

Voxel-based partial volume correction of amyloid PET images incorporating non-local means regularization

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ABSTRACT—Amyloid PET imaging is increasingly utilized to assess Alzheimer’s disease. Nonetheless, PET imaging can be significantly degraded by the partial volume effect (PVE). This issue has been tackled via a number of post-reconstruction partial volume correction (PVC) methods. In our work, we proposed a voxel-based PVC method using non-local means (NLM) regularization under the weighted least squares framework that models the point-spread function of the PET system. The NLM algorithm has been proposed to suppress image noise while preserving edge information for natural images. This algorithm utilizes the high degree of information redundancy that typically exists in images and reduces image noise by replacing each pixel intensity with a weighted average of its non-local neighbors. Based on its advanced property, we propose to employ NLM as a regularization term in PET PVC. For a penalized weighted least squares (PWLS) objective function, we used the Gauss-Seidel (GS) optimization algorithm regularized with one-step-late (OSL) framework. Under the assumption of independent, identically-distributed (iid) Gaussian noise, the PWLS framework becomes standard least squares. When the steepest descent scheme is applied to the problem, it leads to the iterative ‘reblurred’ Van Citter (VC) method. We tried both the VC method, and GS which involves a more sophisticated step-size method. In any case, the iid assumption is especially violated in OSEM reconstruction where the variance image is roughly proportional to the image (thus not uniform as in FBP). In the present work, we assessed the impact of appropriate variance weighting, as well as added NLM regularization. Our results demonstrate that statistical weighting improved quantitative bias vs. noise performance; and also, NLM regularization method exhibits improved performance. These were especially the case in the small regions relevant in Alzheimer’s disease research.

I. INTRODUCTION

Amyloid PET imaging allows for improved assessment of Alzheimer’s disease, enabling quantitative estimation of amyloid- β plaques aggregation presenting in the brain. However, its application is degraded by the partial volume effect (PVE). There are a range of partial volume correction (PVC) methods^[1]. Post processing PVC methods, such as Van Cittert (VC) or “reblurred” VC, have the advantage that no MRI anatomical information is required. However, the simple application of VC method will amplify noise levels^[2]. As such, regularization may be considered. Nonlocal means (NLM) algorithm has been proposed to suppress image noise while preserving edge information for natural images^[3]. It employs high degree of information redundancy that typically exists in images and reduces image noise by replacing each pixel

intensity with a weighted average of its nonlocal neighbors. Based on its advanced property, we implemented it as a regularization term in our post-reconstruction PVC work.

When the penalized weighted least squares (PWLS) objective function is used, the Gauss-Seidel (GS) algorithm combined with one-step-late (OSL) framework can be exploited for our optimization task. The weighting coefficient in the NLM regularization term is computed on the current image estimate and assumed to be constants when updating the whole image. When the noise distribution follows independent, identically-distributed (iid) Gaussian, the PWLS turns into least squares (LS) form. The steepest descent scheme is applied to minimize the objective function, and the VC method can be derived. In this work, we further extend application to model beyond the iid assumption. In the present work we assessed the performance of VC (with and without weight) and GS (with and without NLM) methods under the PWLS framework.

II. MATERIALS AND METHODS

Our aim is to assess the impact of applying VC (with and without weight) and GS (with and without NLM) methods under the PWLS framework. First, we generated realistic amyloid PET simulation phantom based on real patient data from human amyloid dynamic PET (¹¹C-PIB) and MRI images. Given areas of interest for Alzheimer’s disease research, we labeled regions including GM, WM, CSF, caudate, putamen and thalamus. We incorporated realistic clinical data activity distributions in our simulation studies based on participant images. Noise-free projection data were generated following forward projection using the phantom. Noisy data were generated by adding Poisson noise. After MLEM reconstruction, the noisy reconstructed PET images are generated. We present the images used in our amyloid brain simulation phantom generation experiment in Fig.1.

