Multi-Subject Image Synthesis as a Generative Prior for Single-Subject PET Image Reconstruction

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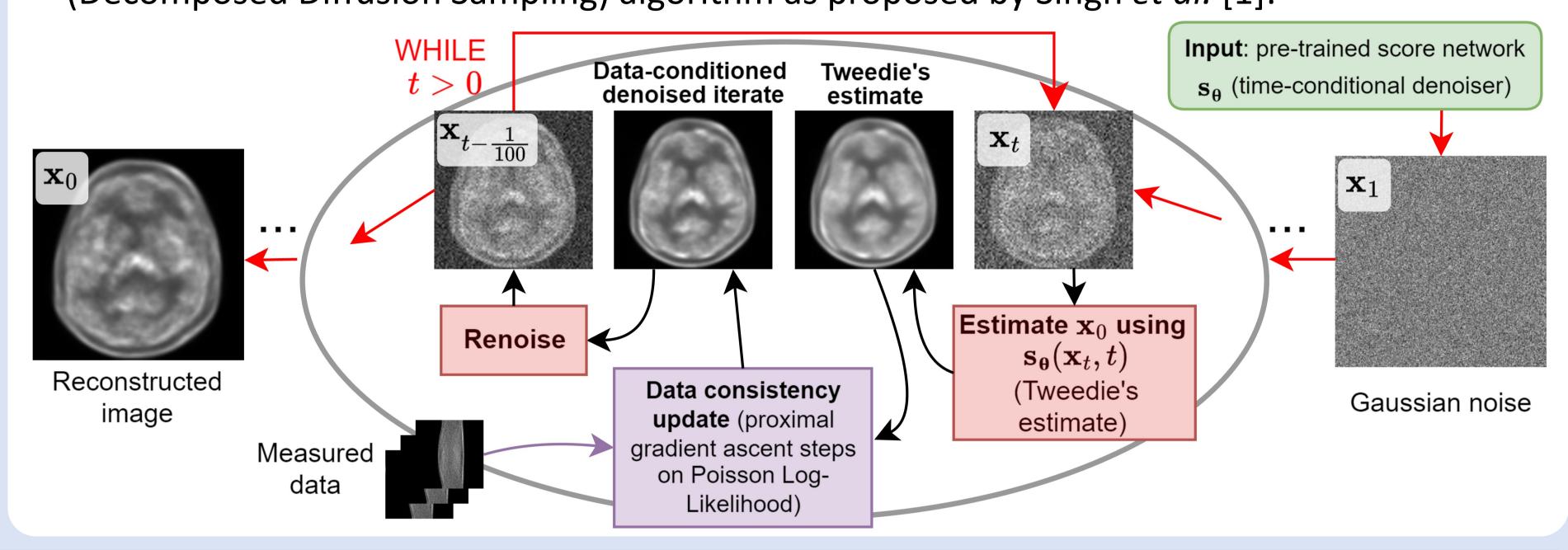
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Introduction

