

Synthetic PET images generation from small datasets

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Aim

Generation of synthetic brain PET images to overcome privacy issues about management of sensitive data.

Nonlinear Dimensionality Reduction

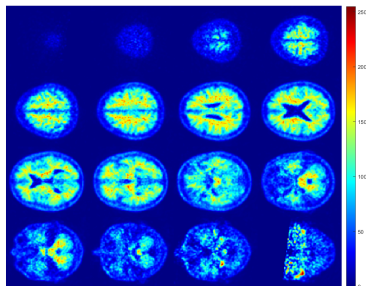
Data Manifold mapping inversion

Dataset

1001 brain PET images from 21 European research centres
457 negative, 540 positive Alzheimer's disease diagnosis and 4 unknown patients

PET images: 97-by-115-by-97 matrices, reshaped into 1082035-dimensional vectors

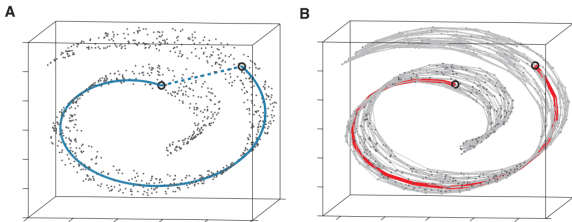
Gray levels standardized at single-patient level



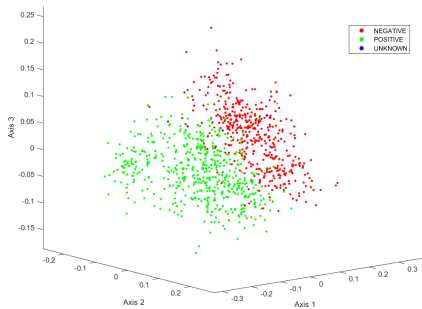
Dimensionality reduction: PCA and Isomap

PET image $\vec{x} \in \mathbb{R}^{1082035} \rightarrow \vec{z} = \Phi(\vec{x}) \in \mathbb{R}^{10}$

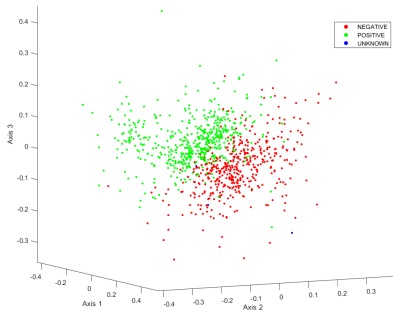
- 1) PCA: covariance matrix diagonalization.
- 2) Isomap: non-invertible generalisation of MDS algorithm.



PCA and Isomap dimensionality reduction



PCA



Isomap

Back to original image space

- 1) PCA: analytical backprojection onto original space
- 2) Isomap: cubic RBF interpolant

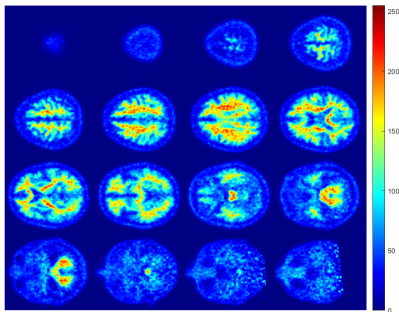
Comparison of reconstruction:

LOOCV Cross-validation of inverse mapping algorithm.

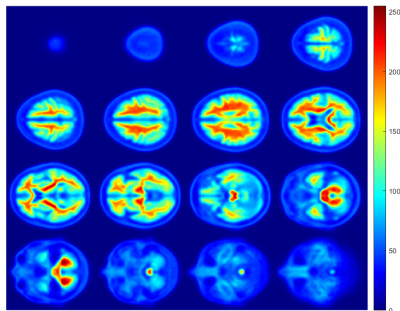
Reconstructed and original images comparison:

- Euclidean distance reconstruction error RMSE
- Structural Similarity Index SSI

Image reconstruction with PCA

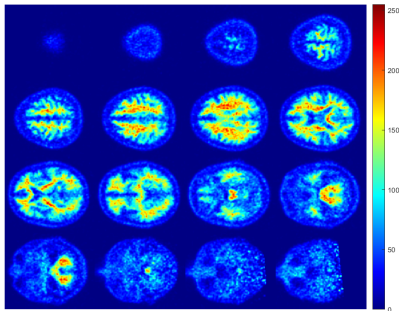


Original PET image

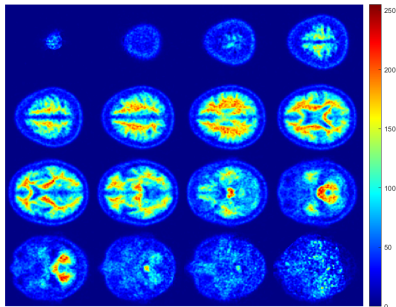


PCA reconstruction
SSIM ≈ 0.83

Image reconstruction with cubic RBF interpolant

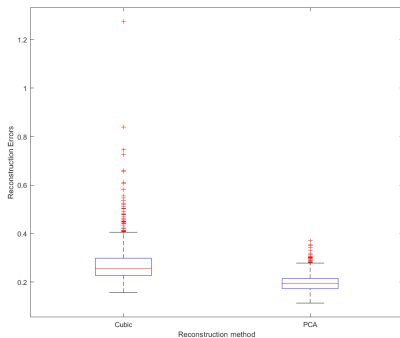


Original PET image



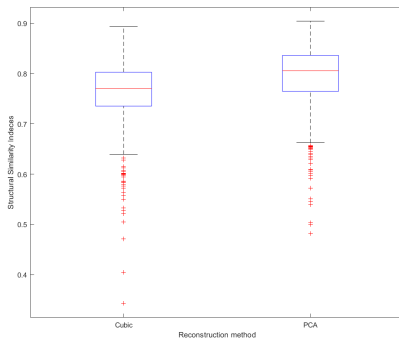
Cubic RBF reconstruction
 $\text{SSIM} \approx 0.78$

Dataset statistics: PCA is better!



$$E_{\text{cubic}} = 0.24 \pm 0.03$$

$$E_{\text{PCA}} = 0.18 \pm 0.02$$



$$\text{SSIM}_{\text{cubic}} = 0.76 \pm 0.06$$

$$\text{SSIM}_{\text{PCA}} = 0.79 \pm 0.06$$

Synthetic brain PET images

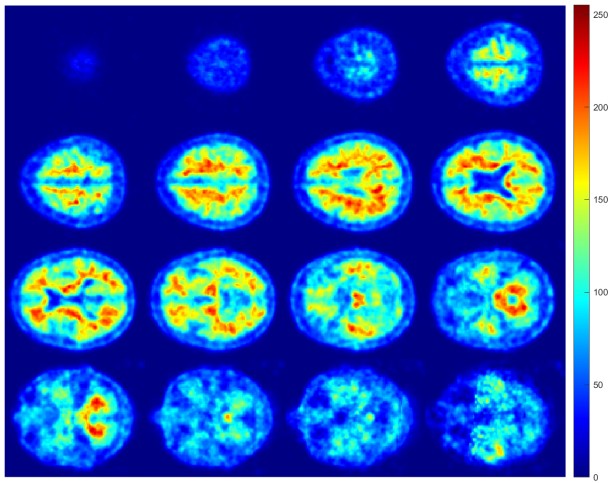
- Random choice of 2 neighbouring data points \vec{z}_1 and \vec{z}_2 from same patient class on 10-d Isomap space;
- interpolation of a random point \vec{z} :

$$\vec{z} = \vec{z}_1 + r \cdot (\vec{z}_2 - \vec{z}_1) \in \mathbb{R}^{10} \quad r \in (0, 1)$$

