

Improving PET Imaging with Guided Filtering

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Abstract

Dynamic positron emission tomography (PET) is a nuclear medicine imaging technique that is used to observe biochemical changes in body tissues over time, such as the progression of a disease or the chemical response to a specific stimulus. Due to constraints on the time and radiation dose of the examination as well as limited scanner sensitivity, PET images usually suffer from poor signal-to-noise ratio (SNR). Noise can be suppressed by incorporating filtering into the reconstruction process through a statistical approach called the *method of sieves* [1]. In this paper, a fast, edge-preserving smoothing operator, the *guided filter* [2] is proposed for PET image denoising. In addition to smoothing, this technique makes it possible to use additional anatomical information and previous reconstruction results to improve the contrast of the reconstructed image.

Another challenge in PET imaging is the *partial volume effect (PVE)*, a phenomenon that causes blurring on the reconstructed image. In this paper, we propose an efficient, guided-filter-based partial volume correction technique.

Guided Filtering

The key assumption of the guided filter is a local linear model between a *guidance image* G and the output image Q . This guidance can be the input image itself or another image of the same target object. We assume that Q is a linear transform of G in a window ω_k centered at the voxel k :

$$Q_i = a_k G_i + b_k, \quad \forall i \in \omega_k,$$

where a_k and b_k are linear coefficients presumed to be constant in the local window ω_k .

Guided filtering aims to find the output image that is the closest to the input, while maintaining its local linear model. To achieve this, the following cost function is minimized:

$$E(a_k, b_k) = \sum_{i \in \omega_k} (\|Q - P\| + \varepsilon a_k^2) = \sum_{i \in \omega_k} ((a_k G_i + b_k - P_i)^2 + \varepsilon a_k^2),$$

where ε is a regularization parameter penalizing large a_k values. The solution is given by

$$a_k = \frac{\frac{1}{|\omega|} \sum_{i \in \omega_k} G_i P_i - \mu_k \bar{P}_k}{\sigma_k^2 + \varepsilon},$$
$$b_k = \bar{P}_k - a_k \mu_k,$$

where μ_k is the mean and σ_k^2 is the variance of G in ω_k , $|\omega|$ is the number of voxels in ω_k and $\bar{P}_k$ is the mean of P in ω_k . Thus the output is calculated as follows:

$$Q_i = \frac{1}{|\omega|} \sum_{i \in \omega_k} (a_k G_i + b_k) = \bar{a}_i G_i + \bar{b}_i,$$

where $\bar{a}_i = \frac{1}{|\omega|} \sum_{k \in \omega_i} a_k$ and $\bar{b}_i = \frac{1}{|\omega|} \sum_{k \in \omega_i} b_k$ are the average coefficients of all the local windows covering voxel i .

Guidances for dynamic PET

We differentiate two types of PET reconstruction, static and dynamic. In the case of static reconstruction, we examine the patient's body at a given moment of time, while in the case of dynamic reconstruction, our goal is to monitor the course of a biological process, for example the progression of a disease over time. In the former case, the total duration of the measurement is treated as one unit, while in the latter, it is divided into smaller time frames. This paper focuses on dynamic PET reconstructions. For dynamic PET, we propose the following guidances:

- the joint/cross bilateral filtered [3] input, using the anatomical image of the patient from a CT or MRI scan as a guide,
- image of the static reconstruction, that is the sum of the activity images of all time frames [4],
- a multichannel guidance, where each channel is the sum of activity images of a group of frames.

Noise reduction results

To examine the proposed method, we used a simulated rat phantom. The simulation covered a period of 1800 seconds, which we divided into 9 time frames of 200 seconds. Time frames were grouped into three groups, where the first group consisted of the first 3 time frames, the second group of frames 4-6 and the third group of the last three frames. Using the activity sums of these groups, we constructed a triple channel guidance. For the reconstructions, we used the Spectral model [5] and 20 iterations.