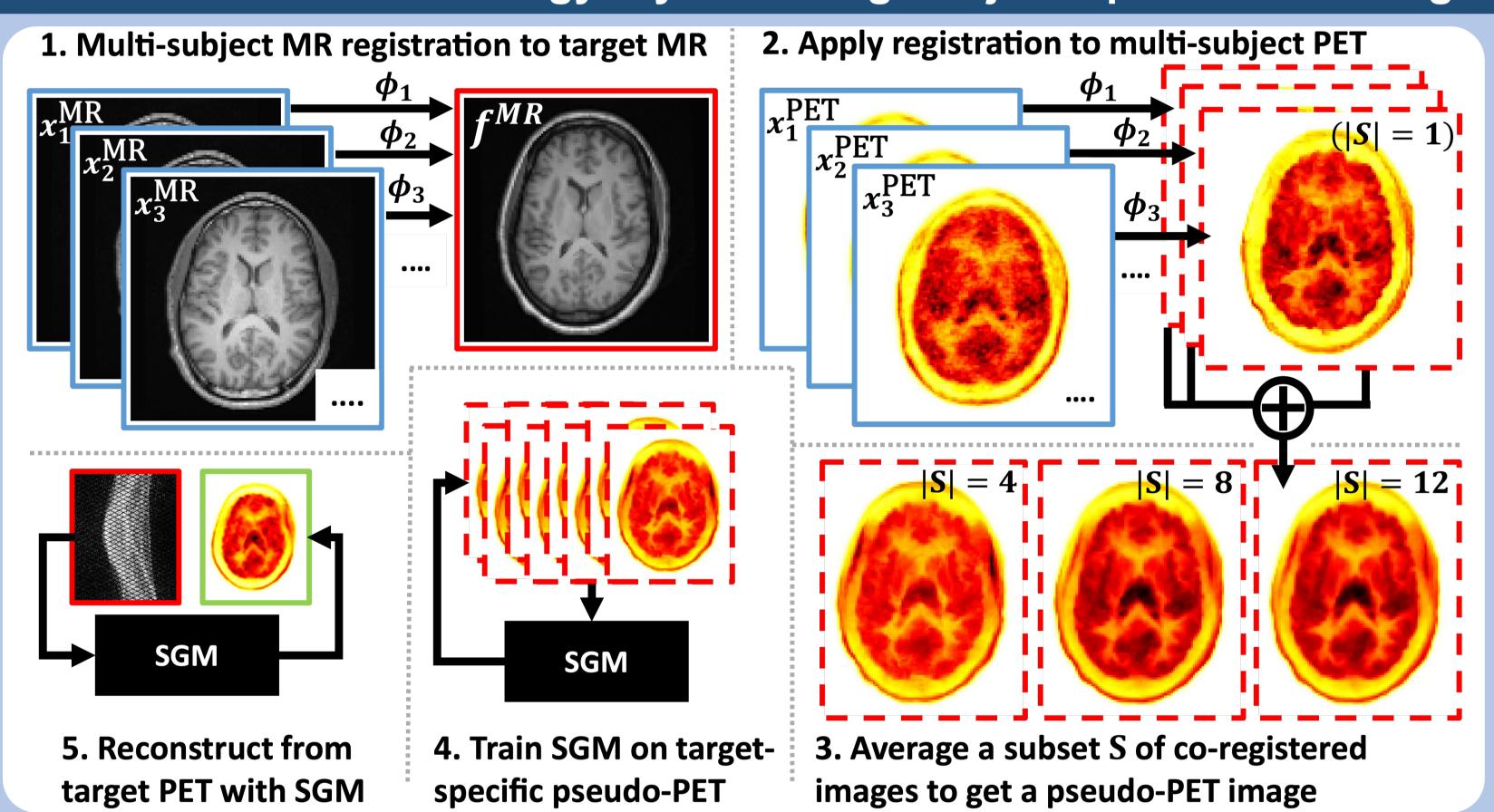
- Score-based Generative Models (SGMs): flexibly enhance Positron Emission Tomography (PET) image reconstruction accuracy, by leveraging prior information learnt only from high-quality PET images
- Challenge: can an SGM adequately generalise from scarce data to an unseen patient's brain anatomy?
- **Proposal:** train an SGM on *diverse*, *high-quality* & *subject-specific* pseudo-PET images, that are synthesized by registering PET images from multiple subjects to the reconstruction target subject
- Research question: Does an SGM trained with pseudo-PET images achieve superior reconstruction quality to an SGM trained with real PET images?

Score-based Generative Models (SGMs) for PET Image Reconstruction

• After training an SGM s_{θ} , to perform PET image reconstruction we use the PET-DDS (Decomposed Diffusion Sampling) algorithm as proposed by Singh *et al.* [1]:



Methodology: Synthesizing Subject-Specific PET Images from Multi-Subject Images to train an SGM



- Deep-learned registration: use Voxelmorph [2] to register multi-subject MR datasets to target MR
- Synthesis of subject-unique high-quality pseudo-PET images: apply registration fields to corresponding multi-subject PET images
- **Train SGM:** sample 2D transverse slices from pseudo-PET images; train SGM on slices by minimizing the Denoising Score Matching objective
- Reconstruct images: from test dataset's noisy PET sinograms using PET-DDS, for SGMs trained on pseudo- or real PET images
- Two separate data sources: simulated [18F]FDG and real [18F]DPA714 PET images formed using OSEM (resolution 2mm x 2mm x 2mm)

