Image denoising Using Magnetic Resonance Guided Positron Emission Tomography

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Abstract—With the growing interest in conducting multi- centre and multi-modality studies on neurological disorders, post-reconstruction PET image enhancement methods that take advantage of available anatomical information are becoming more important. In this work, a novel method for denoising PET images using the subject's registered T1-weighted MR image is proposed. The proposed method combines the non-local means approach with the twicing strategy from the image denoising literature to restore a reconstructed PET image. Preliminary analysis shows promising improvements in peak signal to noise ratio (PSNR) and contrast recovery coefficients (CRC) of the lesions when denoising simulated images reconstructed using the MLEM algorithm.

Index Terms—PET-MR, denoising, restoration, non-local means, twicing.

1. INTRODUCTION

PET is a powerful tool in both research and diagnosis of various brain disorders. However, reconstructed PET images usually suffer from low signal to noise ratio and low spatial resolution. Therefore, many methods have been devised to address these issues within or after reconstruction. In this work, we are interested in post-reconstruction methods. Post-reconstruction methods have two clear advantages. First, they can be applied to reconstructed images for which the raw measurement data is no longer available. Second, in multicentre datasets, performing minimal set of correction steps (Eg. attenuation/scatter corrections) at the scanner site can reduce the between-centre variability by applying the same post-reconstruction methods for partial volume correction and noise reduction to the whole dataset. Because of the low spatial resolution and high amount of noise in PET images, using anatomical information from MR images in reconstruction, denoising and partial volume correction of PET images has become increasingly popular. In this work, we propose a novel method which incorporates anatomical information from MR images for restoring PET images. Anatomical information has been previously utilized in a non-local means (NLM) method [2] for denoising PET images: authors in [3] have proposed using NLM for PET image denoising while preserving edges, by performing the average in the NLM only in ROIs derived from the subject's CT image. In this work however, instead of only using boundary information from the MR image, the weights in a rotationally invariant NLM method are obtained from the subject's registered T1-weighted MR image. The problem with using a different modality for weight computation is that the resulting image can become excessively blurred in regions where the anatomy in the MR image does not agree with the functional activity in the PET image. To overcome this problem and motivated by the well-known twicing

strategy, the PET-unique signals are denoised using weights obtained form the PET image and the result is added to the denoised image.

2. METHODOLOGY

A. Background

1) Non-local means (NLM): NLM is a simple yet powerful denoising method[1]. It is based on the assumption that patches extracted from a natural image contain redundant information. In essence, in the NLM method a voxel xˆi in the denoised image xˆ is estimated as the weighted average of other voxels in the image with the weights obtained by a robust similarity measure based on the distance of the patches around voxels.

$$x_i = \frac{1}{\sum \sum_{j \in A} w_i} \sum_{j \in A} x_j w_{ij} \qquad (1)$$

where Λi is the neighbourhood around and including xi, and Pk is the patch centred at location k in the image.

2) Rotationally invariant nonlocal-means (RI-NLM3D): In order to increase the number of samples contributing to the average in the NLM method and thus reduce noise further, several rotationally invariant variations of NLM have been proposed. In this work, we use a very simple and computationally efficient rotationally invariant NLM method proposed by Manjon et al. for denoising MR images [5].

$$w_{i,j} = \frac{e^{-x_i - x_j} + \mu p_i - \mu p_j}{\sigma^2} \qquad (2)$$

where µPi is the mean value of the patch Pi. Note that the above similarity measure is sensitive to noise and hence usually a pre-filtered image is used to compute the weights, for subsequent application to the unfiltered image.Each step of the RINLM3D has 3 parameters: patch size, the σ parameter and neighbourhood size for the average.

