Deep learning reconstruction for PET-MR and total-body PET: present status and future perspectives

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Overview

- **Brief review**
  - Deep learning (DL)
  - Image reconstruction
  - Why include DL?

- **Four main approaches:**
  - **Direct** : use only data to learn the mapping
  - **Direct with physics**: use data as well as our imaging (and noise) model
  - **Iterative reconstruction**: use our known reconstruction algorithms, our imaging model and noise model and data
  - **Use of DL for image representation or filtering**: no training data

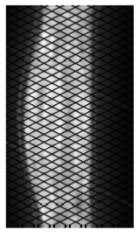
- **Recent directions**
- **Outlook and perspectives**

Deep Learning

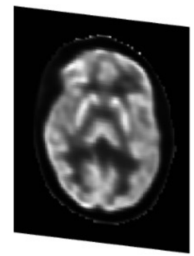
What is deep learning?

- Software which learns from data, …rather than by explicit programming
- Regular programming: take input, write instructions to obtain output

INPUT



CODE

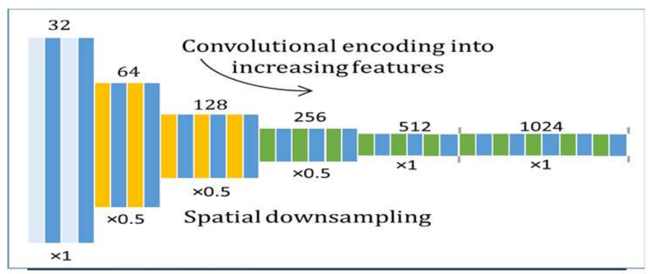


OUTPUT

- Sequential operations → deep *learning* means a cascade of steps with trainable parameters

INPUT

CODE??



Relate latent to OUTPUT
Kingfisher

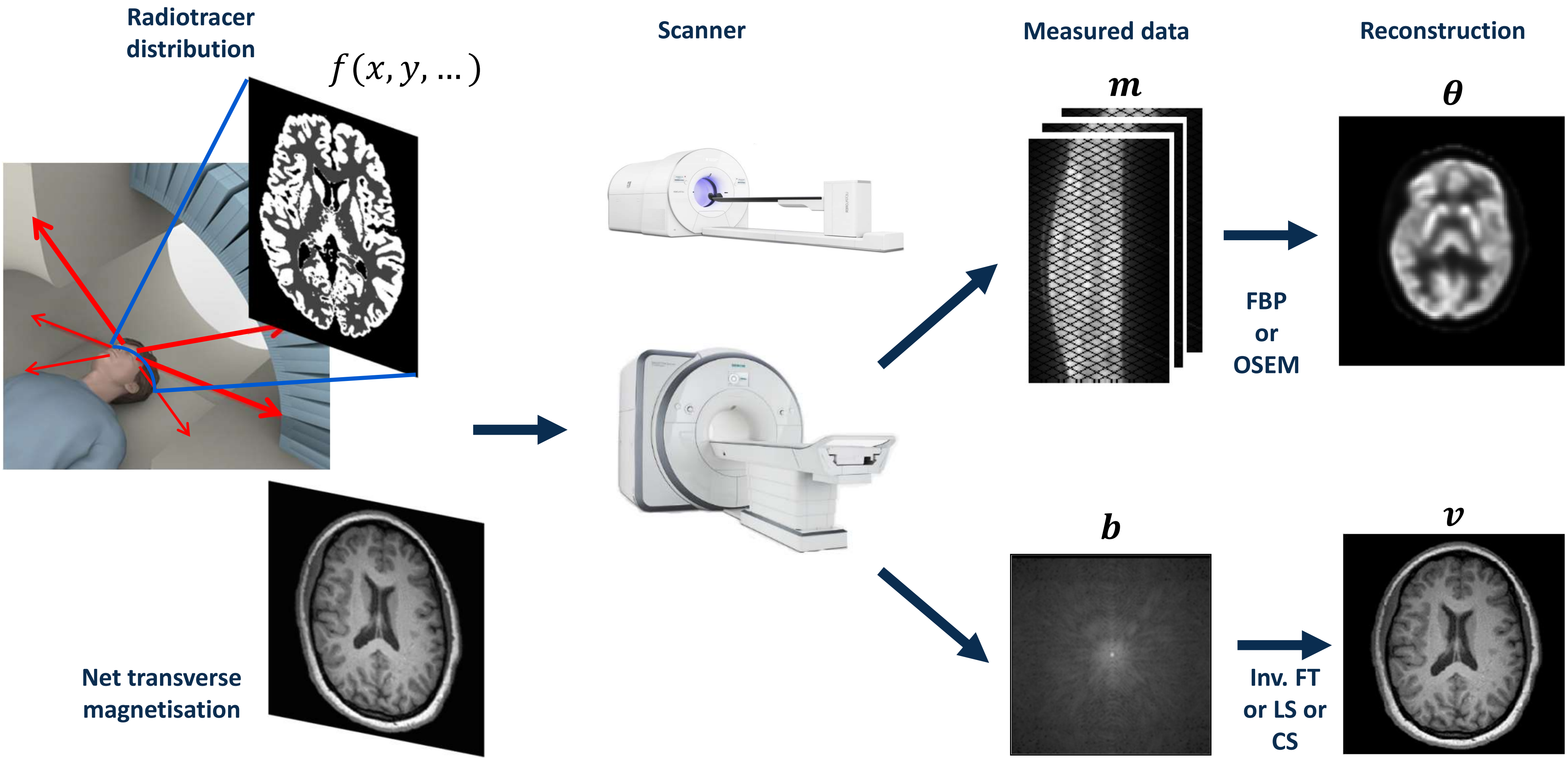
CNNs: depth -> **feature hierarchy**
Increasing context and abstraction.

Or, transformers, for easy long-range context (~ BM3D, ~ NLM)

- Deep learning / networks → trainable code

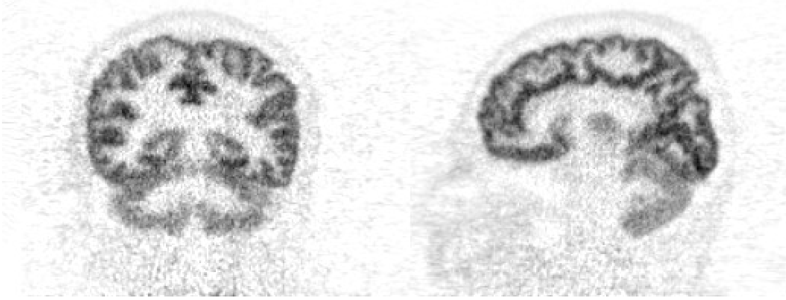
Reconstruction

From data acquisition to image reconstruction

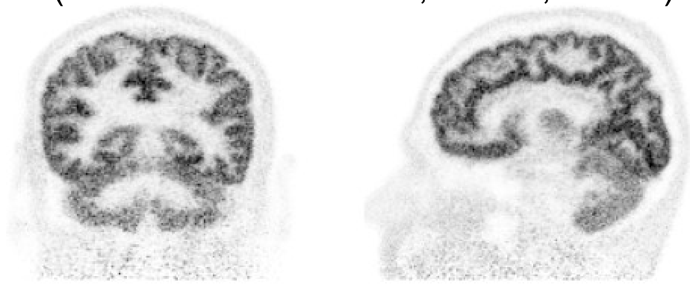


From Past to Present PET Image Reconstruction

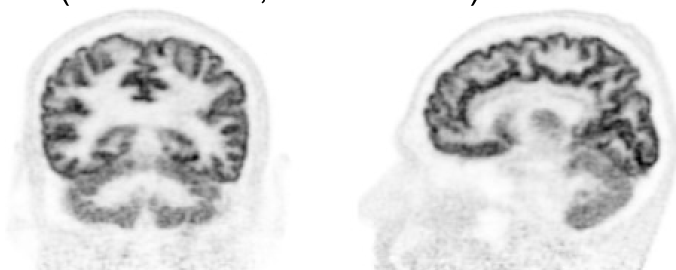
1980s – 1990s (filtered backprojection)



1990s (iterative reconstruction, OSEM, MLEM)



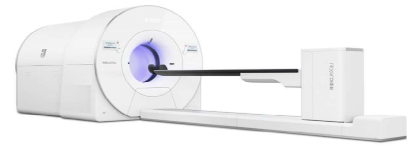
2000s (OSEM+PSF, MLEM+PSF)

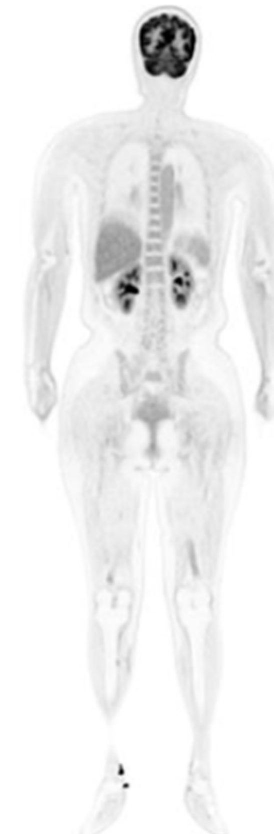


Improved noise modelling
(Gaussian to Poisson)

Improved physics modelling
(e.g. positron range)

TBP:
OSEM+PSF+TOF
192x192x673

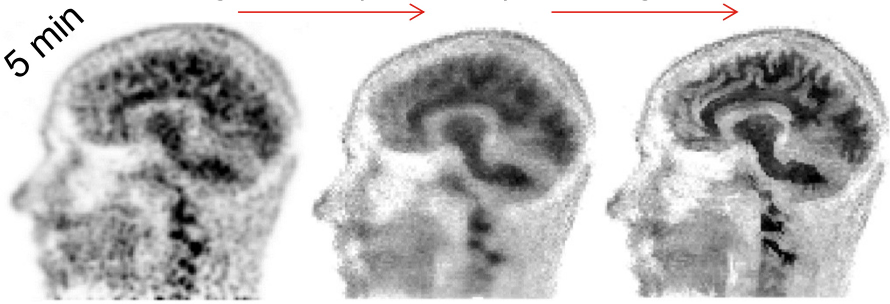




Regularise (MAPEM)

MRI guidance

5 min



Colsher 1980, Kinahan & Rogers 1989,
Shepp & Vardi 1982, Hudson & Larkin 1994

So why the need for deep learning?

- Conventional reconstruction fits images to noisy data -> noisy images
- Conventional noise compensation (regularisation) is by simple mathematically convenient methods (quadratic, TV, …)
- Assumes:
  - Imaging system model
  - Data noise distribution
  - How to exploit multi-modal information (e.g. MRI)
  - How to regularise

  ….but do we really know these things?

- Deep learning offers improved image quality (use as is, else dose or time reduction) by
  - Learning the system model (and its ‘inverse’) from examples of real data
  - Learning the noise from real data
  - Use of ground truth or high-quality reference data
    - Sophisticated manifolds to define acceptable images

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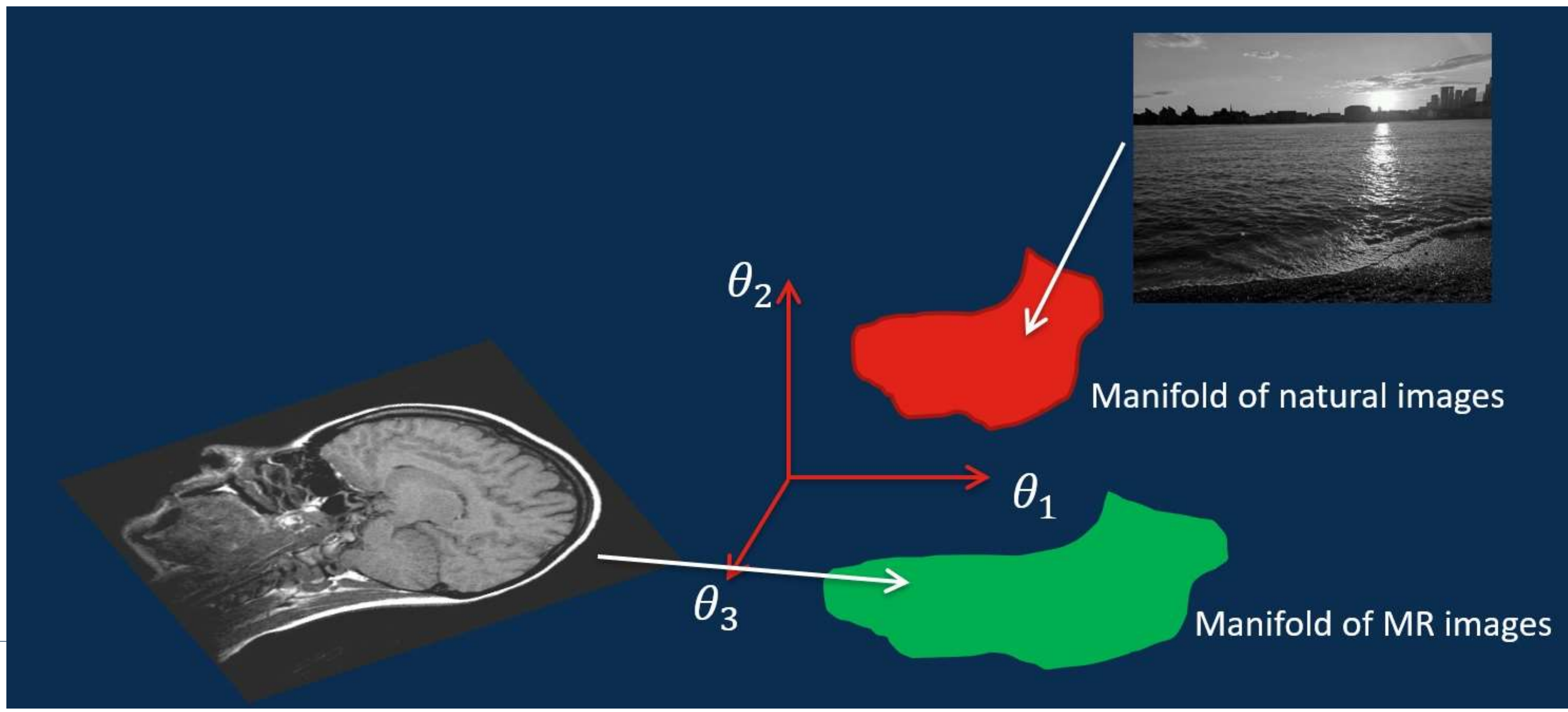
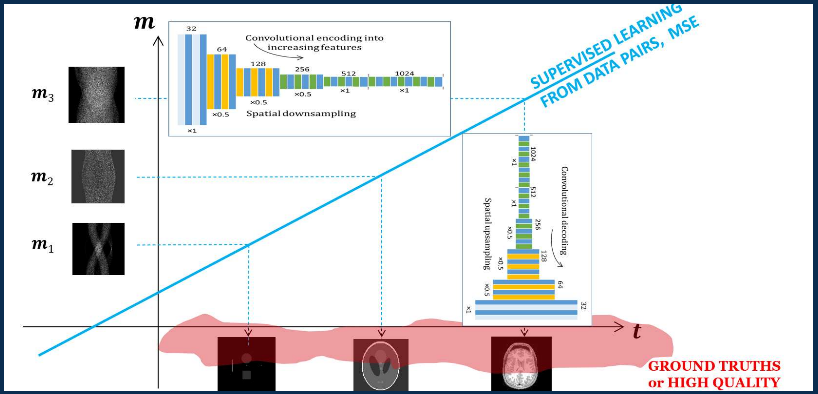


Basic approaches for DL in image reconstruction

- **Four main approaches:**
  - **Direct** : use only data (e.g. DeepPET, AUTOMAP, …)
  - **Direct with physics**: use data as well as our imaging (and noise) model
    (e.g. LPD)
  - **Unrolled iterative reconstruction**: use our known reconstruction algorithms, our imaging model and noise model and data
    Use data to define the prior probability of certain images (the manifold)
    (e.g. FBSEM-Net)
  - **DL representations** (e.g. deep image prior): use DL for the image, and for the optimisation

