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Partial Volume Correction on ^{177}Lu -SPECT sinogram with Deep Learning trained on synthetic data

T. Kaprelian¹, A. Etchebeste¹, D. Sarrut¹

Abstract—This study introduces PVCNet, a deep learning-based method for Partial Volume Correction for ^{177}Lu -SPECT imaging, aimed at improving quantitative accuracy and image resolution prior to reconstruction. The method utilizes a large synthetic dataset derived from real patient images. PVCNet employs a dual neural network architecture, processing sinograms and projected attenuation maps as inputs. Its performance is evaluated using both real experimental phantom data and Monte Carlo simulations, and it is benchmarked against conventional Resolution Modeling (RM) and Iterative Yang (iY) methods, demonstrating promising results. On phantom data, PVCNet demonstrated superior performances (0.80/0.93/1.00 for Recovery Coefficients on 22/28/37 mm diameter spheres) than RM (0.52/0.66/0.77) but slightly lower than iY (0.96/0.99/1.06) which benefits from exact object segmentation, not required by PVCNet. On patient simulation, PVCNet showed the best results both in terms of Normalized Root Mean Squared Error (2.786/2.635/2.345 for RM/iY/PVCNet respectively) and mean Recovery Coefficients in background (1.05/0.95/1.03 for RM/iY/PVCNet respectively), kidneys (0.93/1.16/0.97 respectively) and lesions (0.66/1.14/0.91 respectively).

Index Terms—Partial Volume Correction, Deep Learning, SPECT Imaging, Image Reconstruction

I. INTRODUCTION

Quantitative Single Photon Emission Computed Tomography (SPECT) is a key tool during ^{177}Lu -PSMA therapy for absorbed dose computation in organs and tumours [1]. It is however still limited by the poor spatial resolution of gamma cameras whose Point Spread Functions (PSF) have a Full Width at Half Maximum (FWHM) usually comprised between 10 and 15 mm [2]. This large PSF leads to blurred reconstructed images and under-(or over) estimated activity concentrations, especially in objects of size below twice the system’s FWHM. These are known as Partial Volume Effects (PVEs) and are primarily due to the gamma camera’s collimator distance-dependant geometric response [3]. Several Partial Volume Correction (PVC) algorithms have been proposed to mitigate PVEs, including PSF modeling [4] during Ordered Subset Expectation Maximization (OSEM) reconstruction, known as Resolution Modeling (RM). RM allows to reduce PVEs but not sufficiently and gives rise to Gibbs artefacts [3]. Another class of methods, such as the Iterative Yang (iY) [3] PVC, relies on a CT-based segmentation of Volumes of Interest (VOIs) to deconvolve each region. These methods are however difficult to apply in clinical settings since region segmentation can be time-consuming and difficult, especially for small lesions. Moreover, these anatomy-based methods assume uniform activity in each VOI and position-invariant PSF.

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We propose a segmentation-free PVC method on ^{177}Lu -SPECT projections by training a Deep Learning model (PVCNet) on a large simulated dataset. Our method is evaluated on simulated and real SPECT acquisitions.

II. MATERIAL AND METHODS

A. Training dataset

Fifteen automatically segmented patient CT images ($0.97 \times 1.25 \times 0.97 \text{ mm}^3$ voxel size) were used to create 5,000 voxelized activity maps with background activity in the whole body and in regions with ^{177}Lu -PSMA uptake (liver, kidneys, spleen, gallbladder, stomach, pancreas, small bowel, colon, duodenum and urinary bladder). Moreover, several synthetic lesions were added to the activity maps, with random shapes, locations and activity ratios. Each region was multiplied by a gradient function like in [5] to model heterogeneity. These 5,000 activity maps were forward-projected with the RTK Software [6], once with PSF modeling to obtain P_{PVE} and once without to obtain P_{noPVE} . All sinograms contained 120 linearly spaced angles (between 0° and 360°), with a 280 mm detector-to-isocenter distance and 128×128 pixels of $4.7952 \times 4.7952 \text{ mm}^2$. PSF parameters were obtained by Monte Carlo (MC) simulations with Gate [7] toolkit of the Siemens Symbia Intevo SPECT system, with a parallel hole Medium Energy (ME) collimator. We obtained $\text{FWHM}(d) = 2.75 + 0.08d \text{ mm}$, with d the source-to-collimator distance (mm). Poisson noise was applied to P_{PVE} to obtain $P_{\text{PVE, noisy}}$. The linear attenuation map was also forward-projected (P_{att}). Finally, $P_{\text{PVE, noisy}}$ was used to reconstruct I_{rec10} with 10 iterations of OSEM (8 subsets) with RTK and then forward-projected (without PSF modeling) to obtain $P_{\text{rec,fp}}$.

B. Networks and training

The PVCNet framework contained two successive convolutional neural networks h_1 and h_2 trained with the loss \mathcal{L} defined such that:

$$\begin{cases} \hat{P}_{\text{PVE}} = h_1(P_{\text{PVE, noisy}}, P_{\text{rec,fp}}, P_{\text{att}}) \\ \hat{P}_{\text{noPVE}} = h_2(\hat{P}_{\text{PVE}}, P_{\text{rec,fp}}, P_{\text{att}}) \\ \mathcal{L} = \|\hat{P}_{\text{PVE}} - P_{\text{PVE}}\|_1 + \|\hat{P}_{\text{noPVE}} - P_{\text{noPVE}}\|_1 \end{cases} \quad (1)$$

Both h_1 and h_2 were 3D-Unets with three input channels corresponding to the three input sinograms, three encoding/decoding layers with skip connections, two consecutive Conv-InstNorm-LeakyRelu sequences in each layer and residual units. The number of channel sequences was 3-16-32-64-128-128-64-32-16-1. All convolution kernel sizes were $3 \times 3 \times 3$, totalling 4 M trainable parameters.

