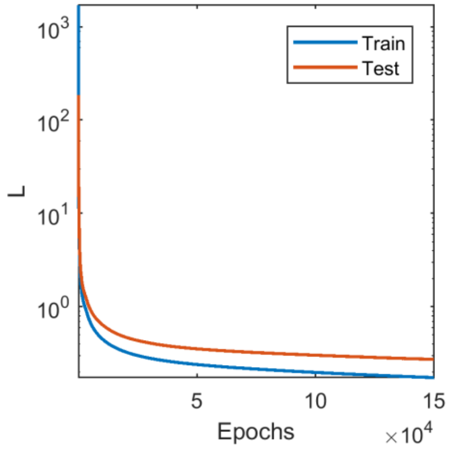
$$L(\beta) = \sum_{n=1}^{N} \|\boldsymbol{h}(\boldsymbol{s}^n;\beta) - \boldsymbol{a}^n\|^2 = \sum_{n=1}^{N}\sum_{m=1}^{M} \|\boldsymbol{h}_m(\boldsymbol{s}^n;\beta) - \boldsymbol{a}^n_m\|^2,$$

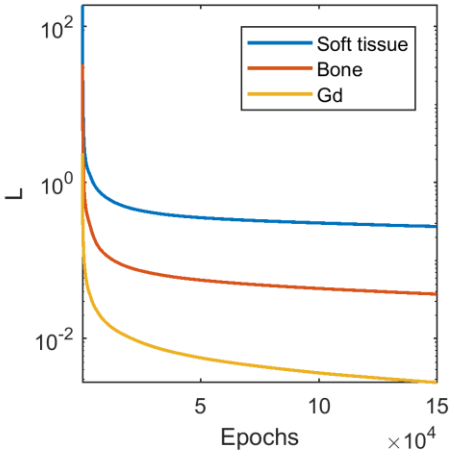
where $(\boldsymbol{s}^n, \boldsymbol{a}^n)$ are input-output vector pairs array pairs of size $(P_x \times P_y \times I, P_x \times P_y \times M)$,

[1] N Ducros *et al. Med Physics*, 2017

# Results - Losses

2k projections




40k projections