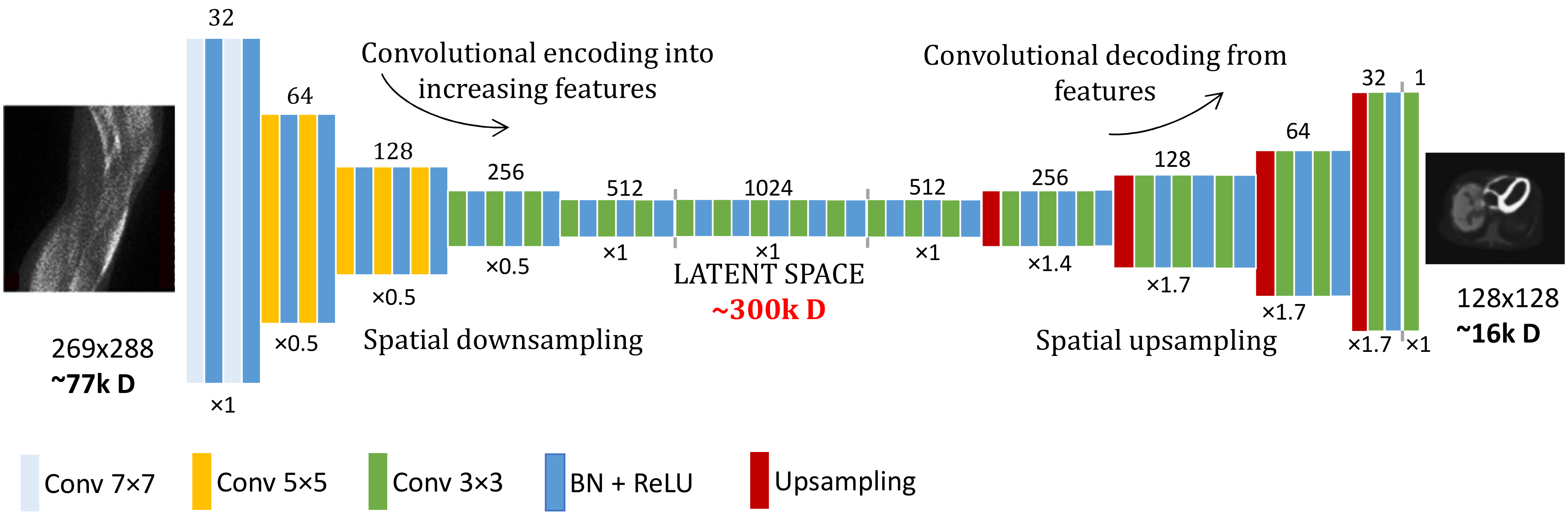


Direct reconstruction with DL

MAPPING BASED

ON DATA

PET reconstruction from sinograms: DeepPET

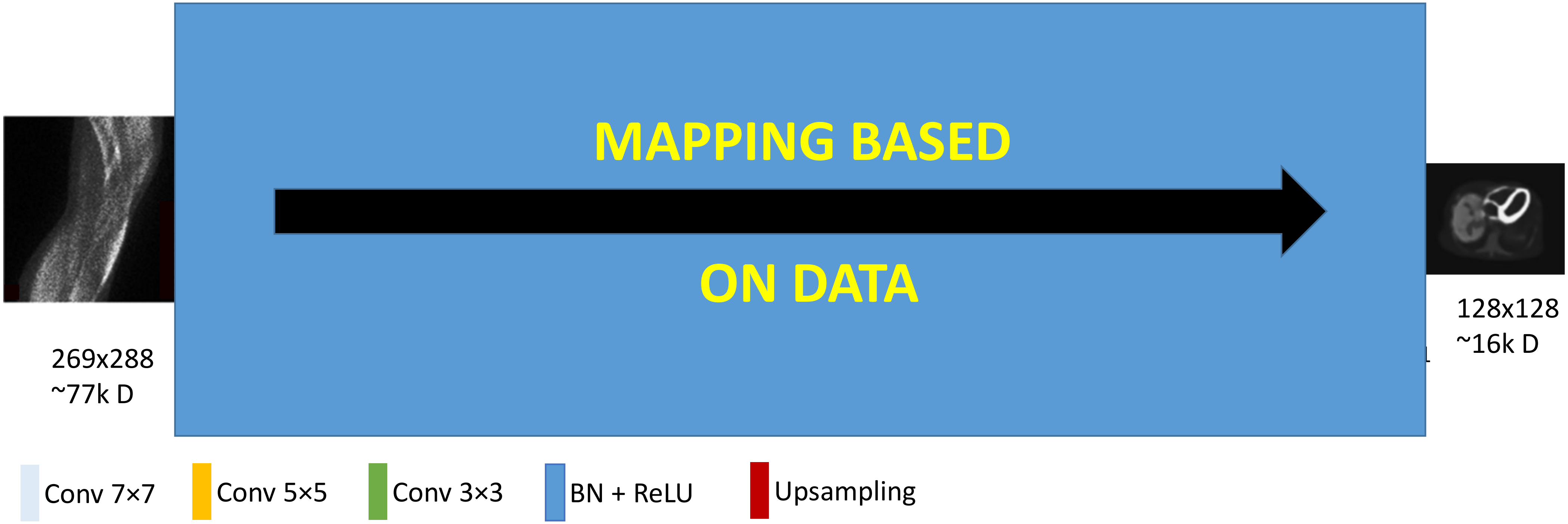


Convolutional encoder decoder:

- **200,000 simulated training data pairs** to learn **~60 million parameters** via MSE
- Note a simple linear mapping would need > 1 billion parameters

Figure represents method of Häggström *et al*, MIA 2019

PET reconstruction from sinograms: DeepPET



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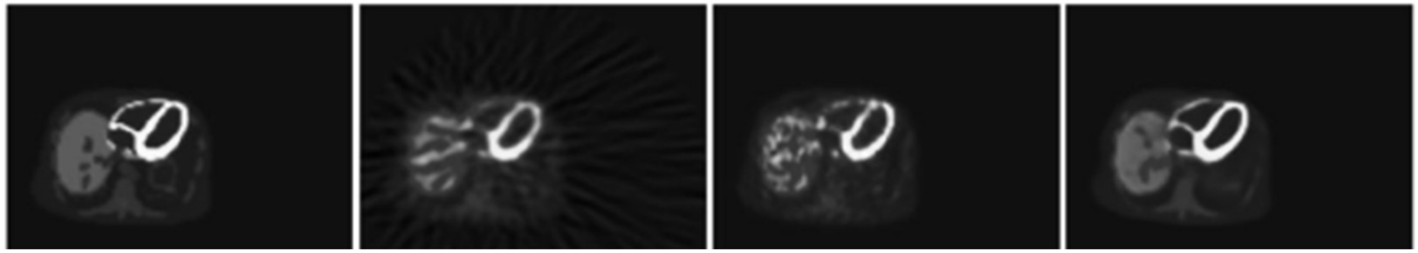
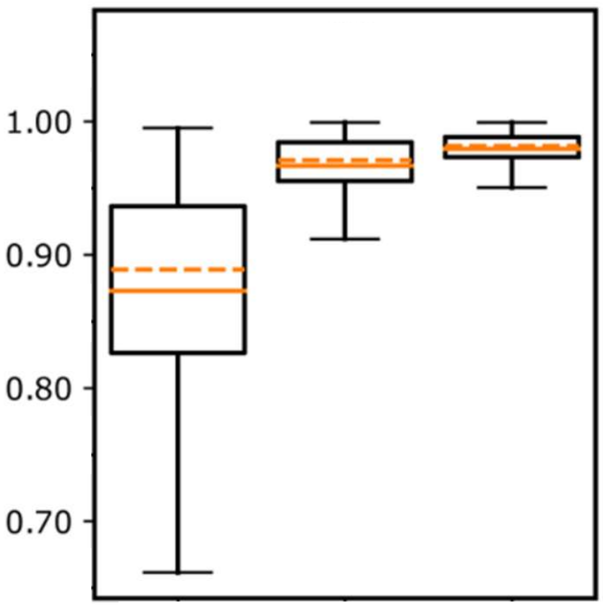
DeepPET: results

True FBP OSEM DeepPET

Simulated data



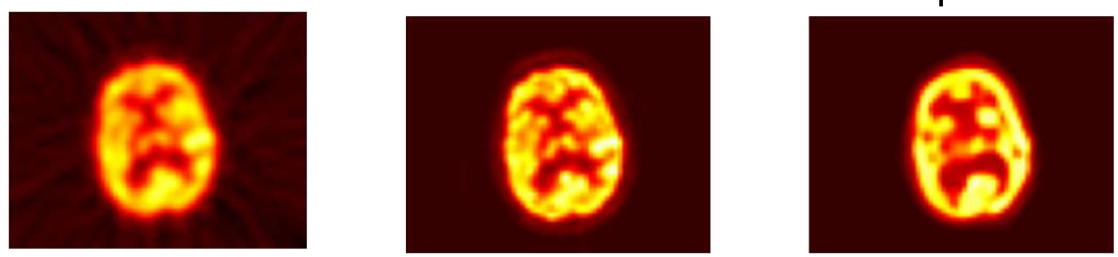
Structural similarity



FBP OSEM DeepPET

Real data

FBP OSEM DeepPET



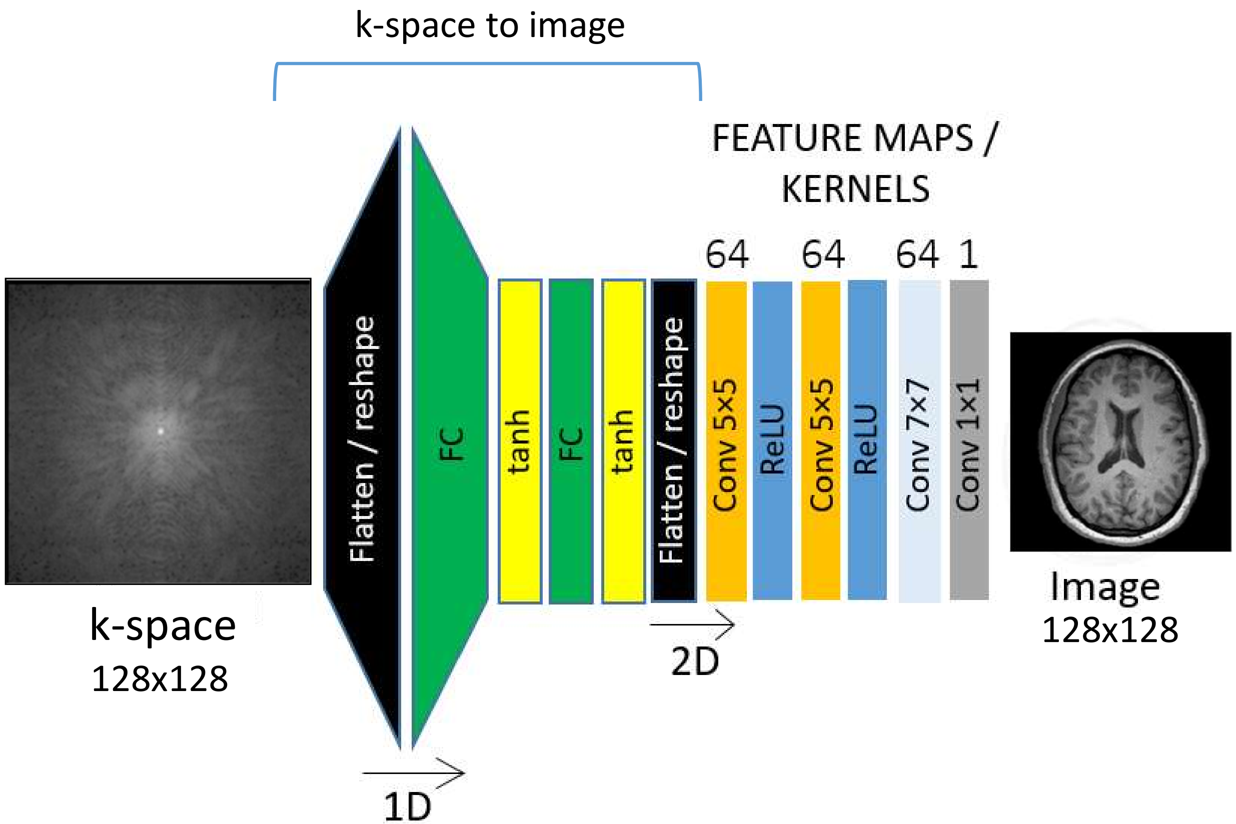
~10% lower noise (RMSE) than OSEM conventional reconstruction

~100x faster than OSEM

Häggström *et al*, MIA 2019

+discriminator, perceptual loss: Zhanli Hu et al, IEEE TRPMS (5) Jan 2021

MRI reconstruction from k-space: AUTOMAP



Training on MR brain data gave best results (compared to natural images, or random noise as data examples)

Compared to conventional reconstruction, RMSE reduced

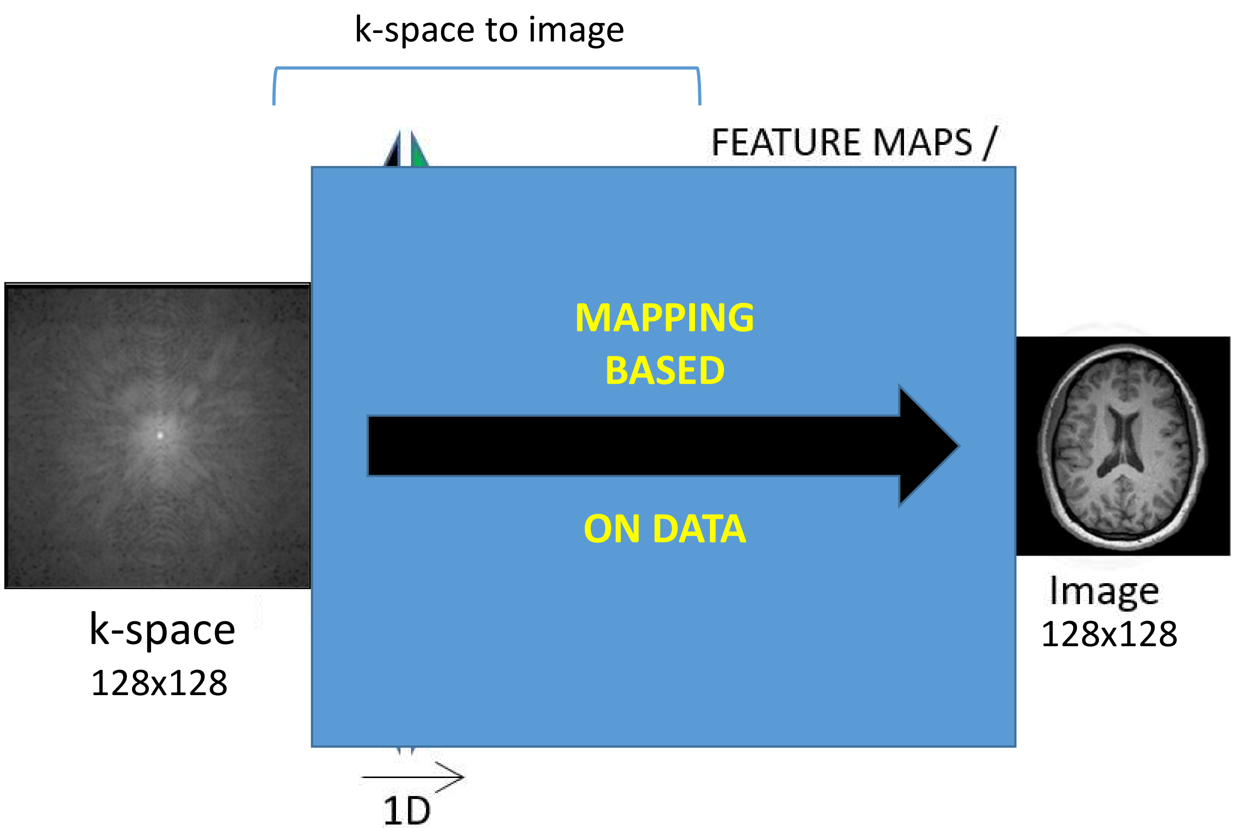
Faster reconstruction!

Demonstrated for PET data also

Uses ~ **50,000 training data pairs** to learn **~800 million parameters**

Figure represents method of Zhu *et al*, Nature 2018

MRI reconstruction from k-space: AUTOMAP



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Direct DL reconstruction summary

PET, MR Examples: DeepPET, DPIR-Net, AUTOMAP, … [not yet TBP!]

