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# Development of a deep learning method for CT-free correction for an ultra-long axial field of view PET scanner

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***Abstract*—Introduction: The possibility of low-dose positron emission tomography (PET) imaging using high sensitivity long axial field of view (FOV) PET/computed tomography (CT) scanners makes CT a critical radiation burden in clinical applications. Artificial intelligence has shown the potential to generate PET images from non-corrected PET images. Our aim in this work is to develop a CT-free correction for a long axial FOV PET scanner. Methods: Whole body PET images of 165 patients scanned with a digital regular FOV PET scanner (Biograph Vision 600 (Siemens Healthineers) in Shanghai and Bern) was included for the development and testing of the deep learning methods. Furthermore, the developed algorithm was tested on data of 7 patients scanned with a long axial FOV scanner (Biograph Vision Quadra, Siemens Healthineers). A 2D generative adversarial network (GAN) was developed featuring a residual dense block, which enables the model to fully exploit hierarchical features from all network layers. The normalized root mean squared error (NRMSE) and peak signal-to-noise ratio (PSNR), were calculated to evaluate the results generated by deep learning. Results: The preliminary results showed that, the developed deep learning method achieved an average NRMSE of 0.4±0.3% and PSNR of 51.4±6.4 for the test on Biograph Vision, and an average NRMSE of 0.5±0.4% and PSNR of 47.9±9.4 for the validation on Biograph Vision Quadra, after applied transfer learning. Conclusion: The developed deep learning method shows the potential for CT-free AI-correction for a long axial FOV PET scanner. Work in progress includes clinical assessment of PET images by independent nuclear medicine physicians. Training and fine-tuning with more datasets will be performed to further consolidate the development.**

***Keywords—total-body PET, CT-free, scatter correction, attenuation correction, deep learning***

## I. Introduction

Positron emission tomography (PET) is one of the main imaging modalities in clinical routine procedures of oncology [1], neurology [2] and cardiology [3]. Quantitative PET is being widely acknowledged as an important tool for diagnosis, monitoring of malignant diseases, and determination of prognosis [4, 5]. With the advent of the long axial field of view (FOV) total-body PET [6], it enables previously unachievable levels of image quality and quantification, with reduced radiopharmaceutical dose [7]. Attenuation (AC) and scatter correction (SC) are essential for precise PET quantification, which require additional structural images to calculate attenuation factors and model scatter. On commercial PET/CT scanners such as Biograph Vision Quadra, computed tomography (CT) imaging is used to generate an attenuation map for 511 keV photons [8], which inevitably introduces additional ionizing radiation to patients [9].

Recent years, artificial intelligence (AI) has developed great success in medical image analysis applications, especially with deep learning techniques [10], several studies have focused on estimating corrected PET images with non-corrected PET with deep neural networks [11, 12]. Inspired by these studies, our study sets out to explore the possibility to develop a CT-free AI-correction for this ultra-long FOV PET scanner, with the help of deep learning techniques.

## II. Materials and Methods

### *A. Patient Cohorts*

Three cohorts with 172 subjects were included in this study (Table 1). The subjects were scanned on 2 different PET scanners (Biography Vision 600 (Siemens Healthineers) and Biograph Vision Quadra (Siemens Healthineers)). The first cohort, collected in Shanghai (SH), consists of 114 subjects referred to $^{18}$F-FDG PET, was employed for the development of our deep learning based method. The other two cohorts, scanned on Vision and Quadra with $^{18}$F-FDG PET at Bern, were recruited for external testing the developed algorithm.

**Table 1. Information on patients' demographics and diagnosis.**

| Patient Cohorts | Source of dataset | | |
|---|---|---|---|
| | *Vision (SH) - FDG* | *Vision (Bern) - FDG* | *Quadra (Bern) - FDG* |
| **Number of Patients** | 114 | 51 | 7 |
| **Total dose (MBq)** | 364.8±82.7 | 253.9±46.8 | 246.9±65.1 |
| **Post-injection time (min)** | 80.7±20.9 | 74.7±12.4 | 230.6±40.4 |
| **Gender (Male/Female)** | 67/47 | 20/31 | 5/2 |
| **Age (Year)** | 57.1±14.7 | Not applicable | 67.6±9.7 |
| **Weight (kg)** | 66.5±15.0 | 71.6±13.1 | 69.1±14.6 |

*B. Deep Neural Network Setup*

To generate corrected PET images without the use of additional structural information, a semi-supervised 2D conditional generative adversarial network (c-GAN) [13] was employed, which consists of a generator network to synthesize the corrected PET images from non-corrected images, and a discriminator to distinguish between the synthesized corrected images and the real inputs. We specifically customized our model by including residual dense block [14], which enabled it to fully exploit hierarchical features from all network layers. The model was trained with Vision data collected from Shanghai, and later tested on datasets of Vision (Bern) and Quadra. Furthermore, we applied transfer learning [15] to improve the performance of our developed model, when applied on the Quadra dataset, due to the lack of available data at the current stage.