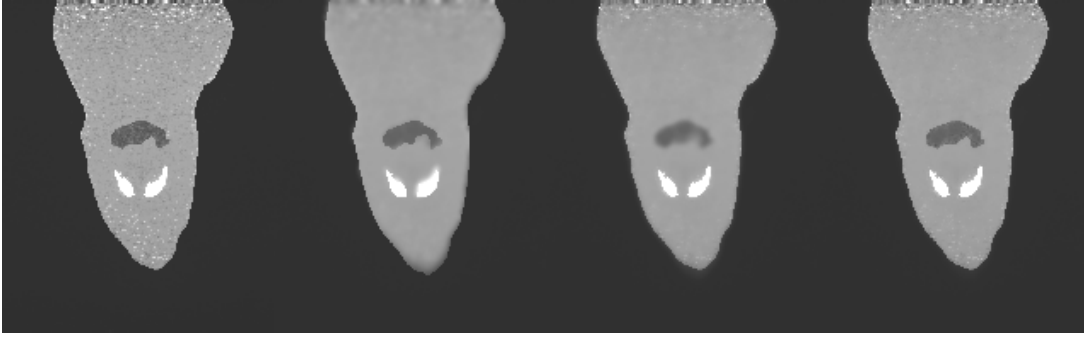


Figure 1. Reconstruction output a) without filtering b) using anatomical-image-guided bilateral filtering result as guidance c) using static reconstruction image as guidance d) using triple channel guidance constructed from the activity sum of the three frame groups. Filtering was applied once, after the last iteration. Filter kernel radius was 4 and regularization was set to $\varepsilon = 100$.

The best results were achieved using the triple channel guidance and applying guided filtering in every iteration of the reconstruction (*method of sieves*). The resulting image is shown in Figure 2.



Figure 2. Reconstruction output using the triple channel guidance in every iteration. Filter kernel radius was 4 and regularization was $\varepsilon = 1$.

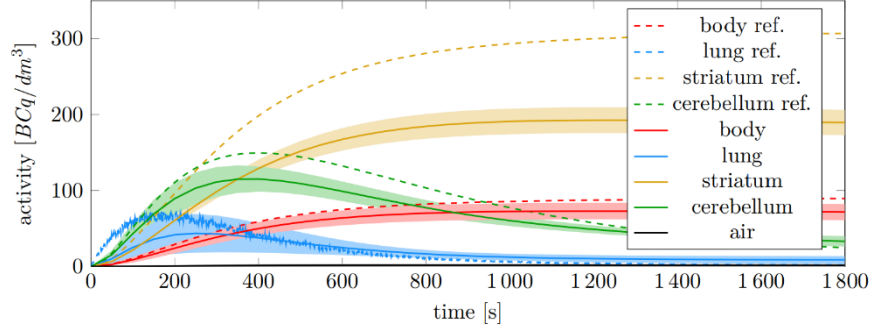


Figure 3. Reconstructed time-activity curve without filtering.

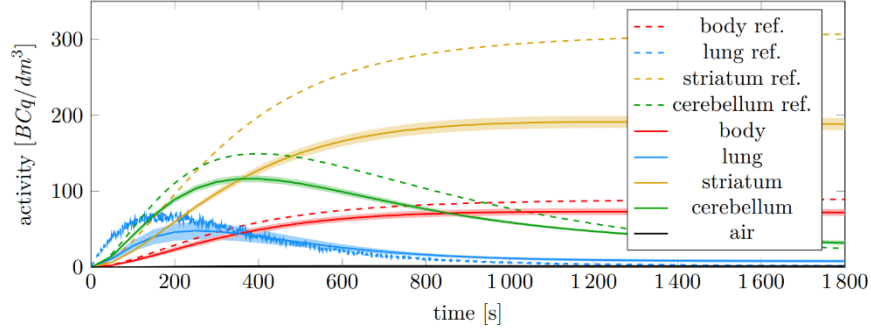


Figure 4. Reconstructed time-activity curve with triple channel guided filtering in every iteration.