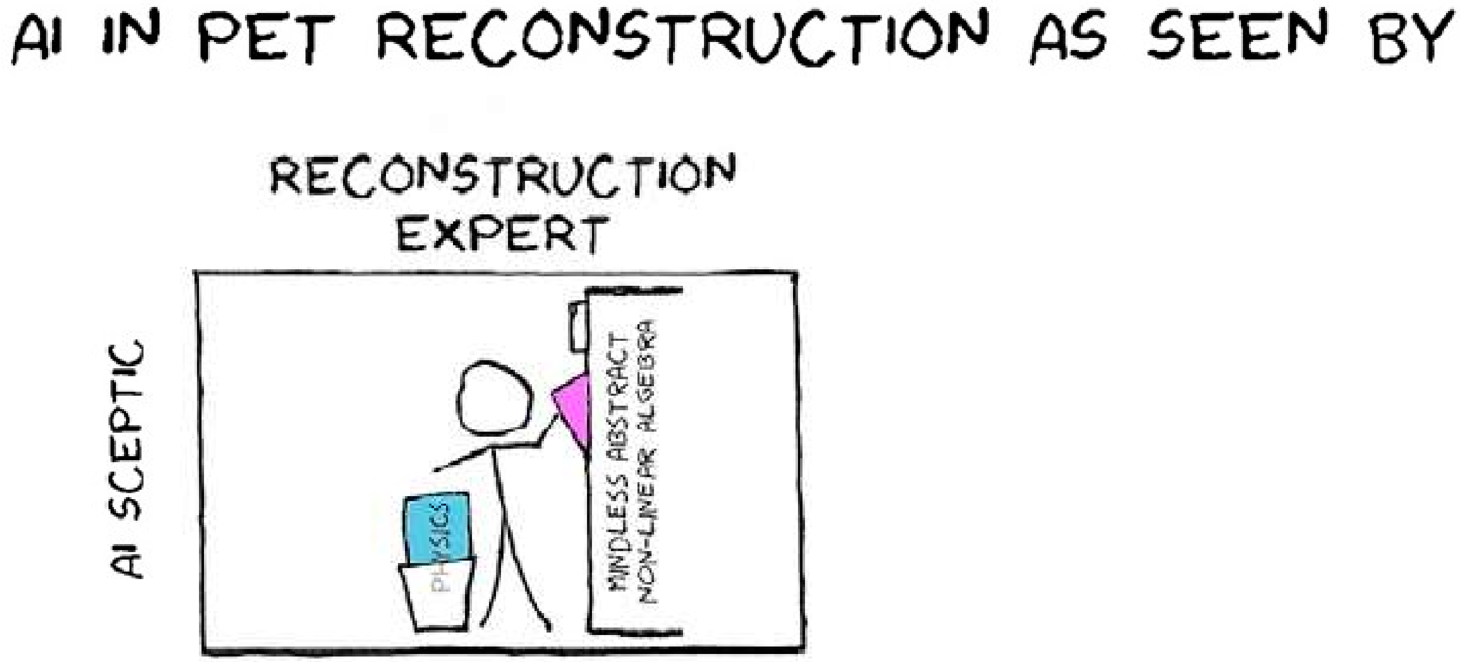
Häggström *et al*, MIA 2019, Zhanli Hu *et al*, IEEE TRPMS (5) Jan 2021, Zhu *et al* Nature 2018

✓ Few model assumptions (avoids system and noise model errors)

✓ Data driven, just the network's inductive prior

✓ Fast reconstructions

- Slow training (but done once)
- **Huge data needs** (>>10k images)
- Relearns imaging physics, relearns Poisson noise model
- Huge network (10-100 million parameters)
- Mainly applied for **2D reconstruction**, not fully 3D
- Generalisation query?



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HOT TOPICS

Artificial Intelligence for PET Image Reconstruction

Andrew J. Reader[1] and Georg Schramm[2]

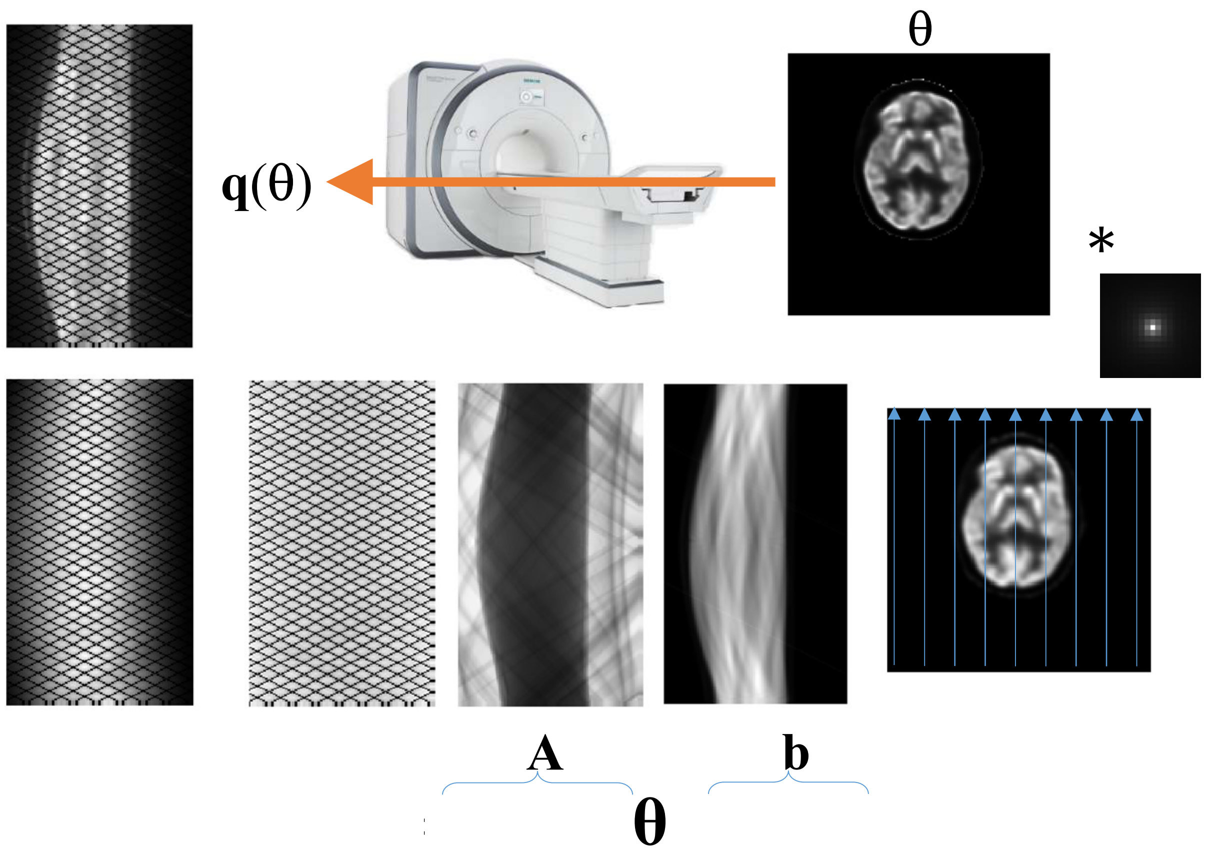
[1]School of Biomedical Engineering and Imaging Sciences, King's College, London, United Kingdom; and [2]Division of Nuclear Medicine,

Direct reconstruction with our imaging model included

MAPPING BASED

ON DATA &
IMAGING MODEL

Physics modelling of a PET acquisition



$\boldsymbol{P}$: positron range

$\boldsymbol{X}$: Radon transform

$\boldsymbol{L}$: attenuation factors

$\boldsymbol{N}$: normalisation related factors

$\boldsymbol{s}$: scatter
$\boldsymbol{r}$: randoms

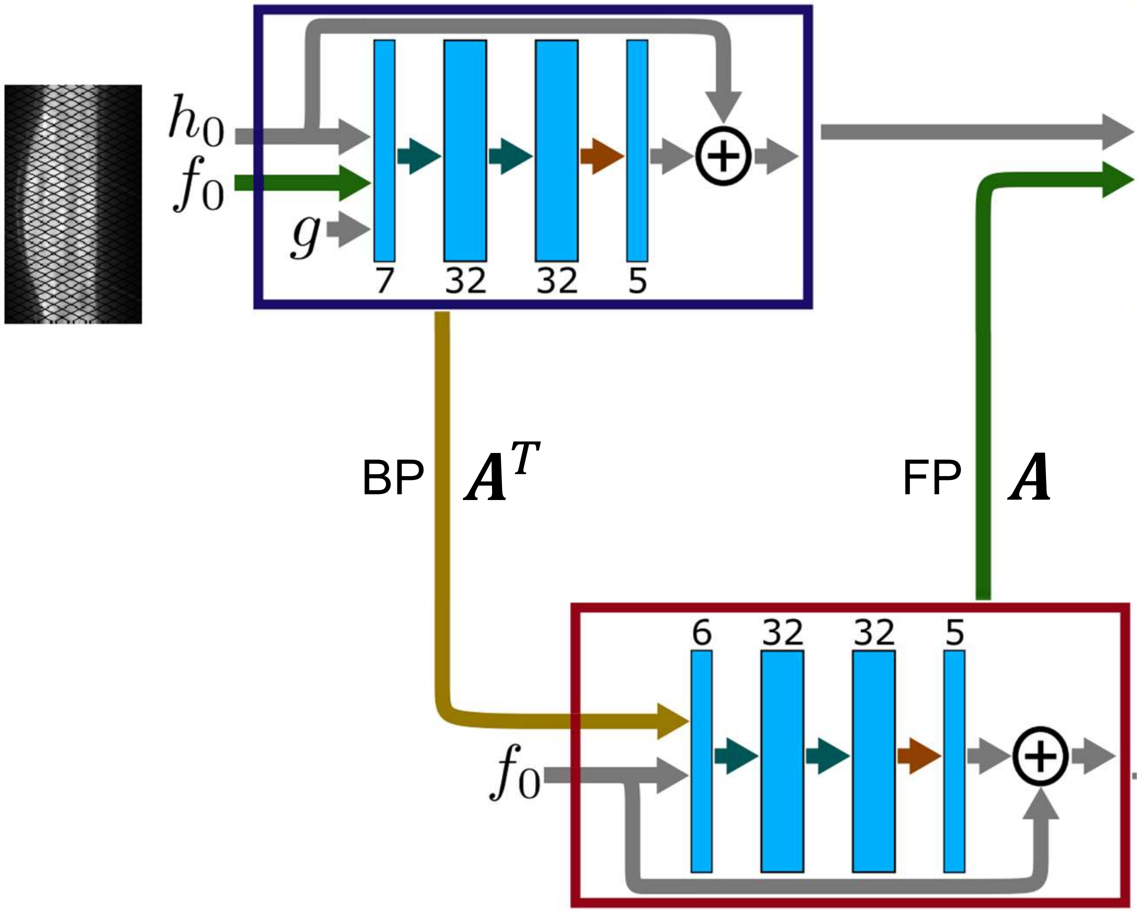
$$\mathbf{q}(\boldsymbol{\theta}) = \mathbf{A}\boldsymbol{\theta} + \mathbf{b}$$

$\boldsymbol{A}$: forward projection, FP
$\boldsymbol{A}^{\boldsymbol{T}}$: backprojection, BP

For MRI: image -> coil sensitivity maps -> FFT -> undersample: $\boldsymbol{q}(\boldsymbol{\theta}) = \boldsymbol{UFC\theta}$

Original method: Adler & Oktem IEEE TMI 2018

Learned Primal Dual (LPD)



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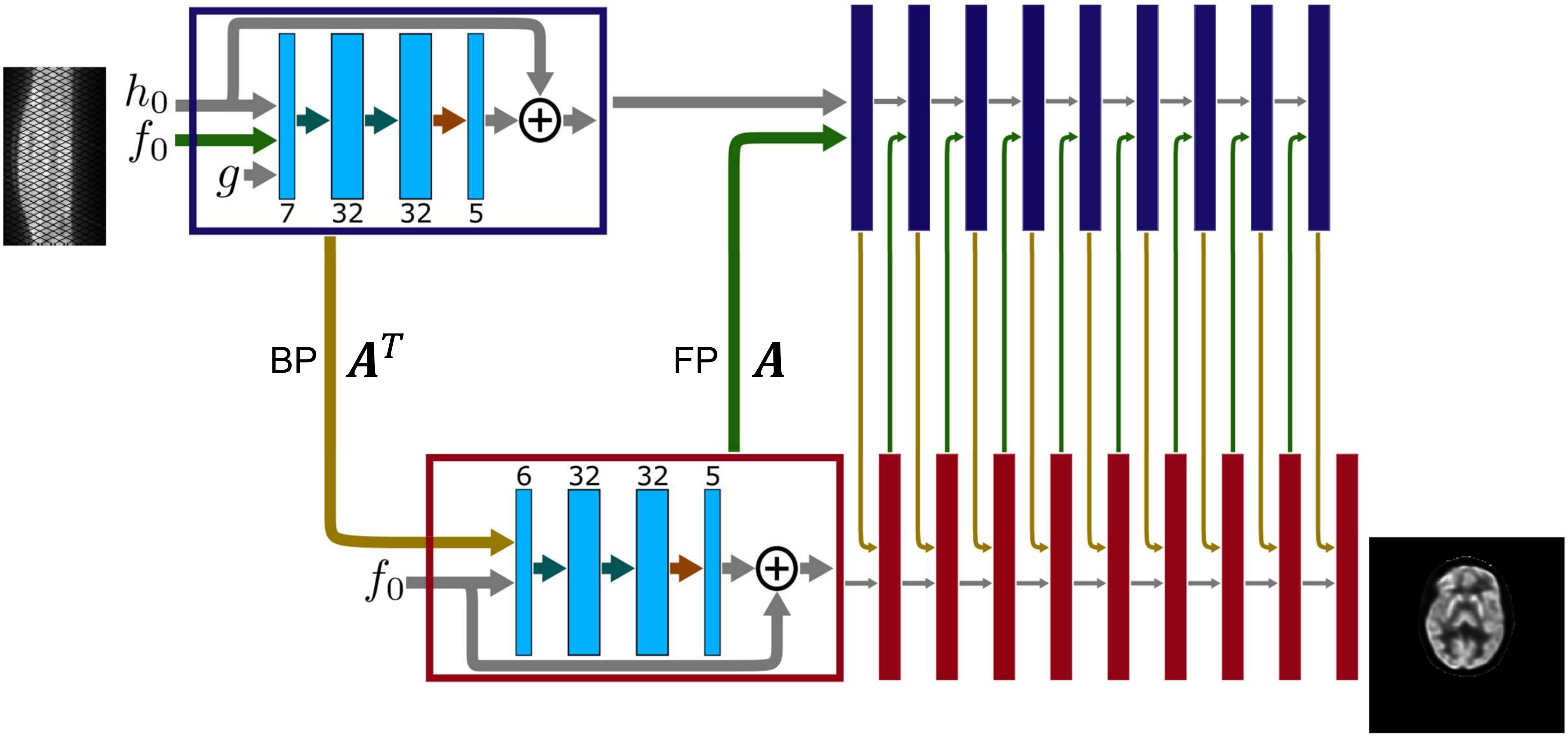

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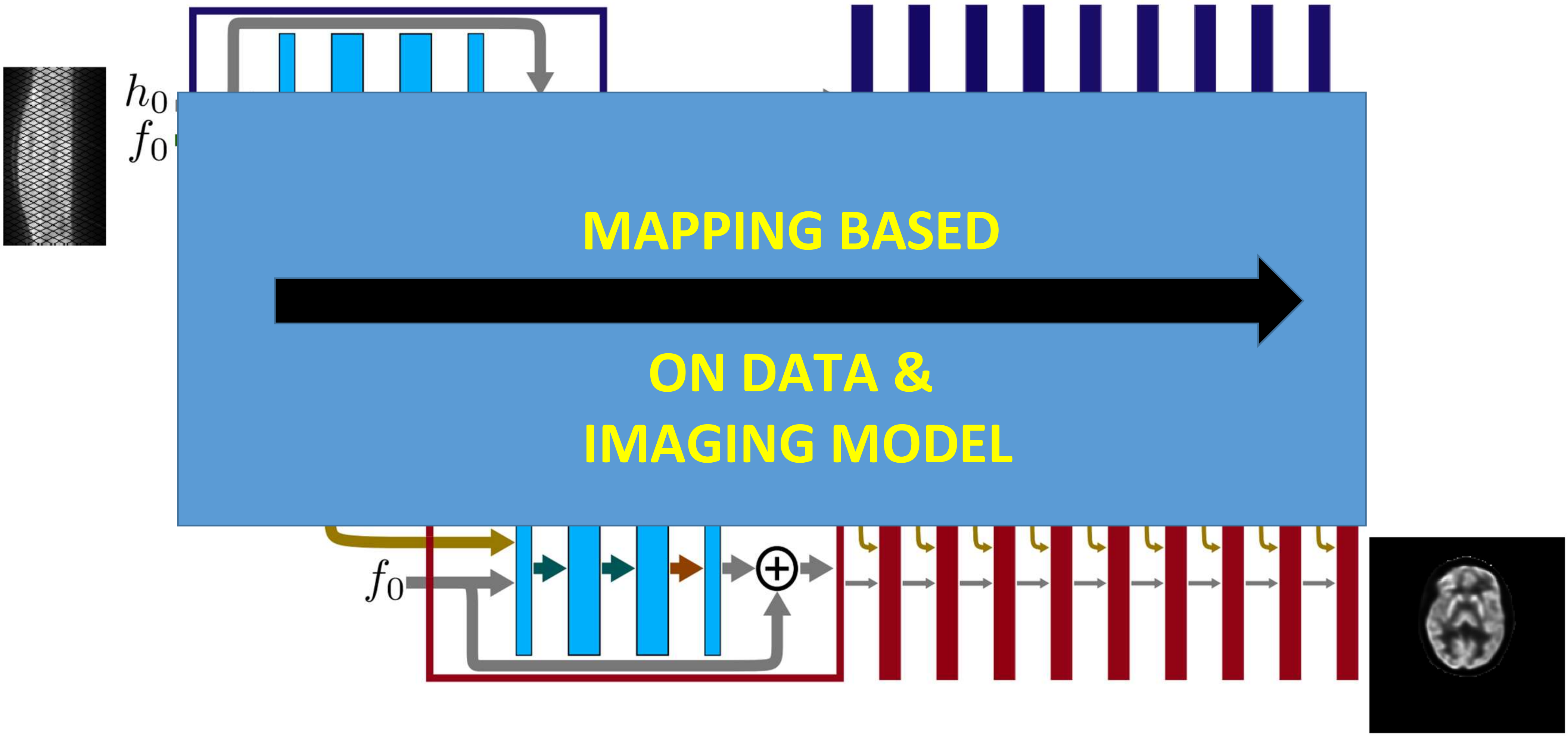