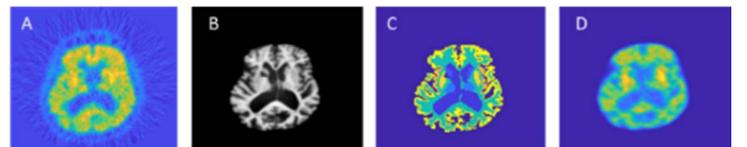


Fig. 1. (A) Real human amyloid PET image, (B) MRI image, (C) Labeled (true) PET image, (D) Simulated and reconstructed brain PET image.

A. PVC method

In PET imaging, the resolution obtained in the measured images is limited by a combination of various physical and instrumentation-related factors, namely (1) positron range, (2) photon noncollinearity, (3) crystal size and decoding of interacting crystals, (4) the acquisition mode and the reconstruction algorithm and associated filtering^[1]. The limited resolution in PET imaging leads to partial volume effects (PVE). PVE impacts structures smaller than ~ 3 times the resolution of PET (~ 5 mm full width at half maximum (FWHM)) especially. Cortical atrophy exacerbates PVE, further reducing the PET signal and undermining the quantitative accuracy and diagnostic efficacy of amyloid brain imaging. This issue has been tackled via a number of Post-reconstruction partial volume correction (PVC) methods including (i) region-of-interest (ROI) and (ii) voxel-based techniques. The latter includes (a) partition-based, (b) multi-resolution, or (c) iterative deconvolution methods. Iterative deconvolution is more practical because it does not require access to well-registered anatomic (e.g. MRI) images. The formulation of appropriate algorithms for PVC is dependent on both the distribution of the signal and the distribution of the underlying noise. A common assumption for many post-processing approaches is that noise in reconstructed image is characterized as Gaussian distribution^[4]. We use penalized weighted least squares deconvolution framework to model the problem. In the present work we assess the impact of VC (with and without weight) and GS (with and without NLM) under the PWLS framework on amyloid PET imaging PVE problem.

B. Nonlocal means method

The NLM algorithm was originally proposed as a non-iterative edge-preserving filter to denoise natural images corrupted by additive white Gaussian noise^[3]. Essentially, it is one of the neighborhood filters which denoises each pixel with a weighted average of its neighboring pixels according to similarity. However, different from previous neighborhood filters, the NLM filter calculates the similarity based on patches instead of pixels. As shown in the Fig. 2, for target pixel i , we make use of all neighbors of itself (e.g. pixel j & pixel k) to denoise it. NLM processing includes calculating the weight parameters between the i^{th} pixel and its neighbor's pixels (e.g. W_{ij} & W_{ik}) based on Euclidean distance. However, since intensity for single pixel can be easily influenced by noise, we usually take match patch to replace one pixel (in our study, we select $7*7$ match patch). The patch of a pixel is defined as a squared region centered at that pixel. Ideally, the more neighbors that we utilize the better, which is the whole image. In practice, in order to increase the computation speed, we usually select a search window (in our study, we set $21*21$ search window). In the previous work, the authors compared the performance of the NLM filter with an array of denoising algorithms including the Gaussian filter, anisotropic filter, total variation (TV), Yaroslavsky neighborhood filter, and observed noticeable improvements over them^[5]. Motivated by this success, a purely NLM-based restoration method in amyloid PET imaging was evaluated in our earlier conference paper^[6]. Inspired by its performance, in this study we extended NLM method to the post-reconstruction voxel-based PVC problem in amyloid PET imaging as a regularization term.