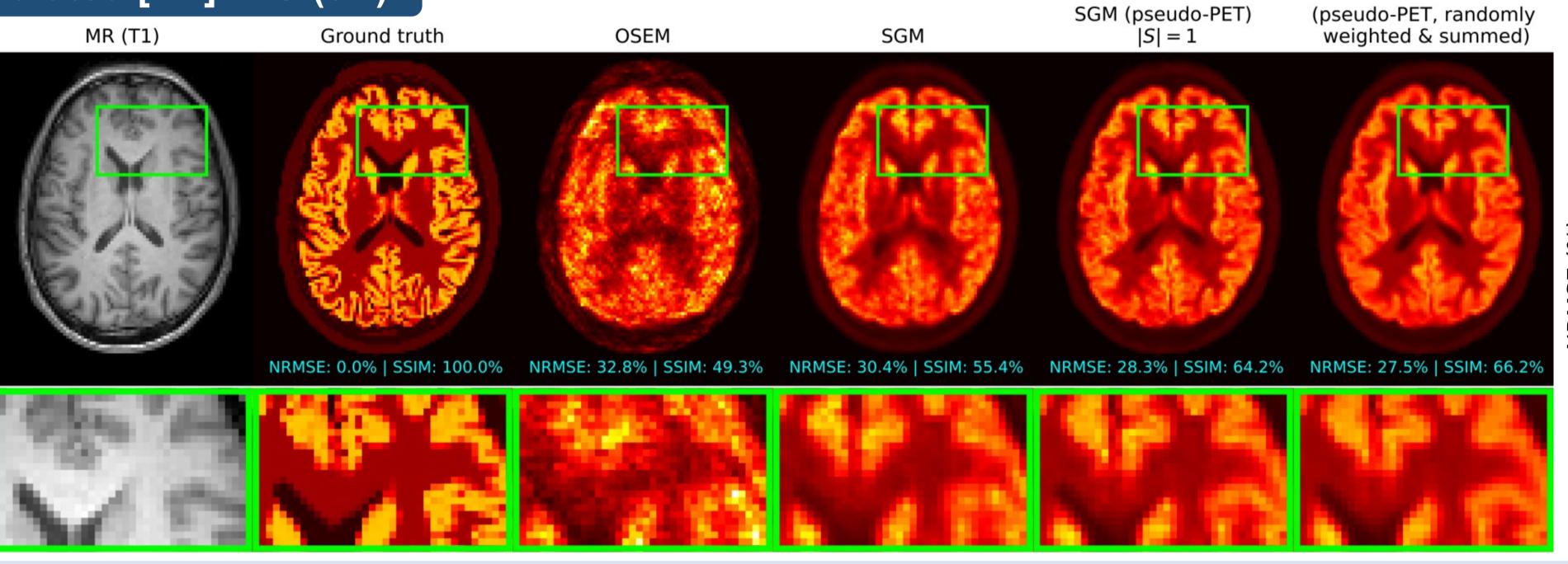
Simulated data: 39 patient-realistic [18 F]FDG distributions were simulated from real T1 MR. Voxelmorph training used 36 training datasets and the test dataset. 2 validation datasets were reserved for to perform early stopping on the SGM's validation loss. Full count data was modelled as 6×10^8 counts. 3D reconstruction was performed from 2.5% of full count.

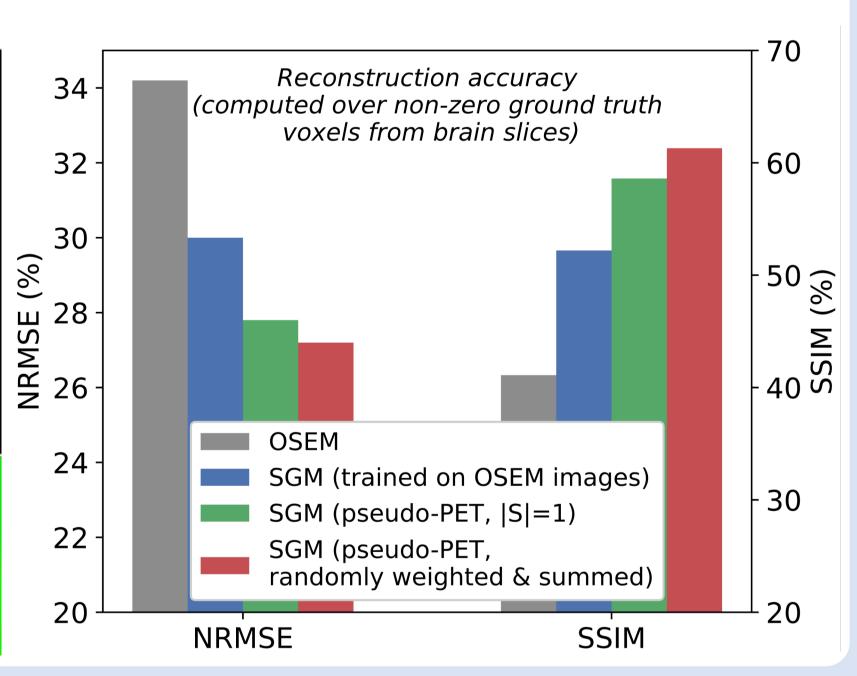
SGM

Real data: 12 real [18 F]DPA714 datasets were obtained from the Inflammatory Reaction in Schizophrenia study [3], which used the Siemens Biograph mMR. The Voxelmorph registration function was trained on all datasets, while SGMs were trained on all datasets except the test dataset. 2D reconstruction was performed from direct plane sinograms with 4.7×10^5 counts (compared to 7.5×10^8 counts in 3D).