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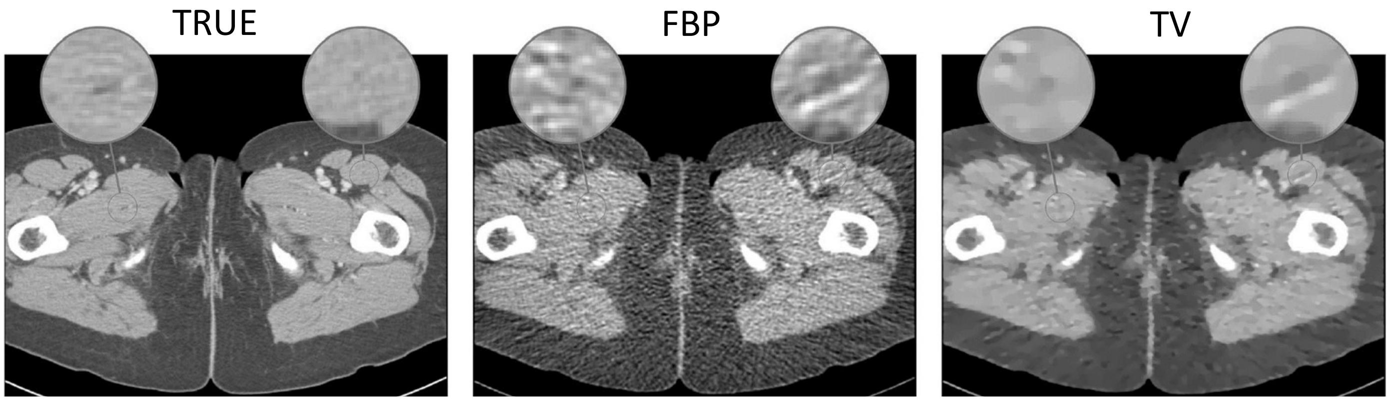

Adler & Oktem IEEE TMI 2018

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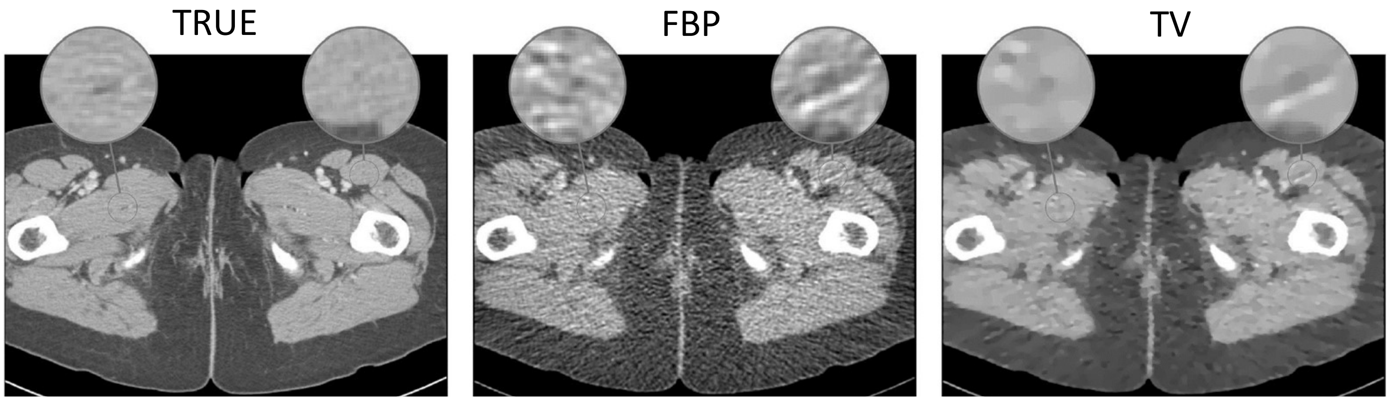
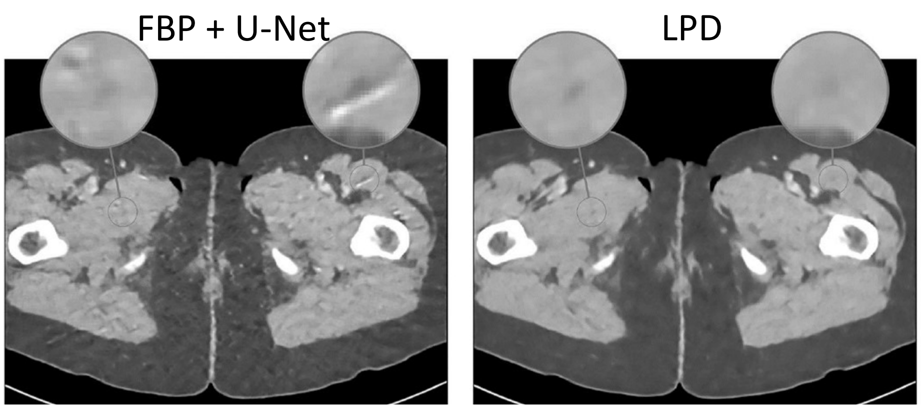




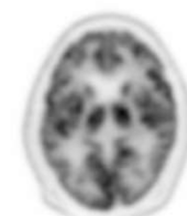
Method	PSNR	SSIM	Runtime	Parameters
FBP	33.65	0.830	**423**	**1**
TV	37.48	0.946	64 371	**1**
FBP + U-Net	41.92	0.941	463	10^7
LPD	**44.11**	**0.969**	620	$2.4 \cdot 10^5$

- **2k training data pairs** to learn **~240k parameters** via MSE

Adler & Oktem IEEE TMI 2018

Fast PET (for TOF histo images – potential for TBP)

Input data compressed
U-Net architecture, only 20 million parameters
3D images
67x faster than OSEM
Noise reductions



Target

Whiteley et al. IEEE TRPMS 2021

Iterative reconstruction with DL

MAPPING BASED ON

DATA, OUR MODELS & OUR CURRENT ALGORITHMS

Embedding deep learning into iterative reconstruction

WHY?

- ✓ Iterative reconstruction uses our known system and noise modelling via a principled objective function and theoretically convergent framework

- ✓ Arguably, the only shortfall is the prior

- ✓ Unrolled methods: keep our iterative algorithm (objective and models), and just use deep learning for the prior (the image manifold)

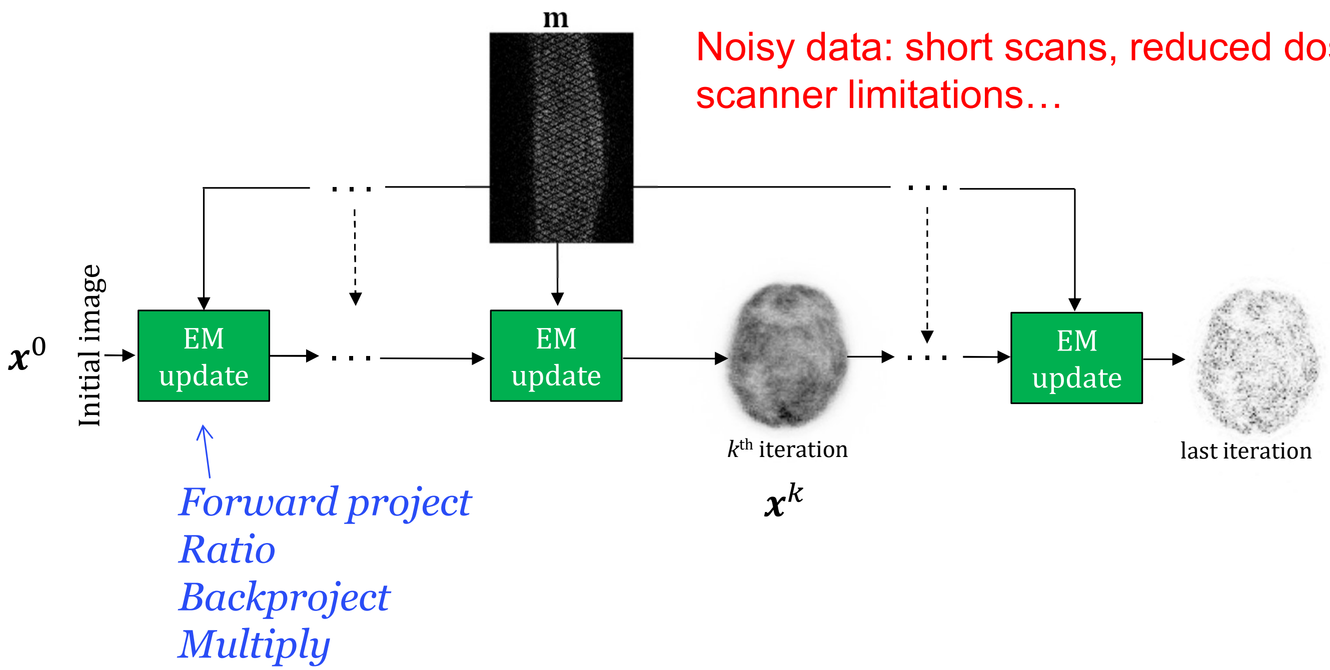
Compared to direct DL:

  - ✓ **Practical for 3D**
  - ✓ **Reduced** training **data** needs (~*tens* of 3D images)

- **Approaches include: a CNN model for the image during iterative reconstruction**
  - Lim *et al* 2018 (BCD-Net for low count PET), TMI 2020 (Iterative NN)
  - Gong *et al* 2019 (MAPEM-Net)
  - Mehranian and Reader 2020 (FBSEM-Net)

Maximum likelihood – expectation maximisation (ML-EM)

Unrolled into a deep network for fixed number of iterations:

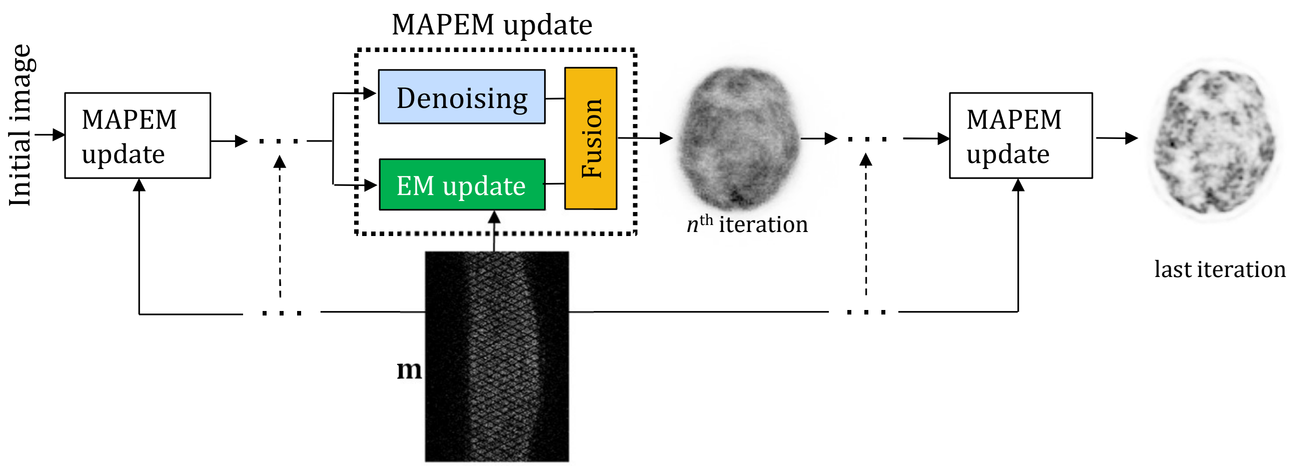


Noisy data: short scans, reduced dose, scanner limitations…

If noisy data, then noisy reconstruction

Unrolling iterative recon: Gregor & LeCun 2010

Simple example of regularisation for PET: quadratic prior

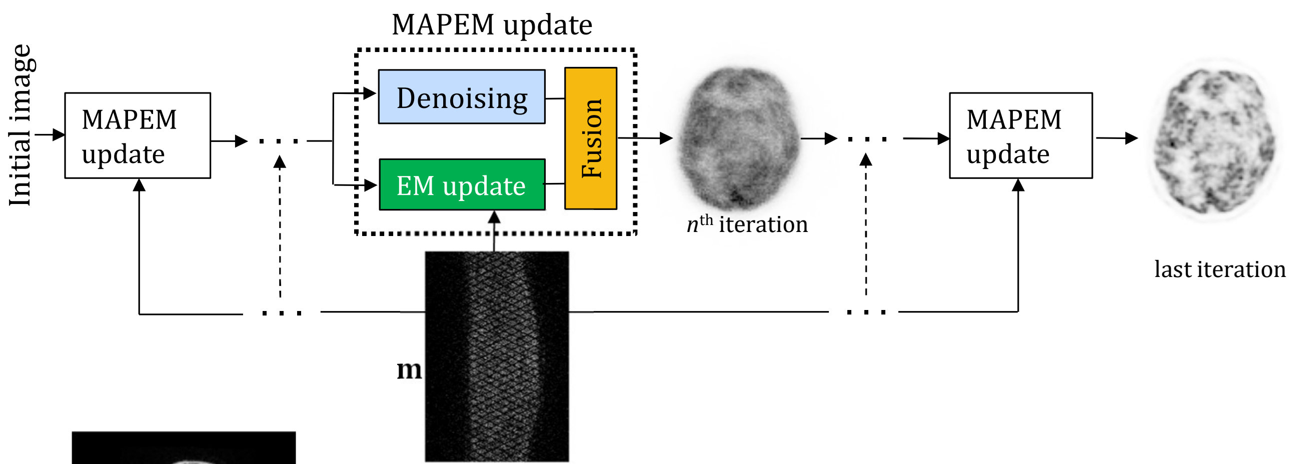


Uses mathematically convenient denoising

Unlikely to be optimal

De Pierro TMI 1995

Example of regularisation for PET: quadratic prior



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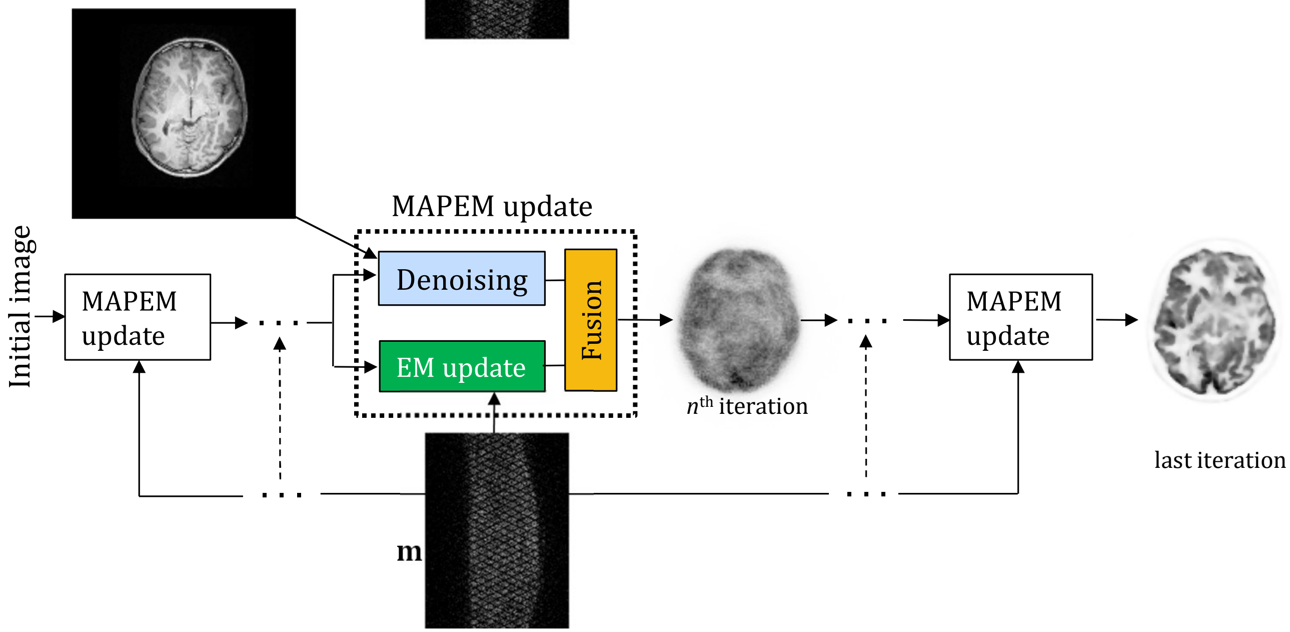
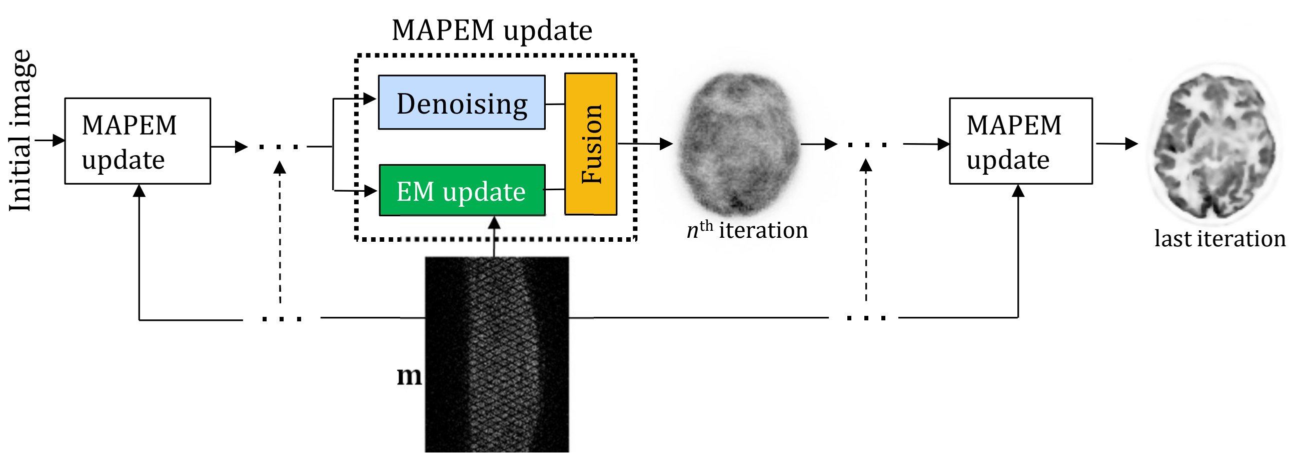


How much MR guidance?