We used the Adam optimizer with an initial learning rate of 2×10^{-4} , halved every 20 epochs. All sinograms were divided by the maximal value contained in $P_{\text{rec,fp}}$ (except P_{att} , divided by its maximum). To promote consistency between corrected sinograms' first and last angles, we padded the input/target sinograms from (120,128,128) shape into (128,128,128) with circular padding on the first dimension.

C. Experiments

The first experiment was a NEMA IEC phantom acquisition with the Siemens-Symbia-Intevo SPECT/CT, containing 6 spheres of 10, 13, 17, 22, 28 and 37 mm diameter filled with 1110 kBq/mL of ^{177}Lu and a target to background (TBR) ratio of 13.3.

The second experiment was a MC simulation of a patient acquisition with the same SPECT system and ^{177}Lu activity in the background and a TBR of 40 in the kidneys, 15 in the liver, and 30, 50, 83 in three manually placed lesions. Computation time was reduced by using an Angular Response Function (ARF) method modelled by a pre-trained neural network [8] which allowed us to simulate only 300 MBq of activity with the same noise level as with ≈ 3 GBq.

For both experiments, 120 angular projections were obtained for 15 seconds each, with a ME collimator, a 20% primary window centered around 208 keV and two surrounding 10% scatter windows. The scatter was corrected using the triple energy window method. Attenuation was corrected using CT-derived linear attenuation coefficients during reconstruction by the OSEM algorithm (8 subsets). Raw sinograms were first scatter corrected (P_{SC}) and then used for reconstruction. The reconstructed image, $I_{\text{rec}10}$, was forward-projected to obtain $P_{\text{rec,fp}}$. PVCNet was then applied with ($P_{\text{SC}}, P_{\text{rec,fp}}, P_{\text{att}}$) as input. The corrected sinograms \hat{P}_{noPVE} were used to reconstruct the final image, I_{PVCNet} , with 10 iterations of OSEM.

Our method was compared with the image reconstructed from P_{SC} with RM during 20 reconstruction iterations (I_{RM}). We used the PETPVC Software [9] to apply iY to I_{RM} , thanks to a CT-based organ and lesion segmentation and the post-reconstruction-estimated 3-dim PSF. We compared the Recovery Coefficients (RC) *i.e.* the ratio between estimated and ground-truth activity and the Normalize Root Mean Squared Error (NRMSE) of the different methods.

III. RESULTS

RCs on the IEC acquisition can be found in Table I. The proposed method yields better results in terms of activity estimation than RM but iY outperforms slightly our method. However, iY needs a segmentation.

Table II shows RCs obtained on the patient MC simulation. PVCNet not only demonstrates superior activity estimation than RM but also than iY on almost all regions, including lesions. The mean RC error is 55% lower with PVCNet than with iY. A reduced PVEs and a good retrieval of organ and lesion contours can be seen for the proposed method in Figure 1 (d). NRMSE value with PVCNet was 15.7 % lower than with RM and 10.8% lower than with iY (2.786 for RM, 2.635 for iY and 2.345 for PVCNet).

TABLE I: Recovery Coefficients for NEMA IEC acquisition for RM, iY and PVCNet correction methods

PVC	Sphere Diameter					
	10 mm	13 mm	17 mm	22 mm	28 mm	37 mm
RM	0.24	0.29	0.36	0.52	0.66	0.77
iY	1.22	0.80	0.73	0.96	0.99	1.06
PVCNet	0.28	0.35	0.55	0.80	0.93	1.00

TABLE II: Recovery Coefficients of the patient MC simulation for RM, iY and PVCNet correction methods

PVC	BG	left kidney	right kidney	lesion 1	lesion 2	lesion 3
RM	1.05	0.94	0.92	0.70	0.75	0.52
iY	0.95	1.16	1.16	1.15	1.25	1.01
PVCNet	1.03	0.96	0.98	0.89	0.88	0.97

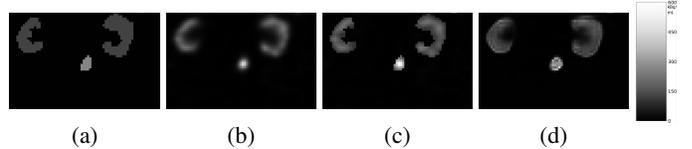


Fig. 1: Patient MC simulation. (a) Ground truth activity map (b) RM (c) iY (d) PVCNet.

IV. CONCLUSION

In this study, we introduced a novel Deep Learning approach for addressing PVC in ^{177}Lu -SPECT projections, prior to reconstruction. Our method, developed on an extensive synthetic dataset, shows promising results in accurate activity estimation, better than the conventional RM method and comparable to the iY method but without requiring any segmentation.

The key elements of the proposed sinogram-based PVC approach are the comprehensive size of the training set, the use of $P_{\text{rec,fp}}$ as input to leverage its noise-reduced and partially corrected characteristics, and the application of circular padding and normalization techniques. These elements collectively enhance the model's ability to generalize and function reliably across different testing scenarios, demonstrating the potential of deep learning in enhancing SPECT image quantification.

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