*C. Evaluation method*

To evaluate the quality of the AI-corrected PET images, we calculated and compare the physical metrics including voxel-wise normalized root mean squared error (NRMSE) and peak signal-to-noise ratio (PSNR).

## III. Results

As shown in Figure 1.A, the preliminary results of physical metrics demonstrated that, the developed deep learning method achieved similar accuracy on two Vision datasets (SH_Vision_AI and Bern_Vision_AI), with an average NRMSE of 0.4±0.3% and PSNR of 51.4±6.4 on external Bern Vision cohort after AI-correction. Figure 1.B provides the visual rendering a test example when applying our developed model to the Bern Vision cohort, which confirmed the effectiveness of our AI-correction.

When applied directly to the Quadra dataset, the performance of the developed algorithm was not satisfactory in terms of the physical metrics. However, with the help of transfer learning based on a small part of the cohort, we were able to achieve similar accuracy as the Vision dataset, with an average NRMSE of 0.5±0.4% and PSNR of 47.9±9.4.

## IV. Discussions

With the currently available datasets collected from the Biograph Vision Quadra PET/CT system, we can only obtain preliminary results, and transfer learning was a suboptimal solution for better performance of a network trained on Vision 600 datasets. As more subjects are added to the ongoing data collection, we will develop a specific long axial FOV PET scanner with optimal performance. At the same time, additional evaluation methods will be applied to help us better understand the true strengths and limitations of the developed algorithms. For example, we will perform organ-wise quantitative analysis

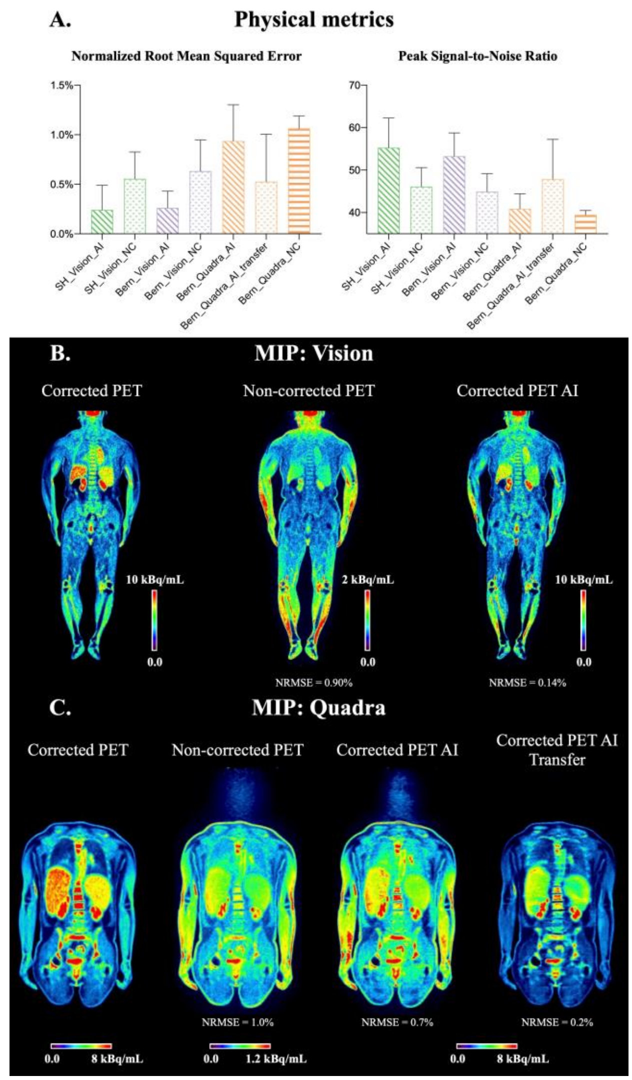


**Figure 1. A: Improvement with the help of the developed artificial intelligence (AI) correction in terms of NRMSE (normalized root mean squared error) and PSNR (peak signal-to-noise ratio) on all three datasets, including Siemens Biography Vision collected from Shanghai (SH) and Bern, as well as Siemens Biograph Vision Quadra. B-C): Example of test results of Vision (Bern) and Quadra.**

and evaluated the feasibility towards clinical practice. Besides, more widely applied physical metrics would be recruited, like mean absolute percentage error (MAPE) and similarity structural index measurement (SSIM) [16].

## V. Conclusions

The developed deep learning method shows the potential for CT-free AI-correction for a long axial FOV PET. Work in progress includes clinical assessment of PET images by independent nuclear medicine physicians. Training and fine-tuning with more datasets will be performed to further consolidate the development.

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