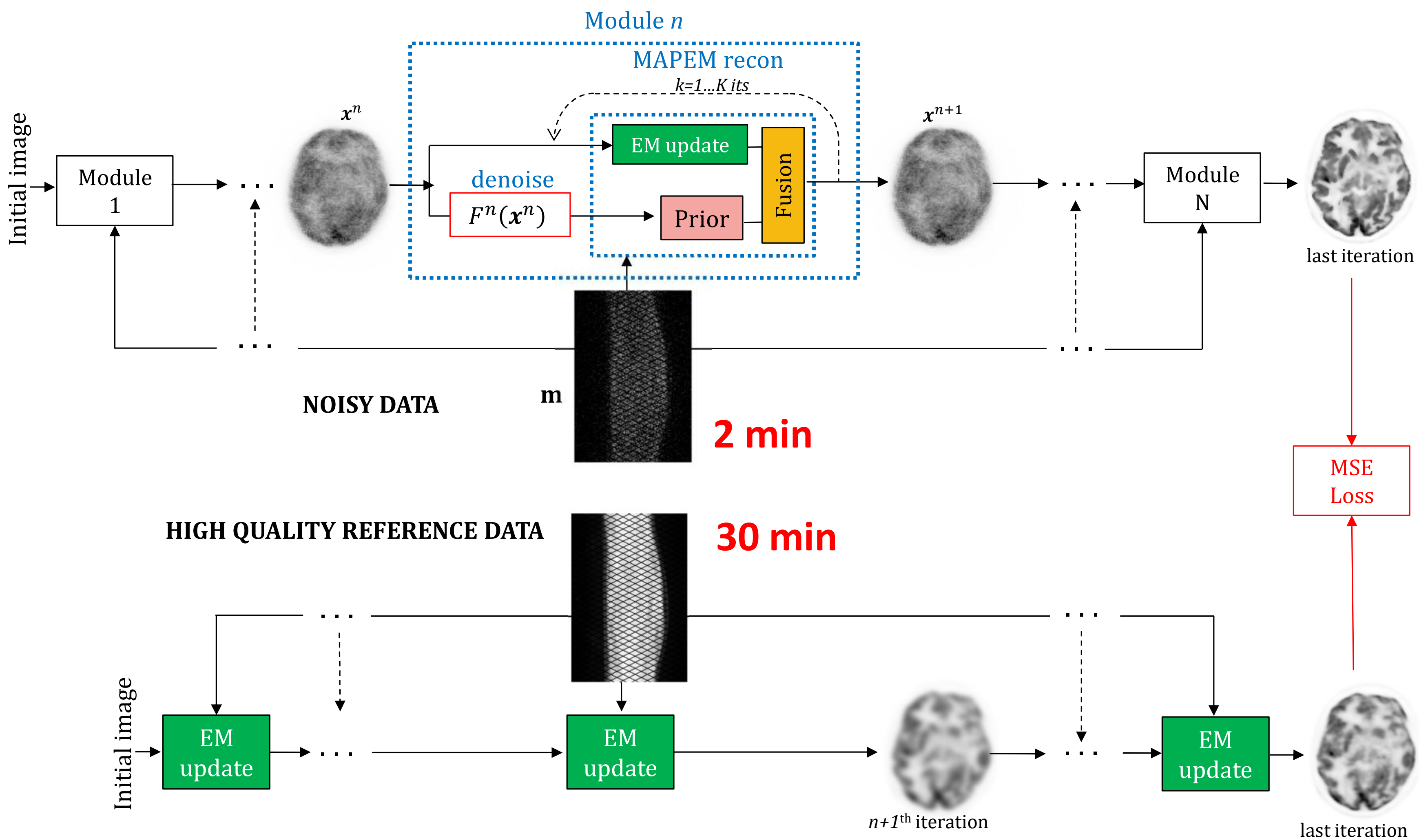
Unlikely to be optimal

…use deep learning

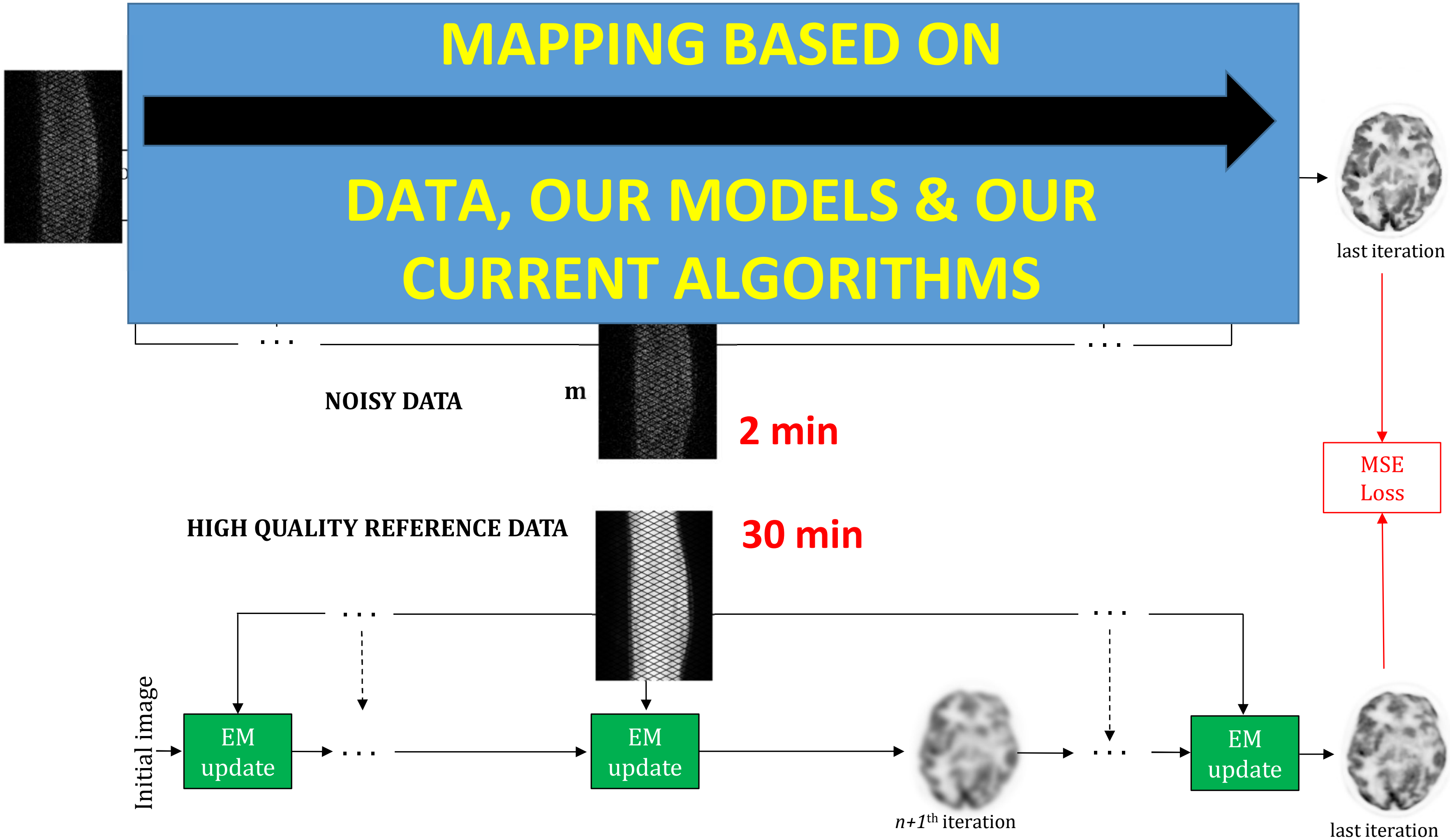
Bowsher IEEE NSS MIC 2004


MAPEM update
Initial image
MAPEM
update
Denoising
EM update
Fusion
n^{th} iteration
MAPEM
update
last iteration
m

Including deep learning: general framework for 3D PET

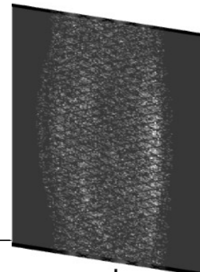


Including deep learning: general framework for 3D PET

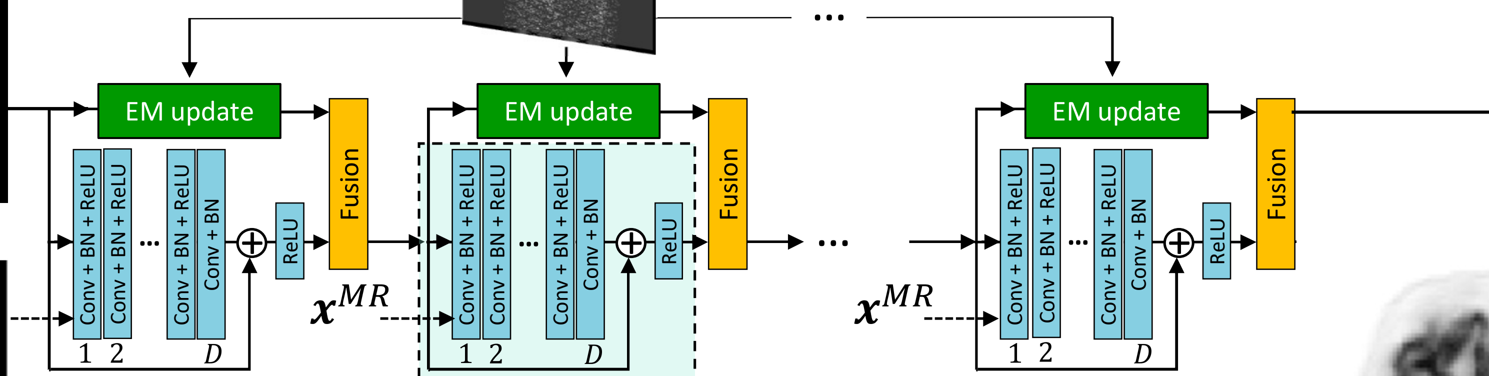


FBSEM-Net: real [^{18}F]FDG data

Initial empty image



PET data
Low count (short scan, or low dose)



MRI

Learns ~77k parameters
N = 35 training datasets

Uses MR, and the physics with AI

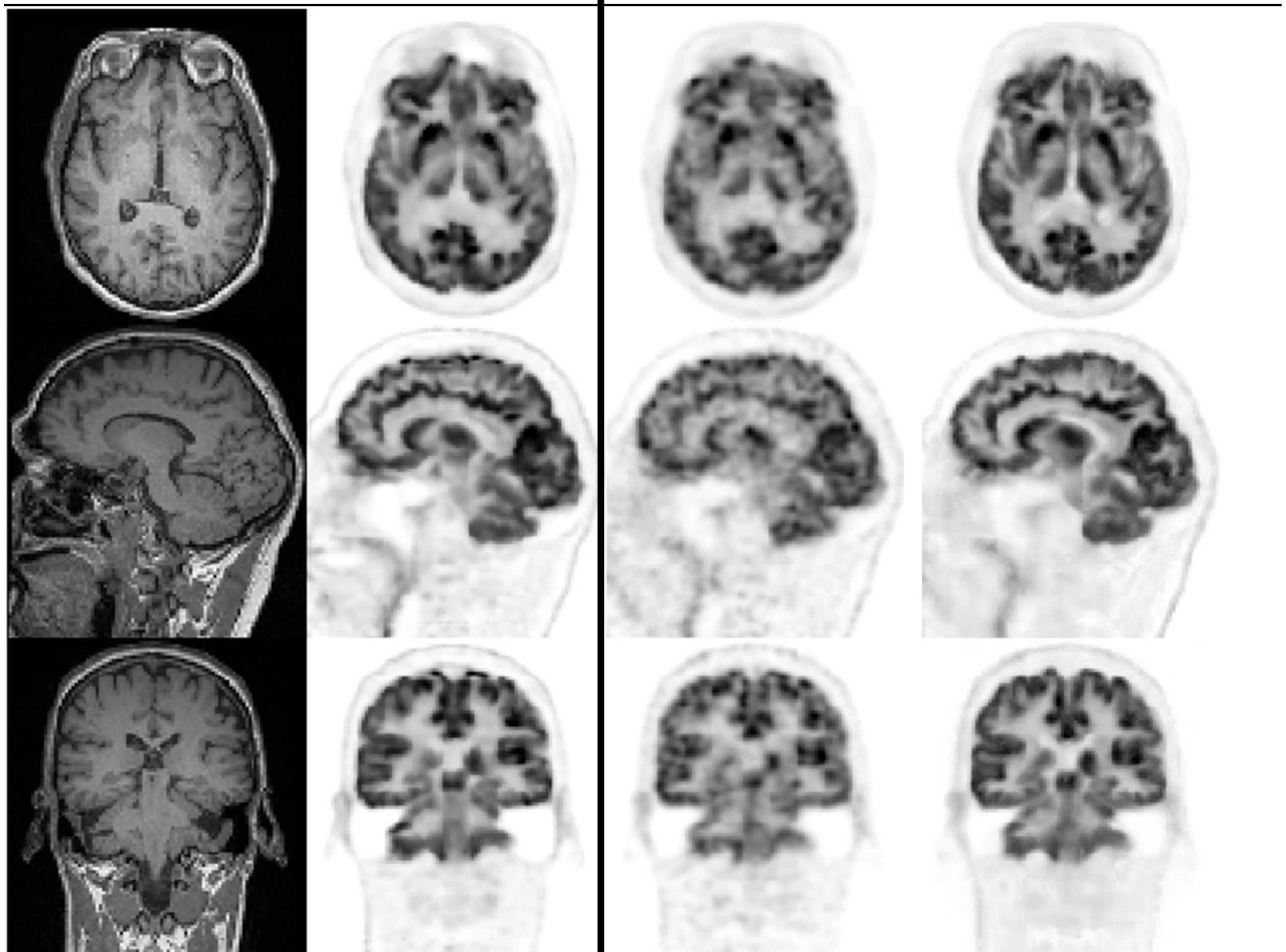
Reconstructed image of [^{18}F]FDG

Mehranian and Reader, IEEE TRPMS 2020

FBSEM-Net: real [^{18}F]FDG data

Uses MRI and AI

MRI | Reference | OSEM | FBSEM-Net



Mehranian and Reader, IEEE TRPMS 2020

30 min | **2 min**

Recent variations:

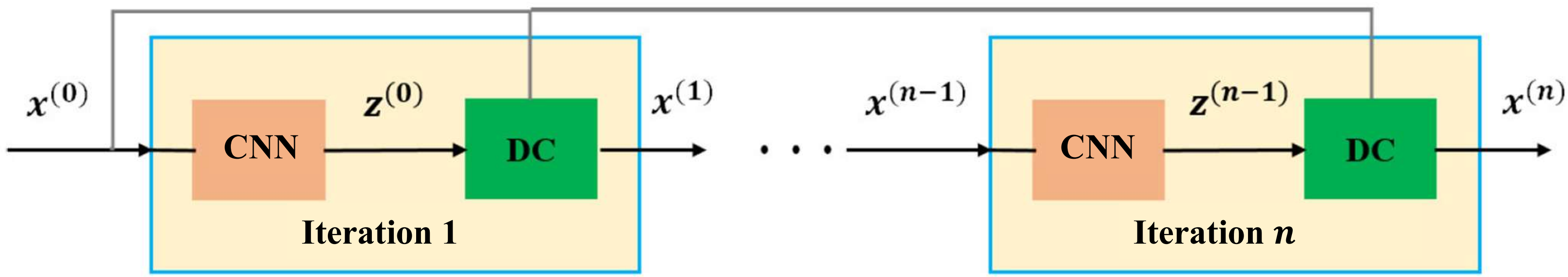
Sequential training [Corda d’Incan et al IEEE TRPMS 2021]