Results: Simulated [18F]FDG (3D)

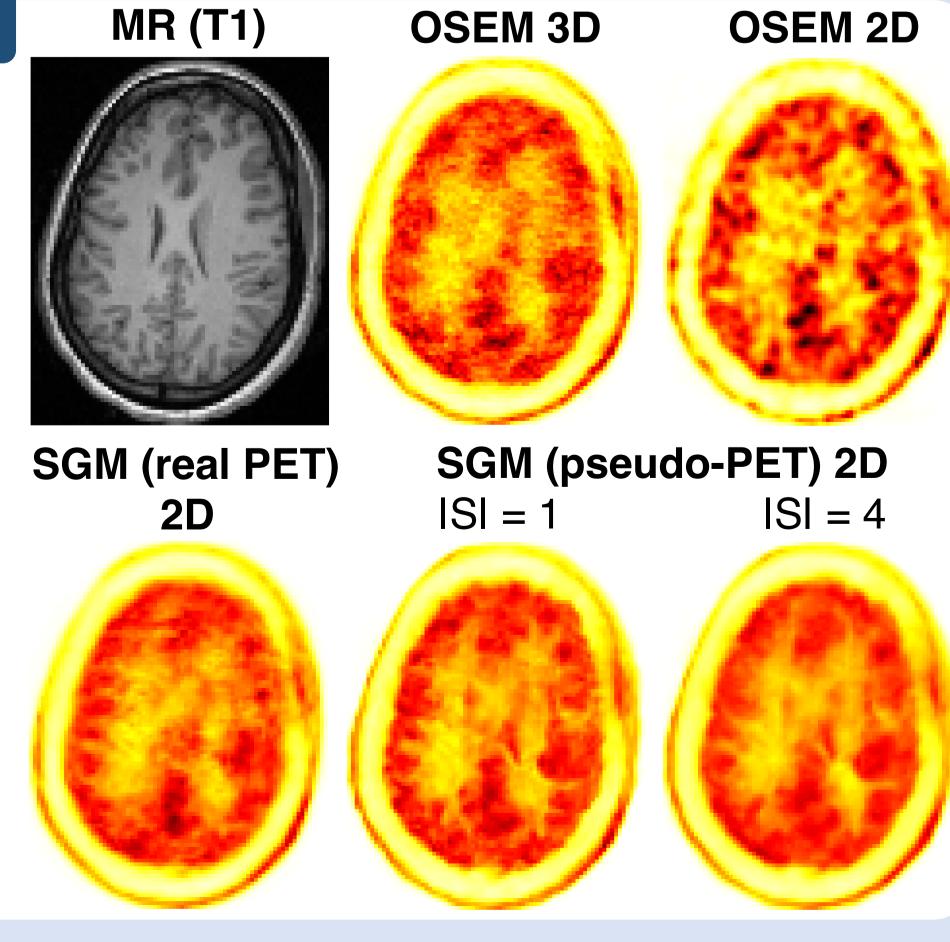
For simulated [18F]FDG, instead of fixing |S|, we investigated choosing N images (with $p(N) \propto 1/N$) then randomly weighting and summing these images. This produces an infinite source of diverse training images with high signal-to-noise ratio.





Results: Real [18F]DPA714 (2D) 1.7 Oita 1.6 1.7 OSEM MAPEM SGM: pseudo-PET |S|=1 SGM: pseudo-PET |S|=4 Normalized standard deviation in white matter background (%) Hyperparameters controlling the regularization strength were varied

for each method, with contrast ratio plotted against background noise



Discussion

- The use of subject-specific priors improves reconstruction accuracy both qualitatively and quantitatively
- Reconstructions from SGMs trained with pseudo-PET are imbued with anatomical features, despite not using explicit MR information during reconstruction
- Using multiple summed PET images as SGM training data suppresses noise in cold regions
- Potential application also to PET-CT reconstruction

Conclusion

- Registering PET datasets using MR information can imbue the registered image with additional anatomical features
- Training an SGM with diverse & subject-specific prior information can improve the accuracy of reconstructions

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for each selection.



References:

[1] I. R. D. Singh *et al.* Score-based Generative Models for PET Image Reconstruction. *MELBA*. 2024;2(Generative Models):547-585

[2] G. Balakrishnan et al. VoxelMorph: A Learning Framework for Deformable Medical Image Registration. IEEE Trans. Med. Imag. 38, 8. 2019 [3] F. Muratib, et al. Dissection of Neuroinflammation in Schizophrenia. BJPsych Open 7, Suppl 1 (June 2021)