C. PWLS incorporating NLM regularization model

Consider an amyloid PET image which has been deteriorated by a known point spread function (PSF) denoted using H . We assume that H is symmetric, nonnegative, and normalized to one. The PSF was approximated by a 2-D Gaussian kernel. The FWHM of the kernel was acquired with MLEM reconstruction of a point source

that was located at the center of the field of view (FOV). A model for the PVE blurred PET image is as follows:

$$g(x) = N(f(x) \otimes H) \quad (1)$$

where f denotes the true image, g is the measured image, \otimes denotes the convolution operation and N stands for noise processes. The task is to estimate f based on this equation. This problem is, in general, ill-posed and similar to the image reconstruction problem. In this paper, we assume that the noise process N is Gaussian distribution including the white Gaussian in the LS criterion and non-white Gaussian in PWLS criterion. For post-reconstruction PVE corrections, implementing iterative deconvolution methods, such as the VC method, will result in noise amplification. Noise control is achieved by adding regularization term in the PWLS objective function, as followed,

$$\varphi(x) = \|g(x) - (f(x) \otimes H)\|_W^2 + \beta R(x) \quad (2)$$

where $R(x)$ is the regularization term, many kinds of regularization form have been reported, including MRF model-based prior, CS-based regularization and HYPR regularization and so on.

In our study, we use the NLM method to regularize this PVE problem. The β is the regularization factor used to control the prior information term, and W is a diagonal weighting matrix with the i^{th} diagonal element W_i representing the fidelity of the i^{th} measurement. When the covariance matrix W equals to 1, the fidelity term becomes LS criterion form.

D. Optimization

In our study, steepest descent scheme and Gauss-Seidel (GS), which considers sets a more sophisticated step-size, combined with one-step-late (OSL) scheme are applied to minimize objective function (2). Following steepest descent optimization, we obtain the 'reblurred' VC method. The update rule of VC is as follows,

$$f^{n+1} = f^n + \alpha H^T W^{-1} (g - Hf) \quad (3)$$

where H^T denotes the transpose of H . The matrix W^{-1} denotes the inverse of diagonal matrix W with i^{th} entry σ_i^2 , an estimate of the variance of the i^{th} precorrected measurement \hat{g} . After OSEM or MLEM reconstruction method, the variance of the image approximately equals the activity distribution value of the PET measured image^[7].

The weighting coefficients in the regularization term is difficult to calculate because it depends on unknown image, so we take Gauss-Seidel (GS) with one-step-late (OSL) scheme to solve this problem. GS method is the special case of (projected) successive overrelaxation (+SOR), which is derived from Taylor expedition, similar to Newton methods, updates each image parameter individually by minimizing the objective function (2) over that parameter while holding the other parameters fixed^[8]. According to the OSL strategy, the NLM weighting coefficients (w_{jk}) are always computed with current image estimate and then assumed to be constants when updating the image.

The update expression of GS without regularization is following,

$$f^{n+1} = \frac{\alpha H^T W^{-1} (g - Hf^n)}{H^T W^{-1} H} + f^n \quad (4)$$

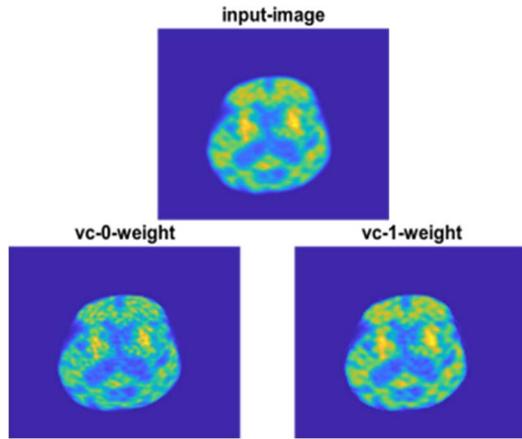
The update expression of GS with NLM regularization is following,

$$f^{n+1} = \frac{\alpha H^T W^{-1} (g - Hf^n) + (H^T W^{-1} H) f^n + \beta \sum_{k \in N_j} w_{jk} f^k}{H^T W^{-1} H + \beta \sum_{k \in N_j} w_{jk}} \quad (5)$$