Partial Volume Correction (PVC)

One of the main challenges of PET imaging is the *partial volume effect* (PVE), the phenomenon of a tissue's activity affecting the reconstructed activity concentration of the surrounding tissues, also called spillover of activity. The main reason for this is the limited resolution of the imaging system and the voxel heterogeneity. Mathematically, the effect of PVE can be described by a convolution operation with the system's *point spread function* (PSF). Applying partial volume correction (PVC) is crucial in quantitative PET measurements. In this paper, we propose an efficient, guided-filter-based PVC technique. We modify the aim of the guided filter to minimize the difference between the output image convolved with the PSF and the input image, that is, $\|(PSF * Q) - P\|$ instead of $\|Q - P\|$. The inverse effect of the blurring, or in other words, the sharpening will appear on the resulting image.

PVC results

Figure 5. shows that without PVC, region boundaries are slightly blurred. By applying the proposed PVC technique, the sharpness of the boundaries are generally restored.

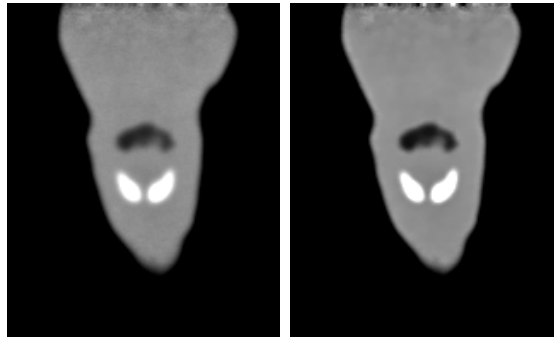


Figure 5. Reconstruction output without PVC (left) and with PVC in the last iteration (right).

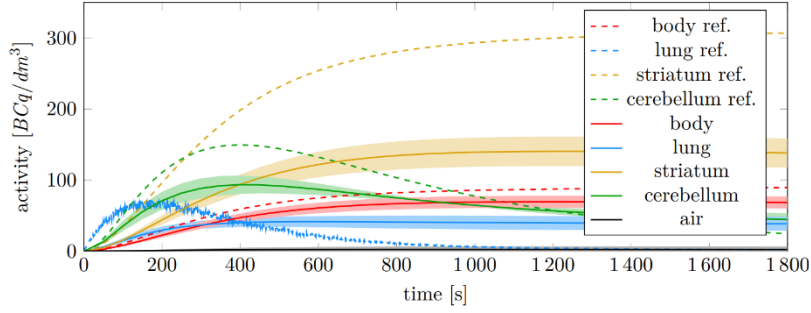


Figure 6. Reconstructed time-activity curve without PVC.

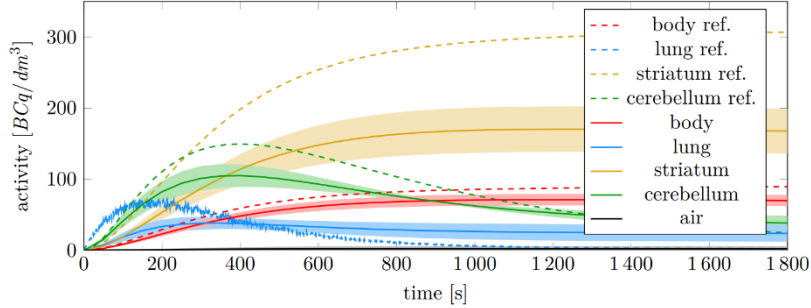


Figure 7. Reconstructed time-activity curve with PVC in the last iteration.

Conclusions

This paper proposed guided filtering for image denoising and partial volume correction to improve the quality and reliability of PET images. It can be concluded that the guided filtering performed very well in both tasks and is thus a very promising technique to be incorporated in PET reconstructions.

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