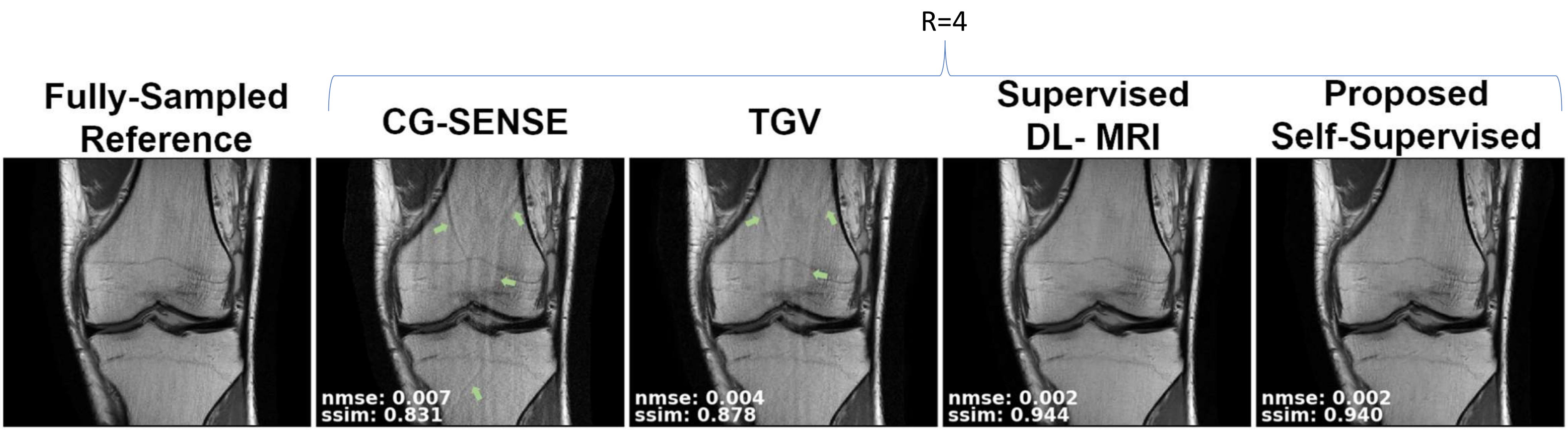
Using **transformers** [Rui Hu, Huafeng Liu 2022]

Yaman et al MRM 2020

Self-supervised MRI reconstruction

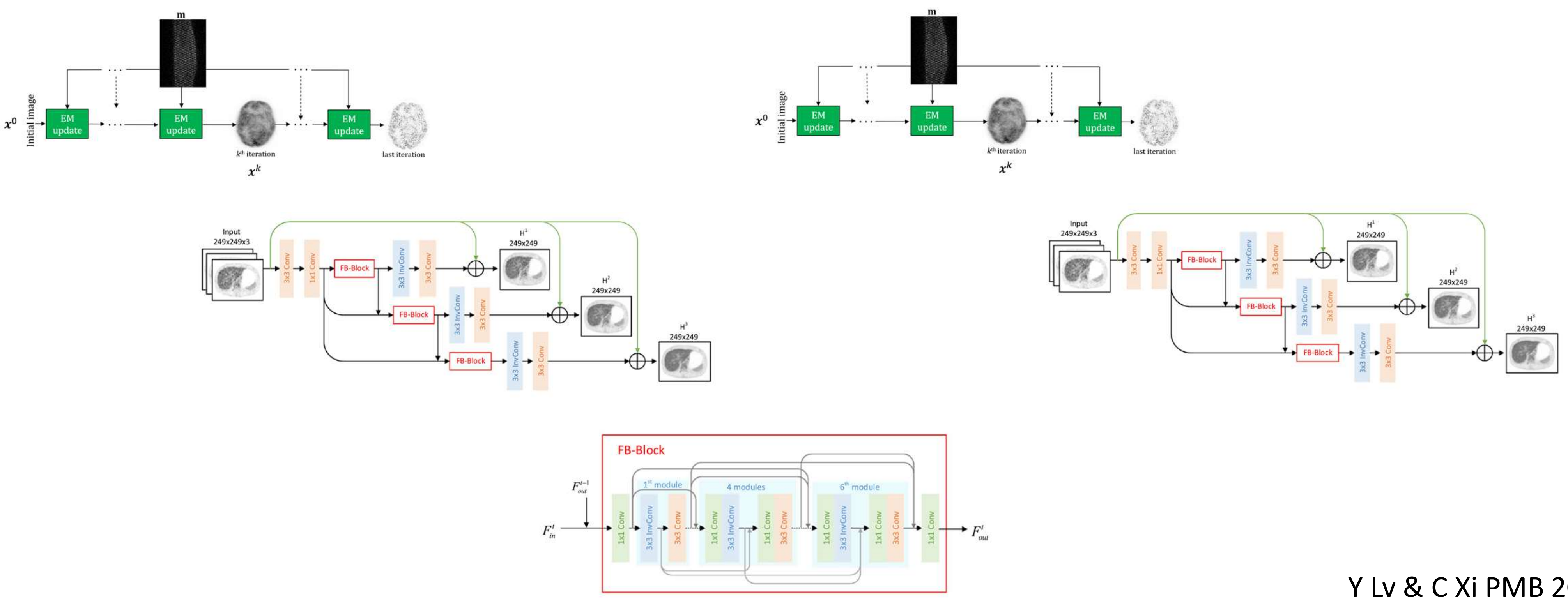
Supervised: images from fully-sampled data used for training
Self-supervised: half data used for k-space to reconstruct from, other half used for loss function





TBP: unrolled reconstruction (DPL)

(1) 1st EM iterations (2) CNN-denoising (3) Edge preserving fusion (4) 2nd EM iterations (5) CNN-enhancement (4) Weighted fusion



Y Lv & C Xi PMB 2021

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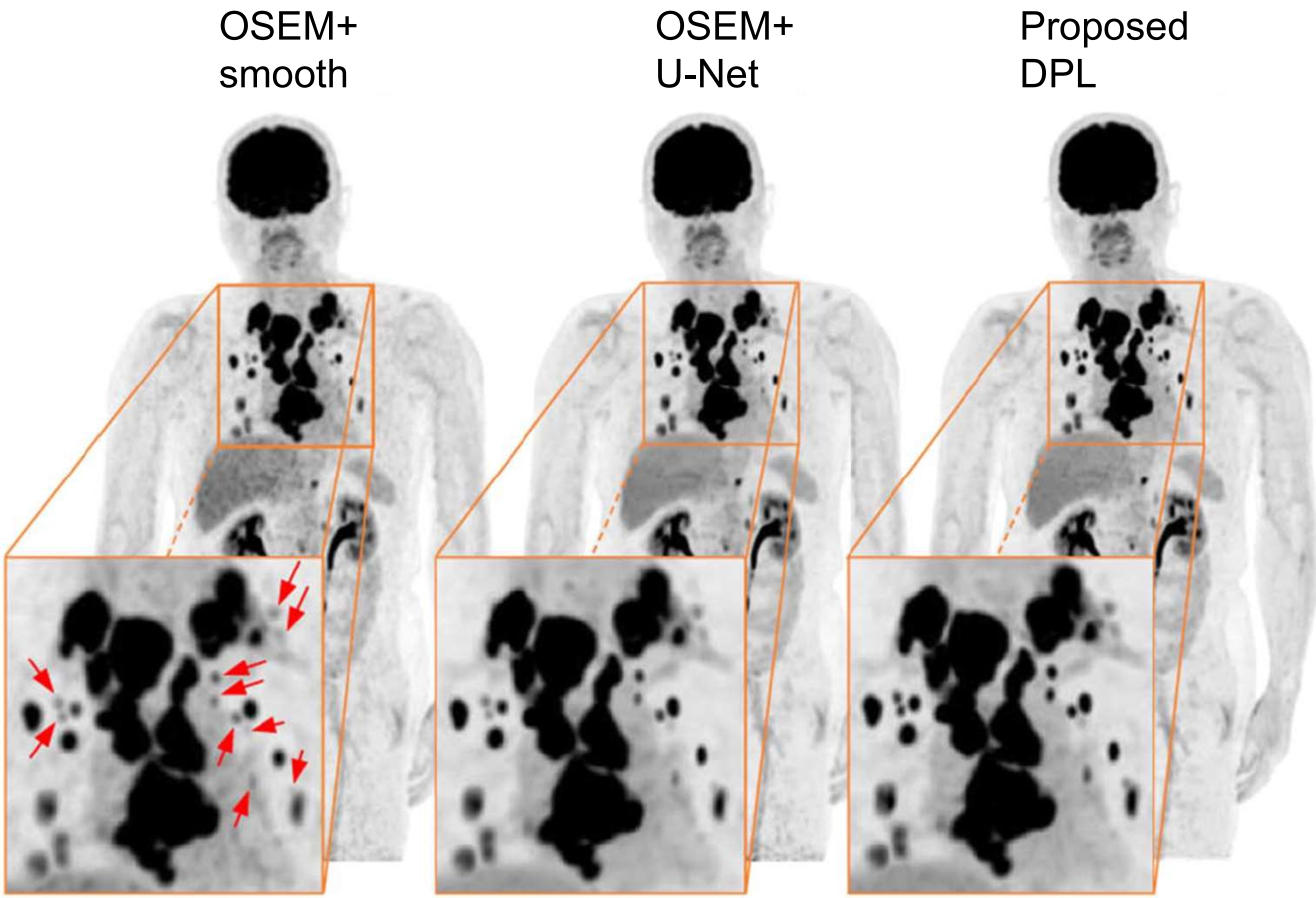


Y Lv & C Xi PMB 2021

Unrolled reconstruction summary

Examples: INN, MAPEM-Net, FBSEM-Net, DPL, TransEM, …

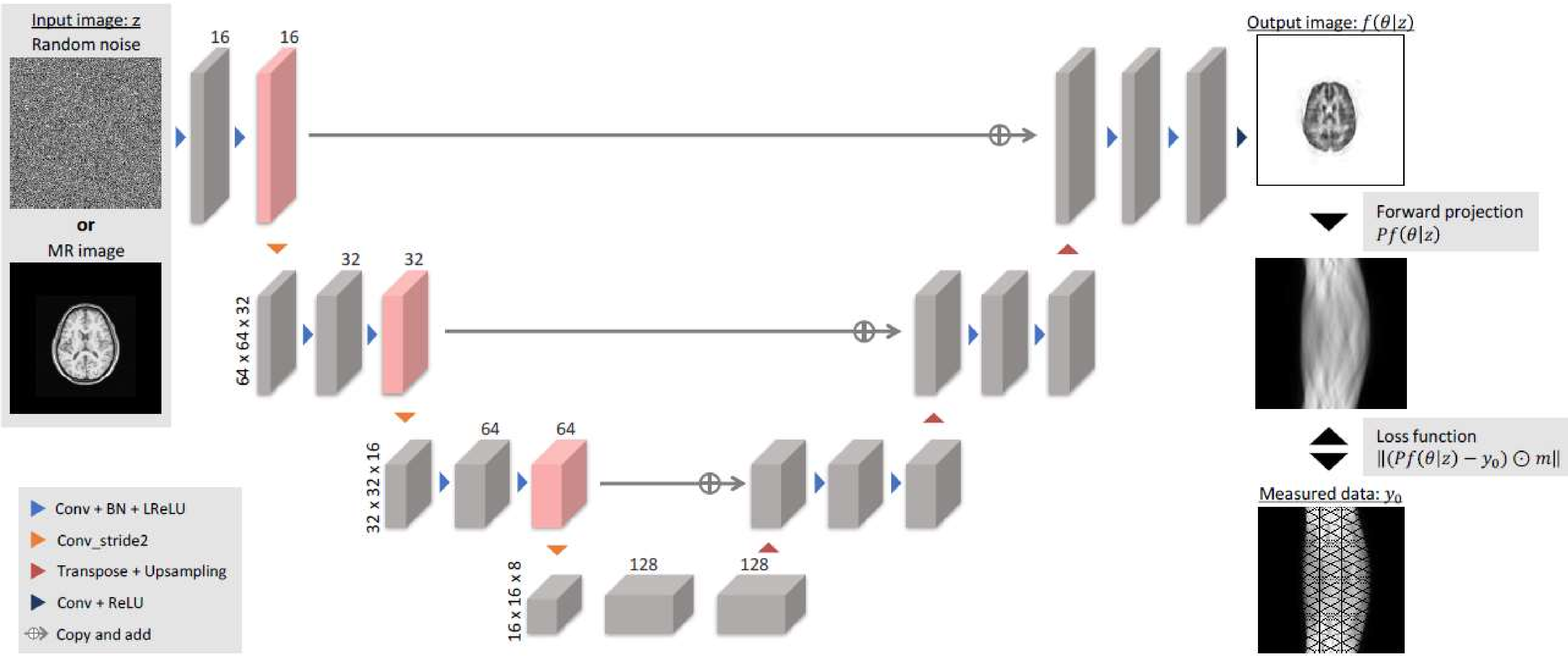
Lim *et al* 2018, TMI 2020, Gong *et al* 2019 , Mehranian and Reader IEEE TRPMS 2020, Y Lv & C Xi PMB 2021, R. Hu & H. Liu 2022, …

- ✓ Uses our physics and statistics knowledge
- ✓ (?) Uses our trusted algorithms for image reconstruction
- ✓ Some of exploit training data to define the image manifold
- ✓ Smaller networks (e.g. ~77k parameters)
- ✓ Smaller training sets (e.g. ~35)
- ✓ Practical for 3D reconstruction
- ✓ Improved generalisation

