DOI: 10.1002/alz.082690

Alzheimer's & Dementia®
THE JOURNAL OF THE ALZHEIMER'S ASSOCIATION

BIOMARKERS

POSTER PRESENTATION

NEUROIMAGING

A 2.5D residual U-Net for improved amyloid PET harmonization preserving spatial information

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Abstract

Background: Multiple amyloid tracers with varying characteristics pose a significant challenge to standardized interpretation and quantification of amyloid PET measurements. We previously demonstrated that a deep learning based 2D residual inception encoder-decoder network (RIED-Net) architecture improved harmonization of florbetapir (FBP) and PiB PET. However, 2D networks fail to capture spatial information among image slices and 3D networks with more parameters require larger datasets and powerful computation for training. Here, we investigate the performance of a 2.5D approach to further improve harmonization preserving spatial information.

Method: 92 PiB-FBP image pairs from Open Access Series of Imaging Studies (OASIS) were processed using established pipelines to extract regional standard uptake value ratios (SUVRs), mean cortical SUVRs (mcSUVRs), and SUVR images. A 2.5D U-Net model with residual connections was implemented to learn the nonlinear mappings from the image pairs. Input to the network is a stack of 3 adjacent FBP slices along a particular view, providing extra spatial information about volumetric data. The output of network is a stack of corresponding 3 PiB slices. Multi-slice output avoids averaging/blurry effects common in traditional 2.5D approaches. 10-fold cross-validation was implemented on axial, coronal and sagittal views separately to generate synthetic PiB SUVR imaging from FBP data. The average synthetic PiB image from axial, coronal and sagittal views was used for performance evaluation. Correlation was evaluated between the virtual PiB mcSUVR derived from imputed PiB vs. the real PiB mcSUVR and voxel-wise between the imputed vs. real PiB SUVR images.

Result: The agreement of mcSUVR improved from $r = 0.90$ between PiB and FBP to $r = 0.95$ between synthetic and real PiB SUVR images ($p<0.0001$) in cross-validation dataset. Additionally, imputed PiB SUVR images were visually more similar to real PiB SUVR images than FBP. Voxel-wise correlation improved from 0.88 to 0.93 ($p<0.0001$).

Conclusion: Our proposed 2.5D Residual U-Net for synthetic imaging was able to learn voxel-wise nonlinear associations between FBP and PiB images. The model trained in 2.5D approach with additional spatial information, was able to significantly improve

agreements of amyloid burden measurement from two tracers and generate PiB SUVR images that are visually more similar to real PiB SUVR images than FBP.

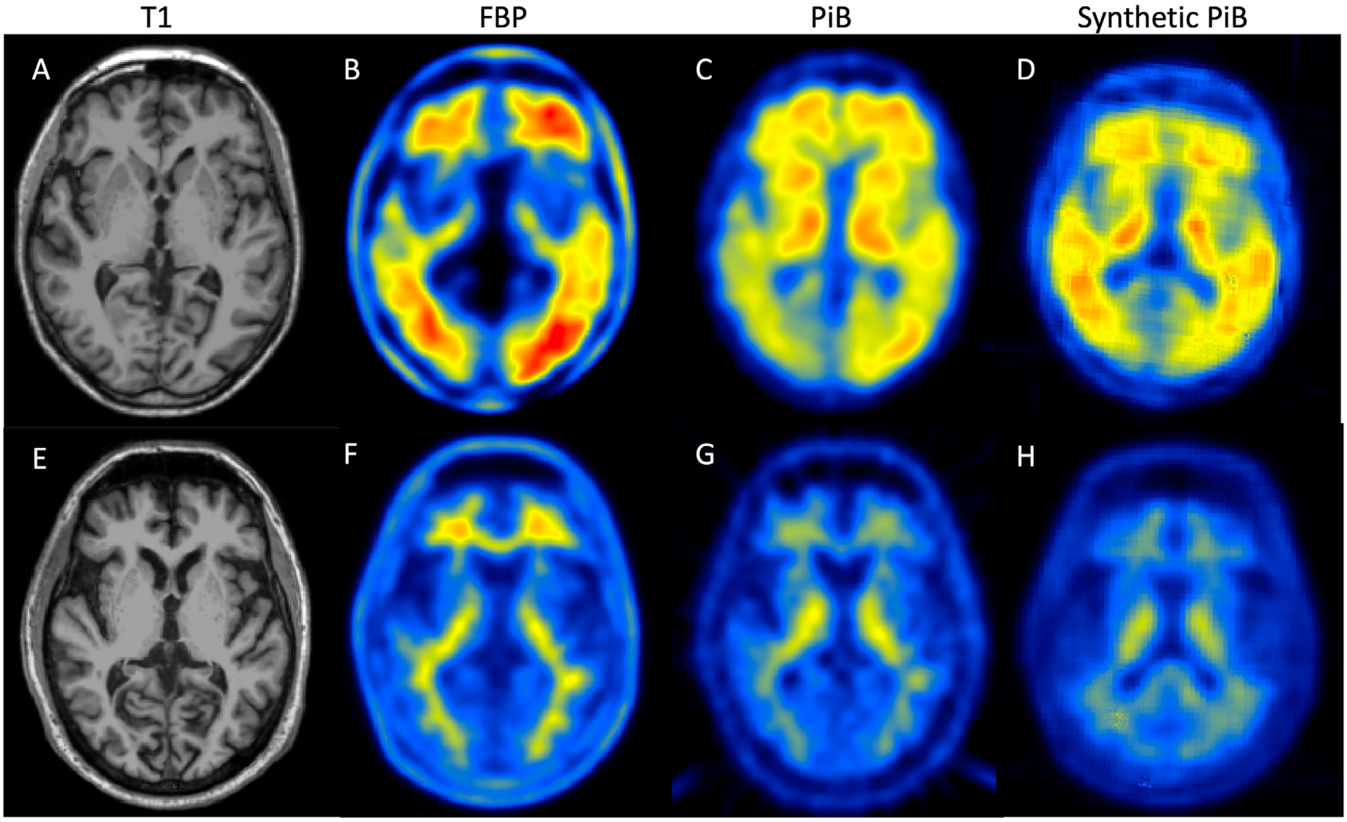

Figure 1. Example of images from cross-validation dataset. T1-weighted image (A, E), florbetapir (B, F), PiB (C, G), and synthetic PiB (D, H) generated from corresponding florbetapir. Synthetic PiBs generated from florbetapir show improved similarity to true PiBs.