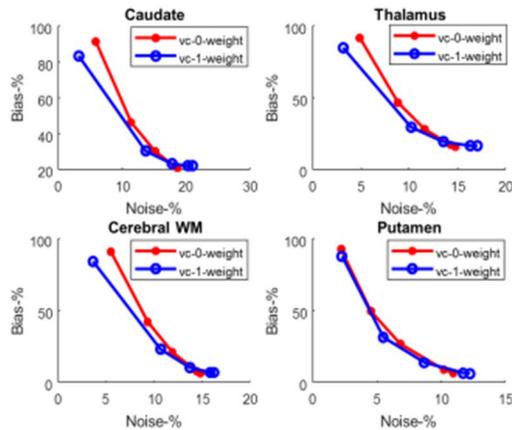
where $\sum_{k \in N_j} w_{jk} f^k$ is calculated from the NLM method.

III. RESULTS AND DISCUSSION

Fig. 3(A) shows the images after PVC with weighted VC (vc-0-weight) and non-weighted VC methods (vc-1-weight). Fig. 3(B) gives bias vs. noise plots of different ROIs for weighted VC and non-weight VC. Fig. 4(A) shows the results after PVC with GS without NLM (gs-0-nlm) and GS with NLM (gs-1-nlm). Fig. 4(B) gives bias vs. noise plots of different ROIs for GS without NLM (gs-0-nlm) and GS with NLM (gs-1-nlm).

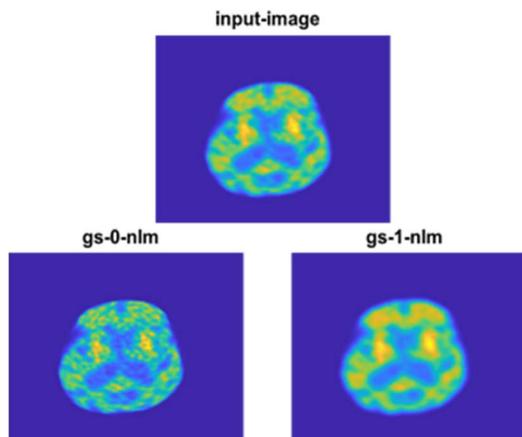


(A)

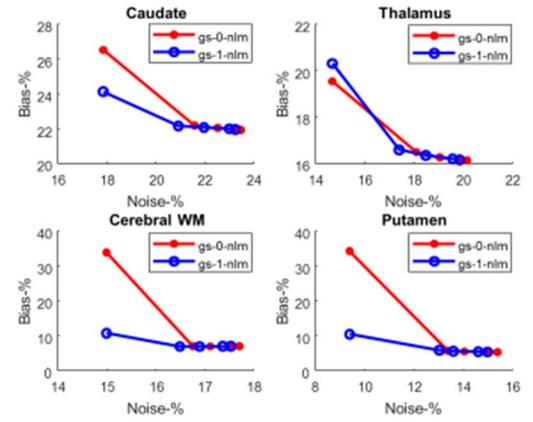


(B)

Fig. 3. (A) Input image and images after PVC with vc-0-weight and vc-1-weight. (B) Bias-noise curve for vc-0-weight and vc-1-weight in caudate, thalamus, cerebral WM and putamen.



(A)



(B)

Fig. 4. (A) Input image and images after PVC with gs-0-nlm and gs-1-nlm. (B) Bias-noise curve for gs-0-nlm and gs-1-nlm in caudate, thalamus, cerebral WM and putamen

In Fig. 3, with a visual check, we notice that weighted VC further reduce the noise compared to non-weighted VC. This is also validated in bias-noise curve, where we see weighted VC gives better bias-noise tradeoff compared to non-weighted VC. In Fig. 4, after the import of NLM regularization, the visual and quality results are all improved. This is especially the case in small ROIs (eg. Caudate & Putama).

IV. CONCLUSIONS

From the visual results and bias vs noise curve in Fig. 3-4, we conclude that using weighting consideration as well as NLM regularization all improve quantitative performance. This is especially the case in small regions involved in Alzheimer's disease research.

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