A New Region Based Volume Wised Method for PET-MR Imaging Using Artificial Neural Network

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Target audience:

Researchers and clinicians interest in PET-MRI imaging and partial volume correction for PET.

Purpose:

Partial Volume Effect is thoroughly studied in Positron Emission Tomography (PET) imaging [1]. Generally, this phenomena results in PET spatial resolution degradation, and it could be defined as a convolution of real radio-activity distribution convoluted with a Point Spread Function (PSF) [2]. To correct PVE, several Partial Volume Effect Correction (PVC) methods have been proposed. Some of them, including Region Based Volume Wised (RBV) are sensitive to inaccuracy of PSF estimation and other prior anatomical information like Magnetic Resonance Imaging (MRI) segmentation [3]. In this work, we proposed a new machine learning method which is insensitive to PSF and MRI segmentation error.

Methods:

Mathematical Description: In general, acquired PET image *PET(r)* could be regarded as a convolution of real radio marker distribution REAL(r) with a PSF kernel which obeys Gaussian function. In other words, finding a real concentration image means to establish a mapping *F(.)* from *PET(r)* to *REAL(r)*:

$$REAL(r) = F(PET(r))$$

In the traditional Region based voxel wised (RBV) method [4], MRI segmentation $mask_i$ (i represent tissue index) is used as anatomical information which could be a good supplementary restriction information for PET PVC. Within each segmented tissue part, the recovery coefficient (RC) is regarded as a constant A_i convoluted by a PSF kernel *h*.

$$RC(r) = \frac{REAL(r)}{RBV(r)}, RC_i(r) = A_i \times mask_i \otimes h$$

Therefore, *RBV(x)* includes both PET radio-activity distribution and MRI segmentation information. Then, our PVC model could be described as followed:

$$argmin_F \|F(PET) - REAL\|, s.t. RBV(r)$$

Simulation Phantom: A MRI image is scanned by *Simen-mMR PET-MRI*, with *TI TIRM_TRA* sequence (*TR=2000ms, TE=9ms*). It covers a *181 x 141 x 146 mm* field of view with *1 x 1 x 1 mm* resolution. A simulation PET phantom is generated by convoluting REAL by a PSF with *5.5 mm* radial and *6 mm* axial Full Width Half Maximum (FWHM) [5]. And a simulated brain lesion with 4 x 4 x 4 mm size in70 to 73 layers was added.

Artificial-Neural-Network Region Based Volume wised (ANNRBV) method: ANN method has been proved to approach any mapping *F(.)* with appropriate parameter settings to wanted accuracy [6]. In this work, neural network training toolbox in MATLAB is used to train 15-brain-layer dataset. The neural network has three layers: input layer, hidden layer (with 25 neurons) and output layer (Figure 1). It took 1 hour to train the network.

Neural-Network Feature selection: Two image features are selected. First is the voxel values of convoluted PET images around voxel x *PET(x)*. Second is the voxel values of RBV corrected images around voxel x *RBV(x)*. Window size is *5 mm*.

These three formula can be formulated as followed:

$$PET(r_0) = \{PET_{values(r)} | r \epsilon windows(r_0)\}$$

$$RBV(r_0) = \{RBV\_values(r) | r \epsilon windows(r_0)\}$$

$$windows(r_0) = \{r \| |x_r - x_{r_0}| \leq 0.5 window_{size} \text{ or } |y_r - y_{r_0}| \leq 0.5 window\_size\}$$

Results:

RBV method and ANNRBV method is applied to correct the PVE. Figure 1 shows the corrected PET images with RBV and ANNRBV method. Red circle shows the lesion region where RBV has more error. Figure 4 shows corrected results with PSF and segmentation error. PSF radial FWHM is 4.5 which is 1 mm smaller than real one, and the segmentation mask has 2 mm shift in axial direction. Line plots with correct and incorrect PSF and segmentation information are shown in Figure 3 and Figure 5, respectively, which demonstrates that ANNRBV fits the reference better than RBV. Root Mean Square Error (RMSE) in overall and in lesion region are calculated to show that ANNRBV has better performance with and without PSF and segmentation error.

Discussion and conclusion:

This work demonstrates that the proposed ANNRBV method is less sensitive to inaccuracy of PSF estimation and MR segmentation error in comparison with the traditional RBV method. The ANNRBV also has better lesion recovery than RBV does. Further study can be carried out in in-vivo data with a larger database.

Reference:

[1] Kjell Erlandsson, et al. Phys. Med. Biol., 2012. [2] Yang J, et al. IEEE Transactions, 1996.

[3] Zaidi H, et al. Neuro image, 2006. [4] Tomas A.B., et al. Eur J Nucl Med Mol Imaging, 2011.

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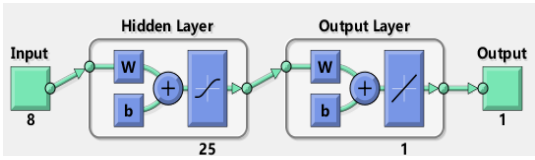

Figure 1 ANN network Profile.

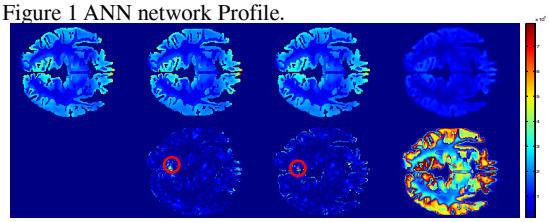

Figure 2 First row is corrected images and second row is their error maps with reference PET. From left to right: Reference PET, ANNRBV corrected, RBV corrected, Uncorrected.

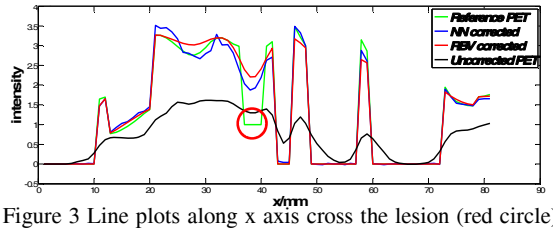

Figure 3 Line plots along x axis cross the lesion (red circle) with real PSF and segmentation across lesion area.

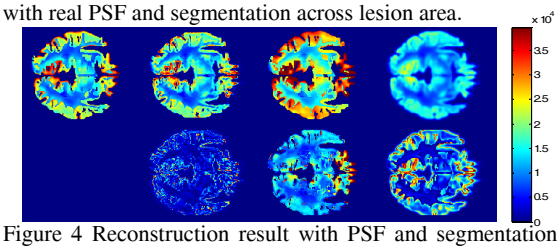

Figure 4 Reconstruction result with PSF and segmentation error. First row is corrected images and second row is their error maps with reference PET. From left to right: Reference PET, ANNRBV corrected, RBV corrected, Uncorrected.

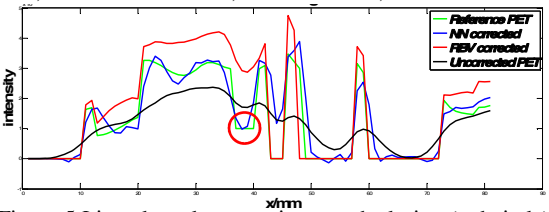

Figure 5 Line plots along x axis cross the lesion (red circle) with wrong PSF and segmentation across lesion area.

	Overall Without error	Lesion Without error	Overall With error	Lesion With error
RBV	0.0841	0.404	0.4878	0.6564
ANNRBV	0.0610	0.2706	0.2231	0.2908

Table 1 RMSE of RBV and ANNRBV method in lesion and overall area.