- Slower than direct reconstruction

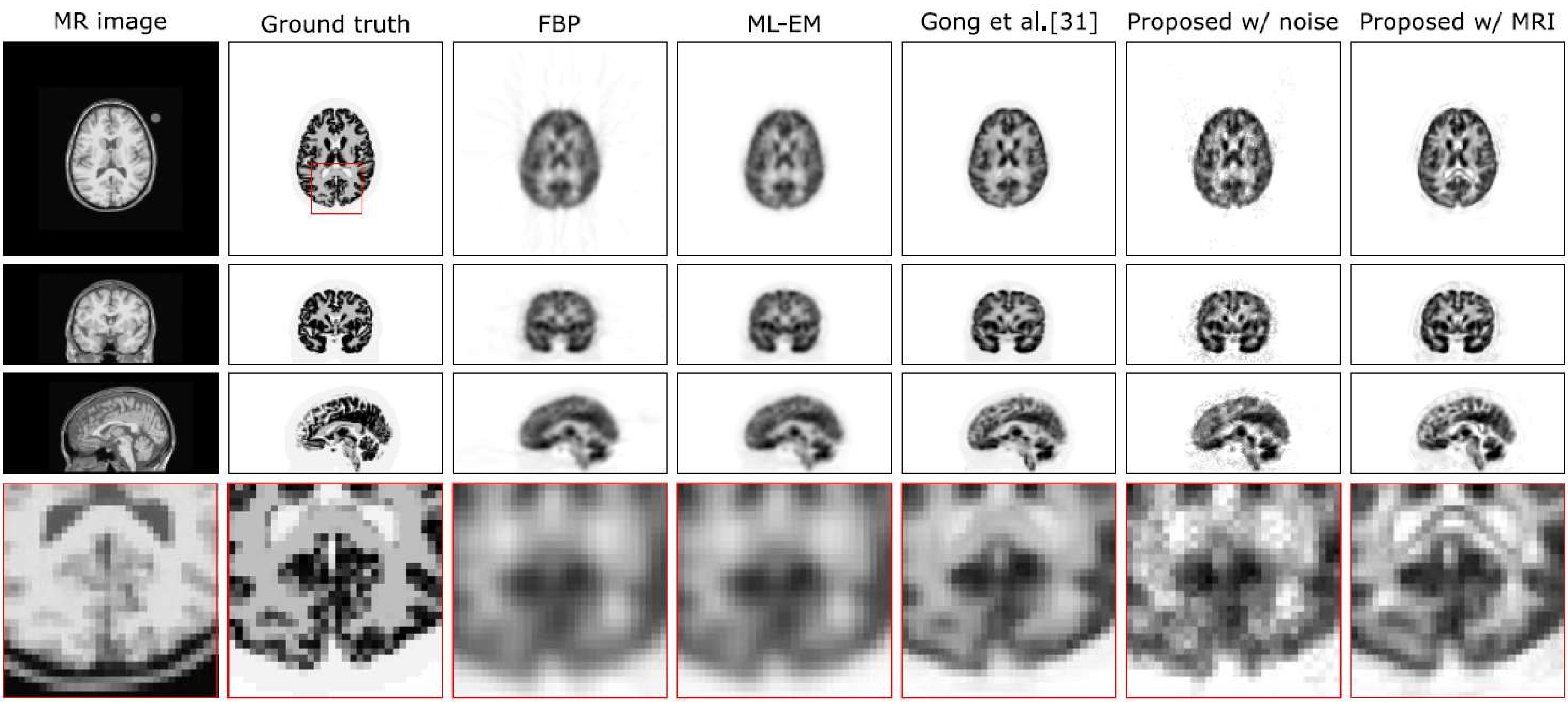
Deep representations

Deep image prior with system model



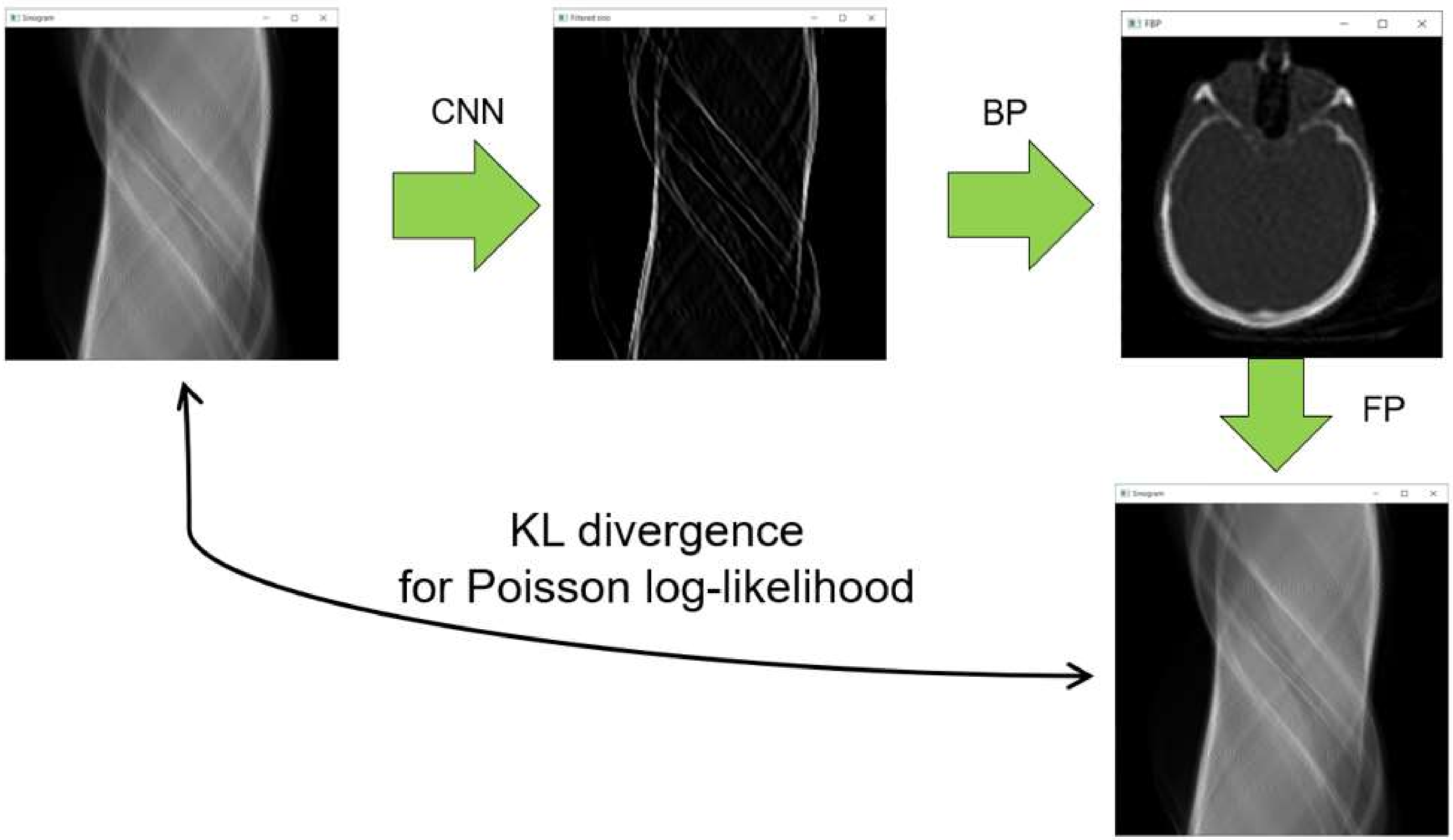
Hashimoto et al IEEE TRPMS 2022

Deep image prior with system model



Hashimoto et al IEEE TRPMS 2022

Deep filter with system model



AJ Reader PSMR 2022

Some recent directions

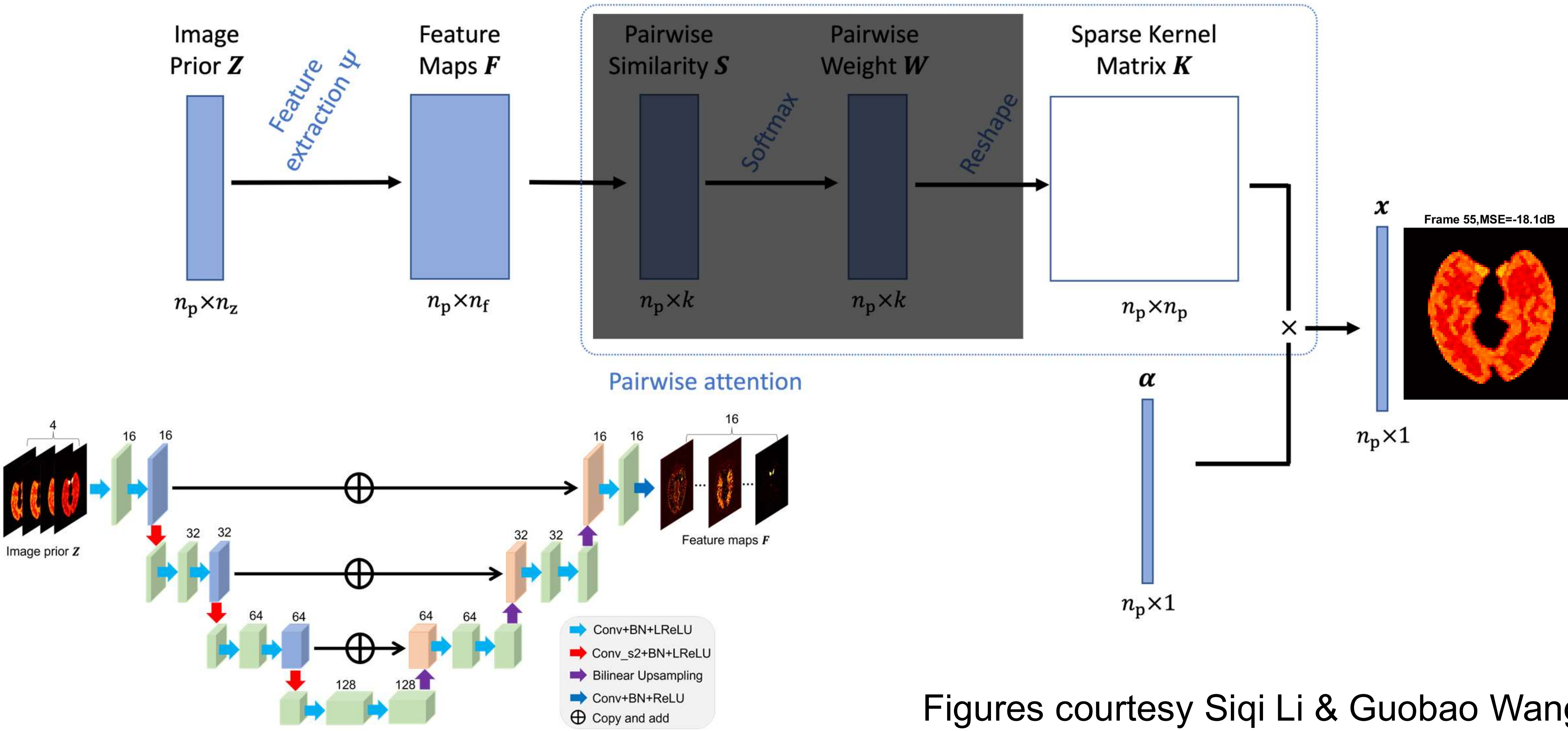
Deep kernel

TBP kinetics

Synergistic PET-MR reconstruction

Deep kernel representation (Li & Wang 2022)

Uses AI to learn the best pixel features for reconstructing short time frames (v. low count data)



Figures courtesy Siqi Li & Guobao Wang

Deep kernel representation results: can reconstruct 2 second frames with much improved quality (GE Discovery ST PET/CT <u>in 2D mode</u>, 20 mCi [^{18}F]FDG, cardiac scan)

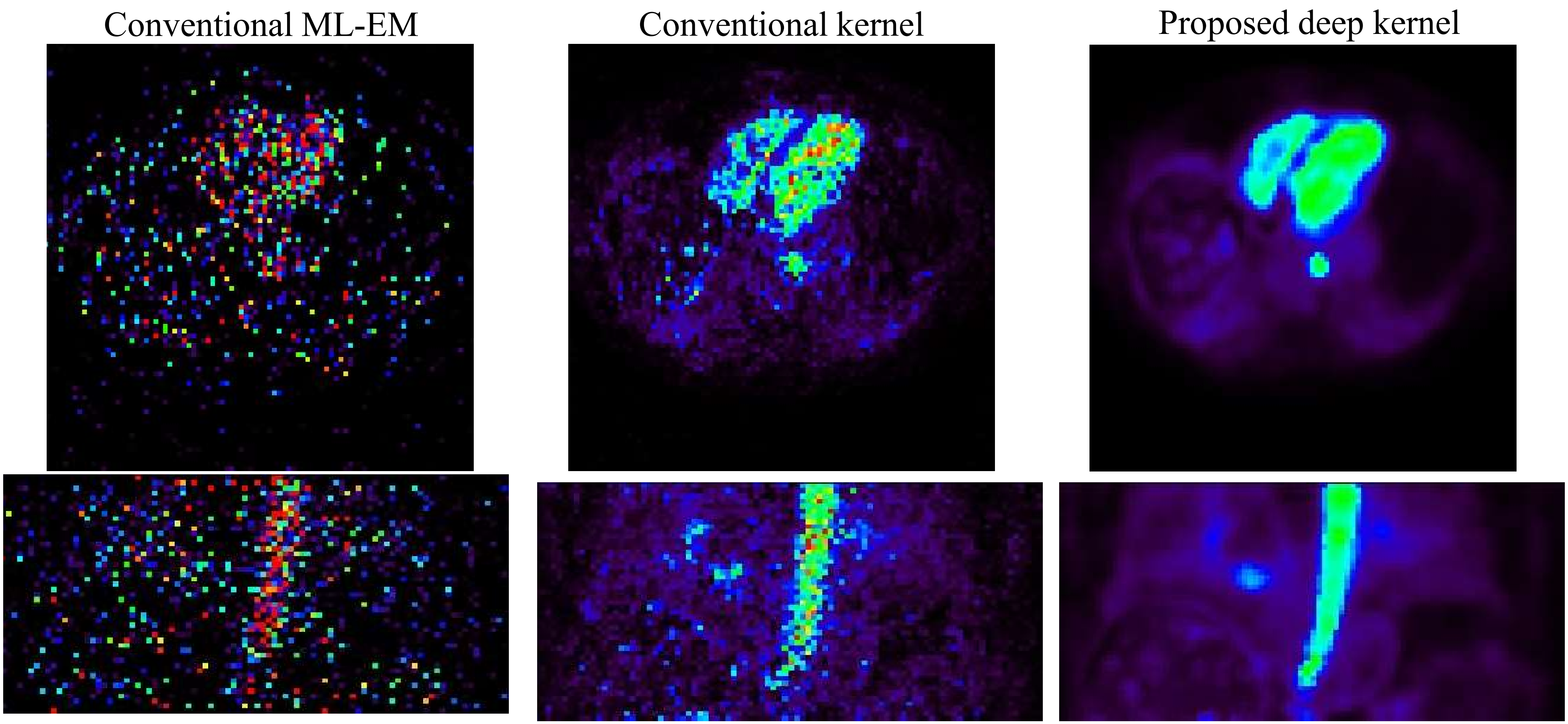
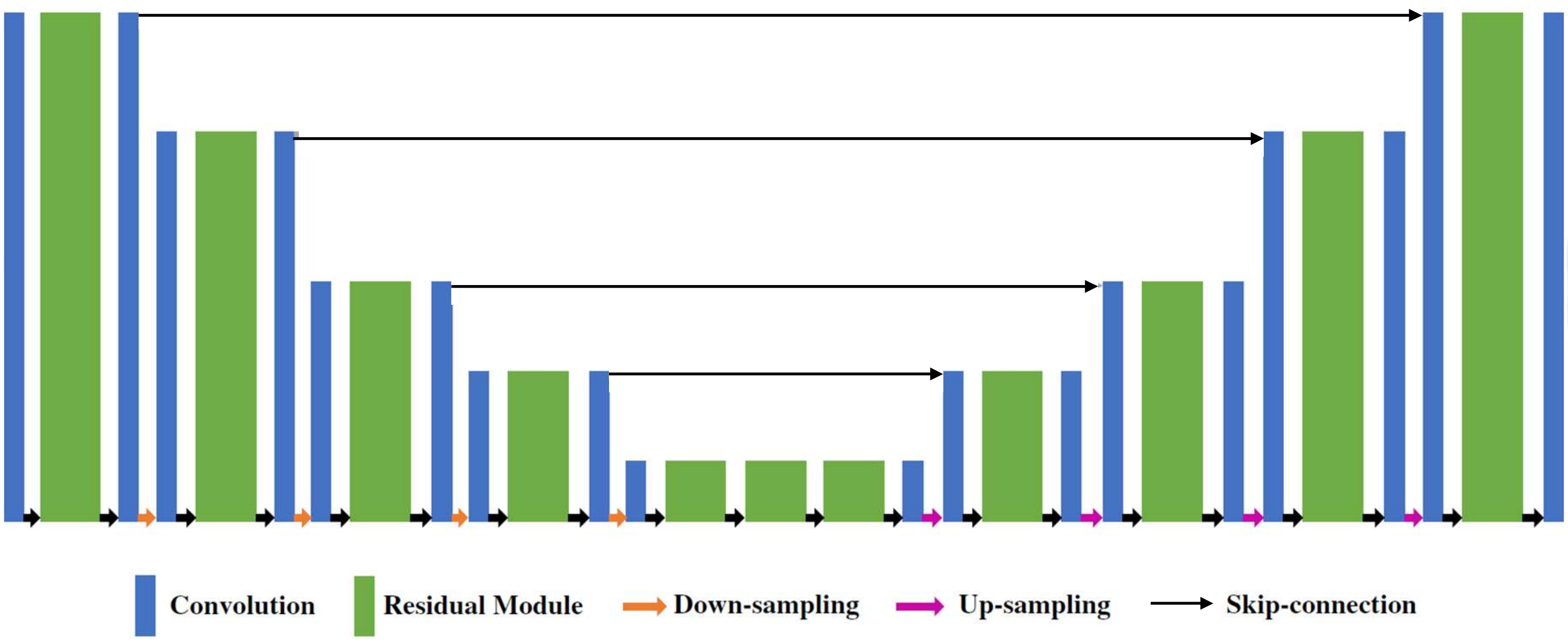


Figure courtesy Siqi Li & Guobao Wang

TB PET using deep learning to predict kinetic parameters

- Direct parametric map generation for [^{18}F]FDG for the uEXPLORER: mapping SUV to Ki

SUV
50-60 min



160 patient datasets for training
20 for validation, 20 for testing

K_i
0-60 min

Figure courtesy Meiyun Wang and Zhanli Hu (based on Huang *et al* EJNMMI 2022)