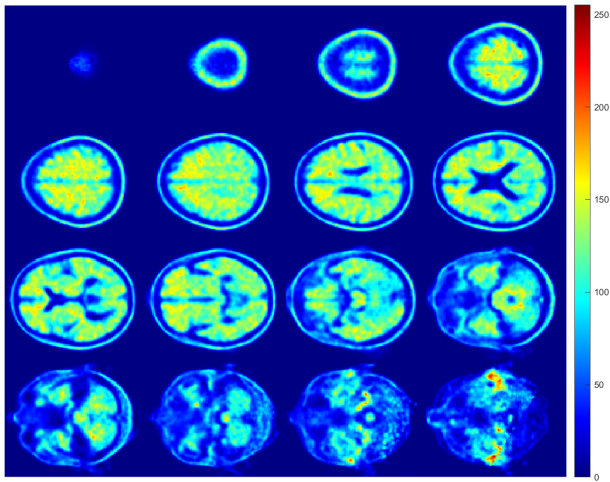
- back-reconstruction of synthetic PET via inverse mapping:

$$\vec{x} = \Phi^\dagger(\vec{z}) \in \mathbb{R}^{1082035}$$

Synthetic negative PET image



Synthetic positive PET image



Manual validation by panel of experts

- 10 synthetic PET images: 5 negative and 5 positive;
- 10 real images: 5 negative and 5 positive;
- visual assessment by 4 experienced clinicians.

	Real	Synthetic	p-value
Clinician 1	2/10	6/10	0.63
Clinician 2	4/10	4/10	0.66
Clinician 3	7/10	8/10	0.07
Clinician 4	5/10	5/10	1

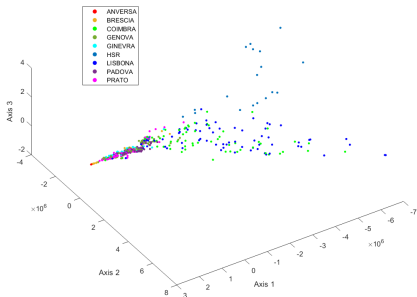
Conclusions

Generation of synthetic PET samples through low-dimensional mapping inversion

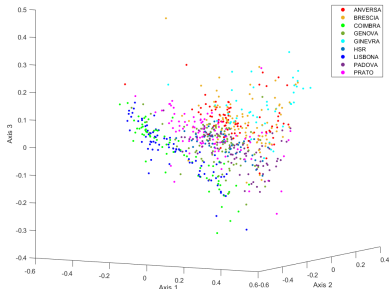
Manual validation by experts suggests good reconstruction quality

RMSE SSI quality indexes less reliable than visual inspection

Effect of data normalization on multi-center acquisition batches

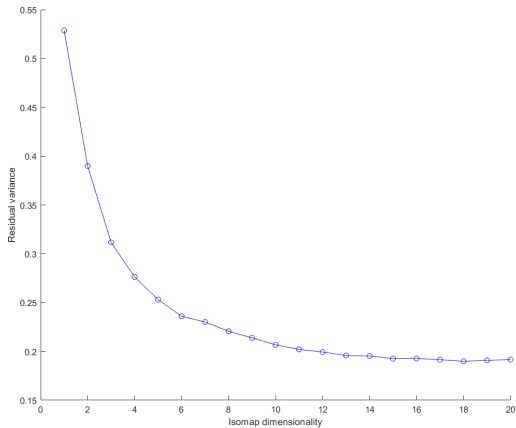


Before normalization



After normalization

Residual Variance by Isomap: flattening around 10



Reconstruction performance measures

Euclidean distance reconstruction Error RMSE:

$$E = \|\mathbf{x}^{(i)} - \Phi^\dagger(\mathbf{z}^{(i)})\|$$

Structural Similarity Index Measure:

$$\text{SSIM}(\mathbf{a}, \mathbf{b}) = \frac{(2\mu_a\mu_b + C_1)(2\sigma_{ab} + C_2)}{(\mu_a^2 + \mu_b^2 + C_1)(\sigma_a^2 + \sigma_b^2 + C_2)}$$

μ_a, μ_b : voxel sample means

σ_a, σ_b : standard deviations

σ_{ab} : cross-covariance of local windows