TB-PET current research

- Direct parametric map generation

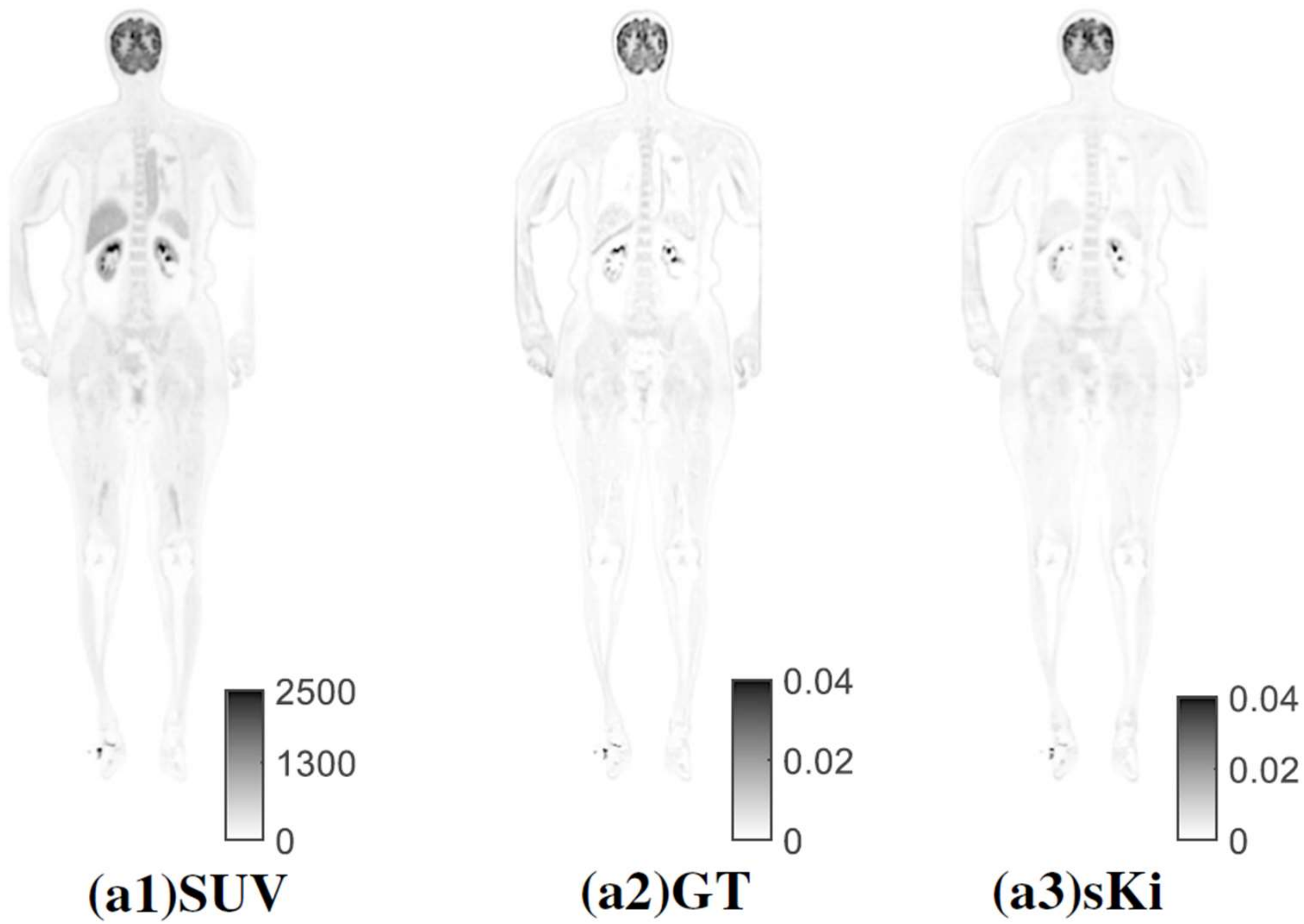
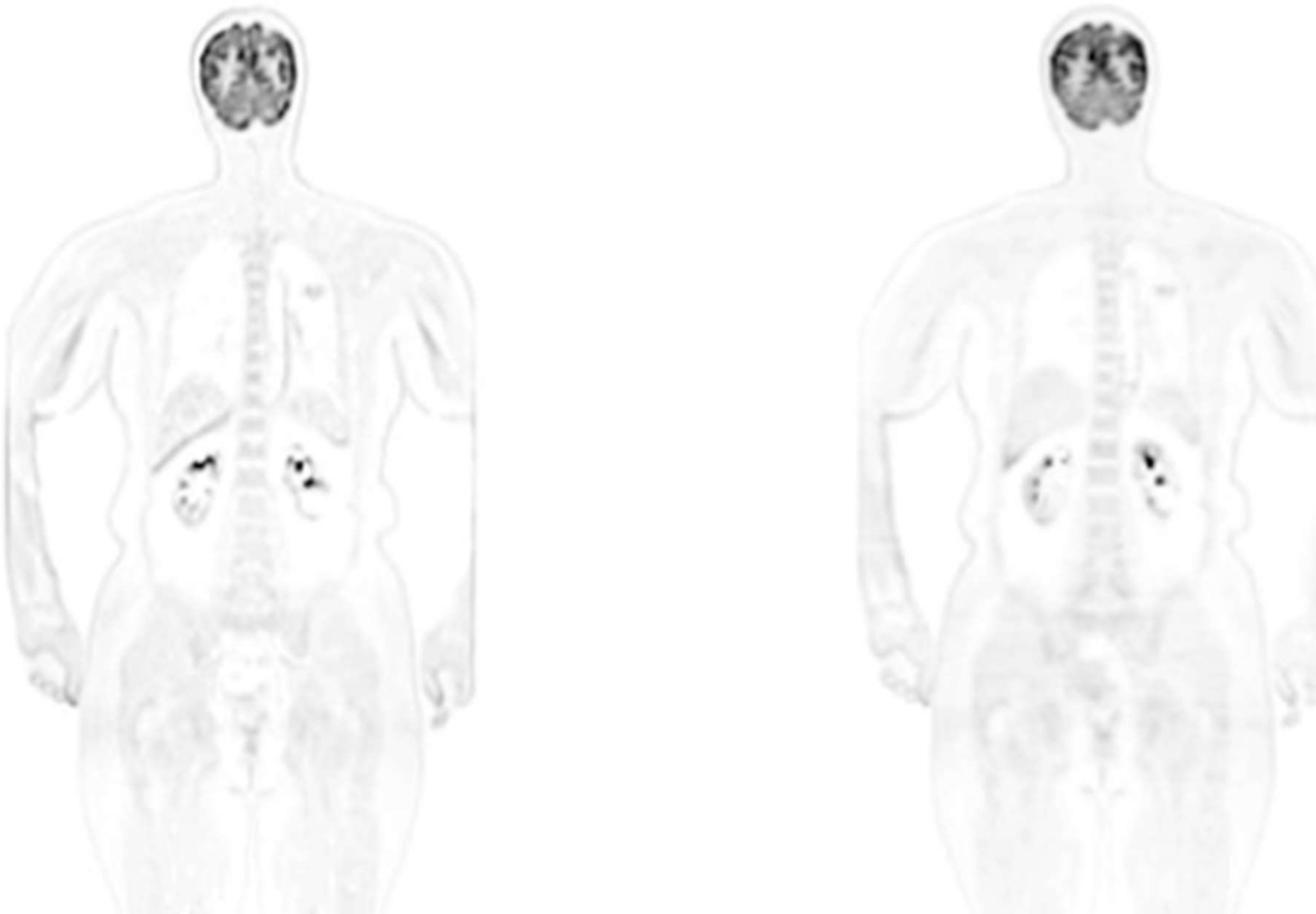
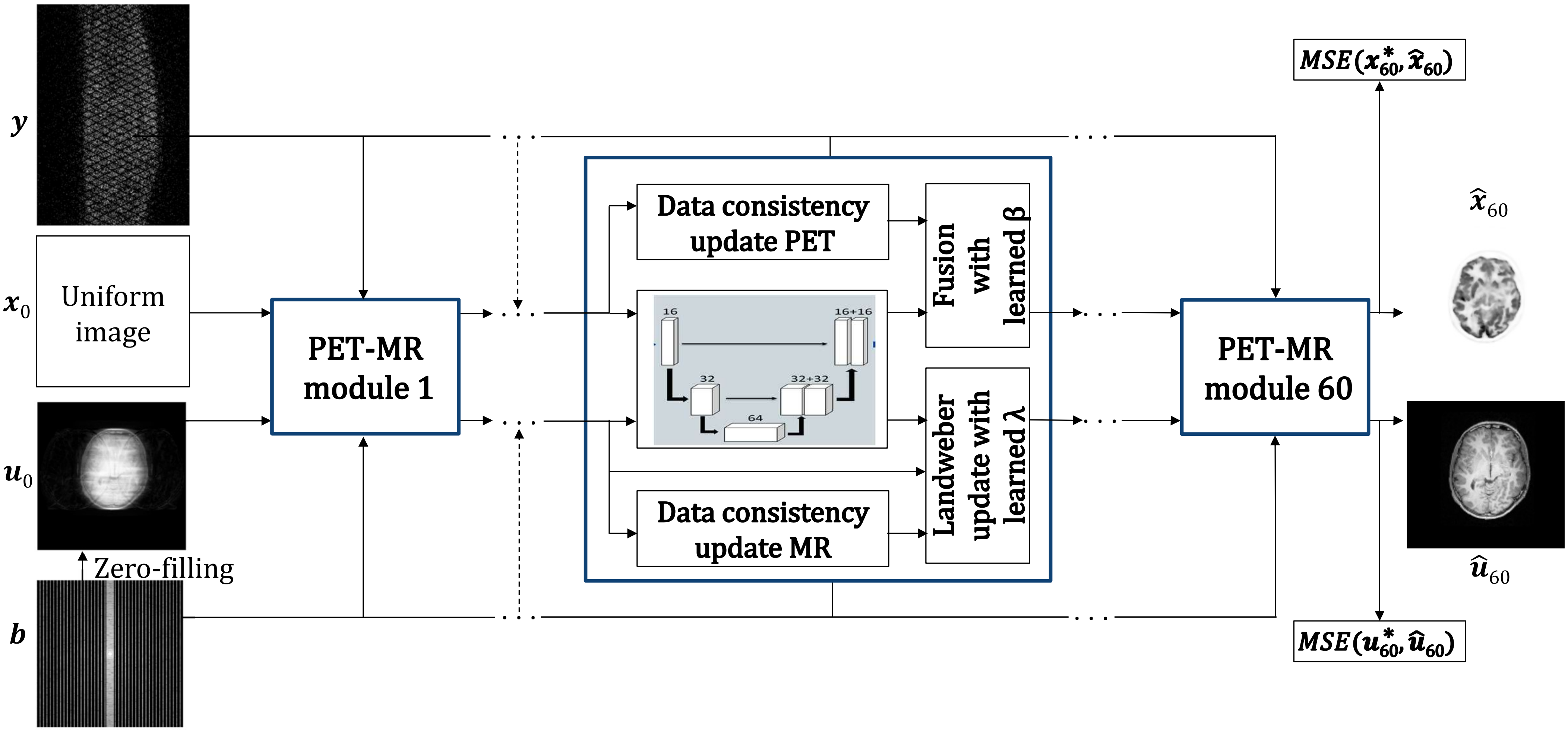


Figure courtesy Meiyun Wang and Zhanli Hu (Huang *et al* EJNMMI 2022)



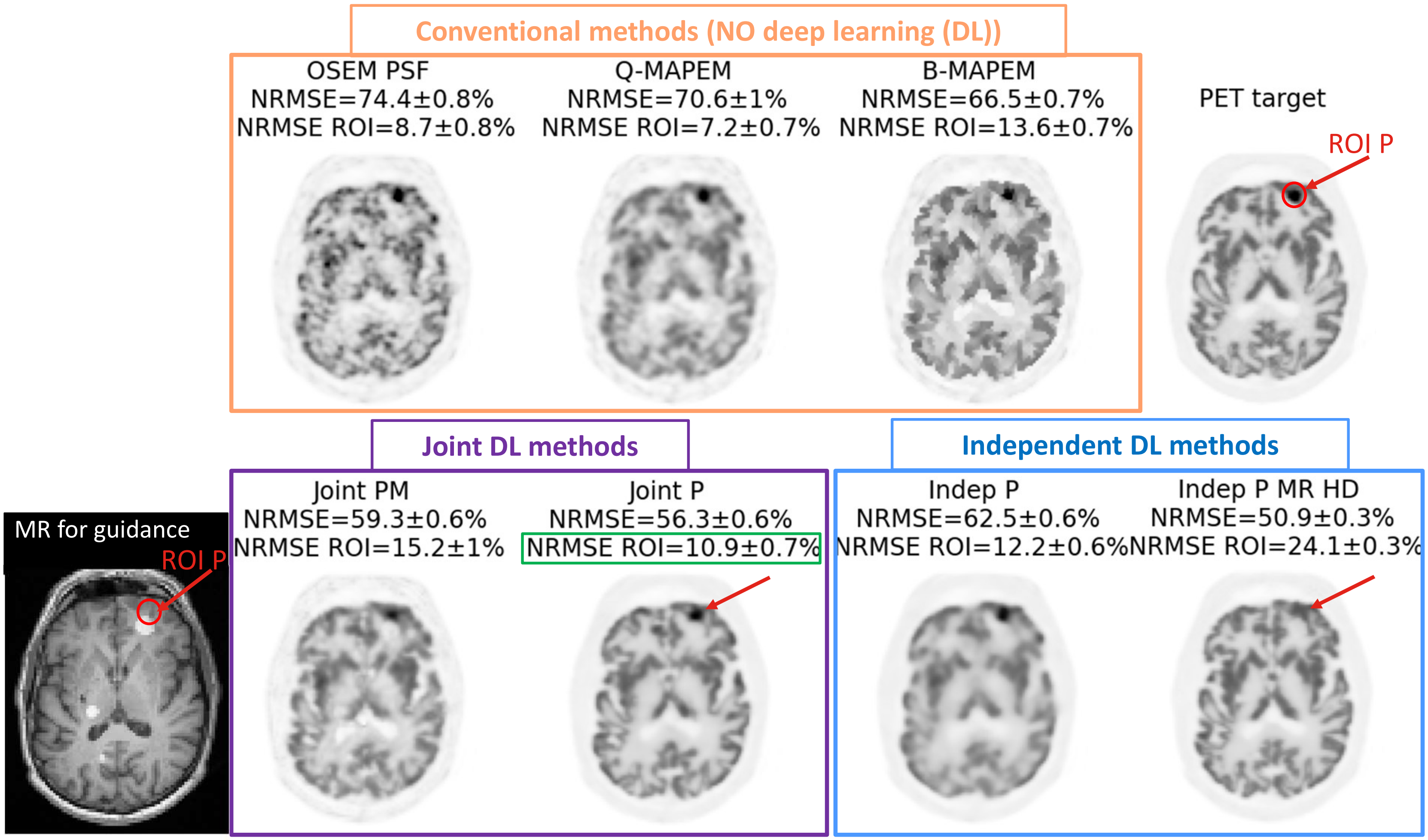
)

Synergistic and Joint Deep-Learned PET-MR Reconstruction



Corda D'Incan, Schnabel and Reader, submitted to IEEE Medical Imaging Conference 2022

PET reconstruction

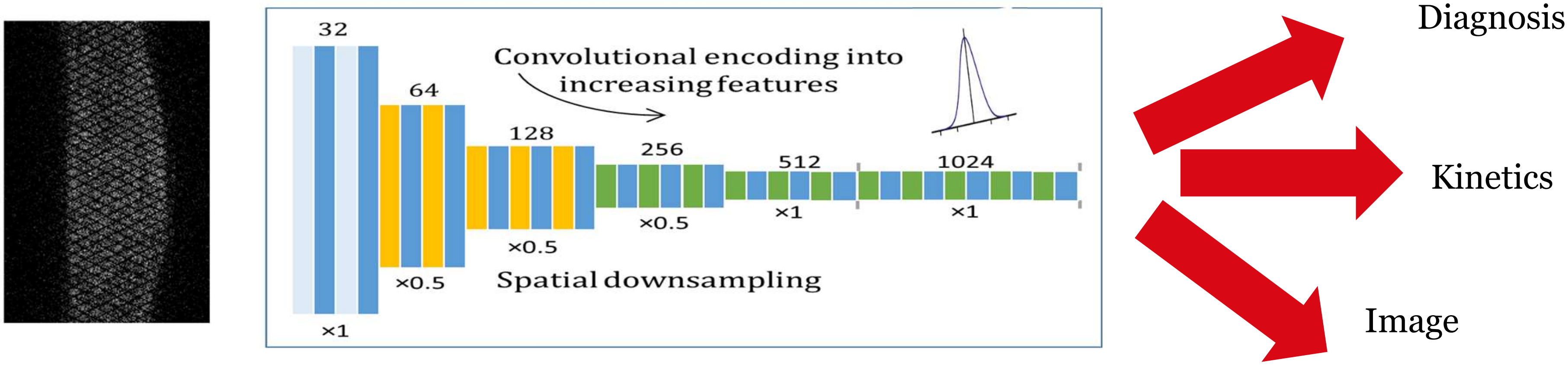


Corda D'Incan, Schnabel and Reader, submitted to IEEE Medical Imaging Conference 2022

Outlook

Future?

- Latent space
  - Encode your raw data into a latent space
  - Decode into an image, parametric map, a diagnosis, …
  - Use data, physics, statistics, analytically informed inductive priors
- Fully Bayesian: latent space as a pdf conditioned on your data
  - Decode multiple samples, to allow expression in each chosen decoded representation
  - Allows degree of uncertainty to be expressed with high quality outputs



"All models are wrong,… but models that know that they're wrong are useful" (J. Snoek)

Future?

- Modular processing for robustness & validation of each component
  - AI module for ‘inversion’ of core scanner forward model
  - AI module for regularisation

- High quality references, vs. self-supervision

- Assess AI reconstruction for clinical tasks, ideally with benchmark datasets (still needed)

- Reminders:
    - Improve image quality for a given count level
      - Or trade this in for lower dose, and/or even faster scans
      - Could keep the lower noise, higher spatiotemporal resolution
      - Best to directly relate raw data to desired endpoints

    - Use of TOF histo images (and other data compression strategies)
    - Uncertainty quantification (aleatoric, epistemic)
    - Multiplexed imaging and disentangling

Thank you

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Deep Learning for PET Image Reconstruction

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HOT TOPICS

Artificial Intelligence for PET Image Reconstruction

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