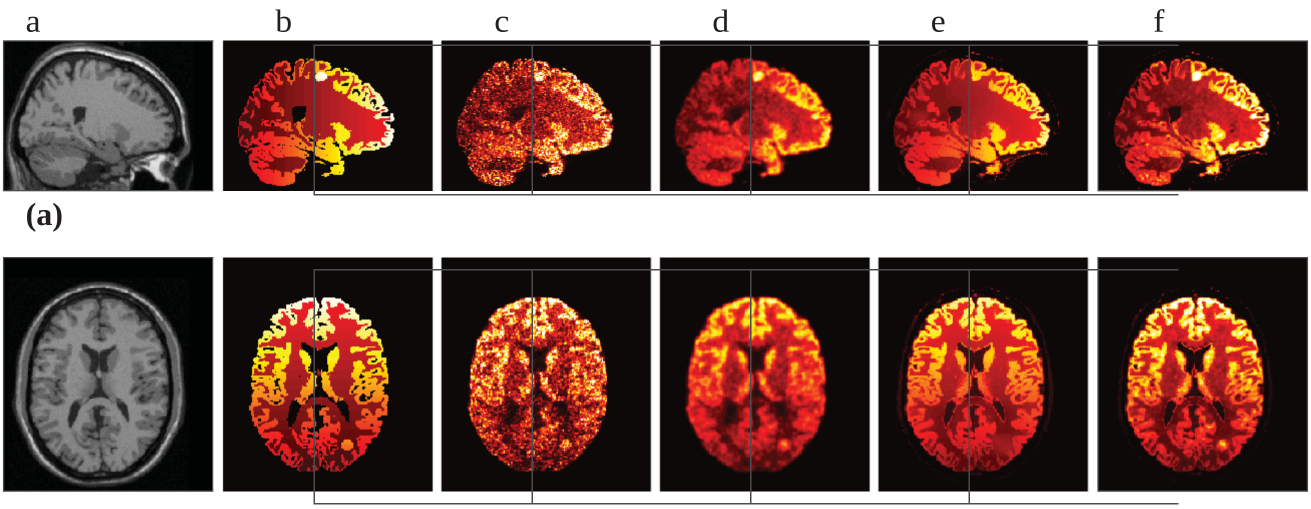


Figure 1: Denoising of a reconstructed image of a sample noisy realization. (a) Registered MR image. (b) The ground truth (c) Noisy reconstructed imageafter 50 iterations(where the best PSNR is obtained). (d) Post-smoothed image after 70 iterations(where the best PSNR was obtained), σ = 1 .2*mm* (CRC oflesions in: WM=0.38,GM=0.56). (e) Denoised image using weights from MR (step 1). (f) Final denoised image after step 2,(CRC of the lesions in:WM=0.58,GM=0.81).

A. *Proposedmethod*

WeproposeatwostepalgorithmforrestoringPETimages.Inthefirststep,thesubject'sregisteredMRimageisusedto compute the weights based on the rotationally invariantformulation in Eq.2. These weights are then used to denoisethePETimage.

The second step is motivated by the twicing method in thedenoisingliterature[7].Inthisstep,firsttheresidualimageisobtainedbysubtractingthedenoisedimageinthefirststep from the noisy image. Then, the noisy PET image ispre-filteredusingaGaussianfilterandtheresultingimageis used to compute weights based on Eq.2. The weights arethen used to denoise the residual image. This way, signalsspecific to the PET image that have been lost in the first step(due to using weights computed from the MR image) areaddedtothedenoisedimage.

I. SIMULATIONSTUDY

Asimulationof[^{18}F]FDGimageswasperformedus-ing the BrainWeb phantom (http://brainweb.bic.mni.mcgill.ca/brainweb) . The corresponding segmented brain was re-sampledtoHRRTimagespace(256x256x256)
Realisticcountratesinthegreymatter (GM) and the white matter (WM), were estimatedusing the radioactivity distribution values from PET SOR-TEO.(http://sorteo.cermep.fr/home.php).Twohotlesions,oneintheGMandoneintheWMwereartificiallyaddedto the simulation. To further investigate the ability of themethod to capture information specific to the PET image andabsent in the MR image, the simulated PET radioactivitydistribution was multiplied by a gradient 3D image in thecoronaldirection(Fig.1.b).Thenoise-free3Dimagewasforwardprojectedtogenerateanoise-freesinogramdata.ThenPoissonnoisewasintroducedtothesinogramdatato

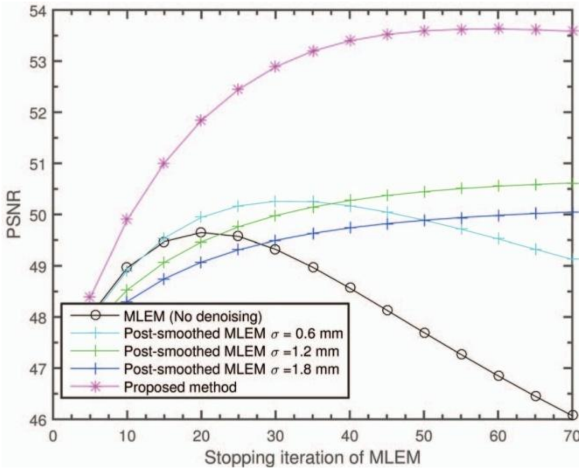


Figure2:Mean PSNR values across 5 realizations for differentmethods as a function of stopping iteration of the MLEM recon-struction

generate 10 noisy realizations. The resulting sinogram datawerethenreconstructedusingtheMLEMalgorithm.
Forbothstepsofthemethod,thepatchsizeissetto
33 3andtheσvalueisset0.05.Theneighbourhoodisapatchofsize 1 5 x 1 5 x 1 5 forthefirststepandapatchof size 999 for the second step. Fig.2 shows the meanPSNRvalueofthedenoisedimageacross5realizationsasa function of stopping iteration of the MLEM algorithm forthe proposed method and also for Gaussian post-smoothingwithdifferentσvalues.Theresultsindicatethesuperiorityoftheproposedmethodto Gaussiansmoothing.ThePSNRof the proposed method reaches a maximum at 50 iterationsandthenplateaus.Fig.1showstheoutputofdifferentstepsofthe proposed method on a reconstructed PET image stoppedafter50iterationsaswellasGaussianpost-smoothingatitsbestperformance(highestPSNR).Notehowthelesions

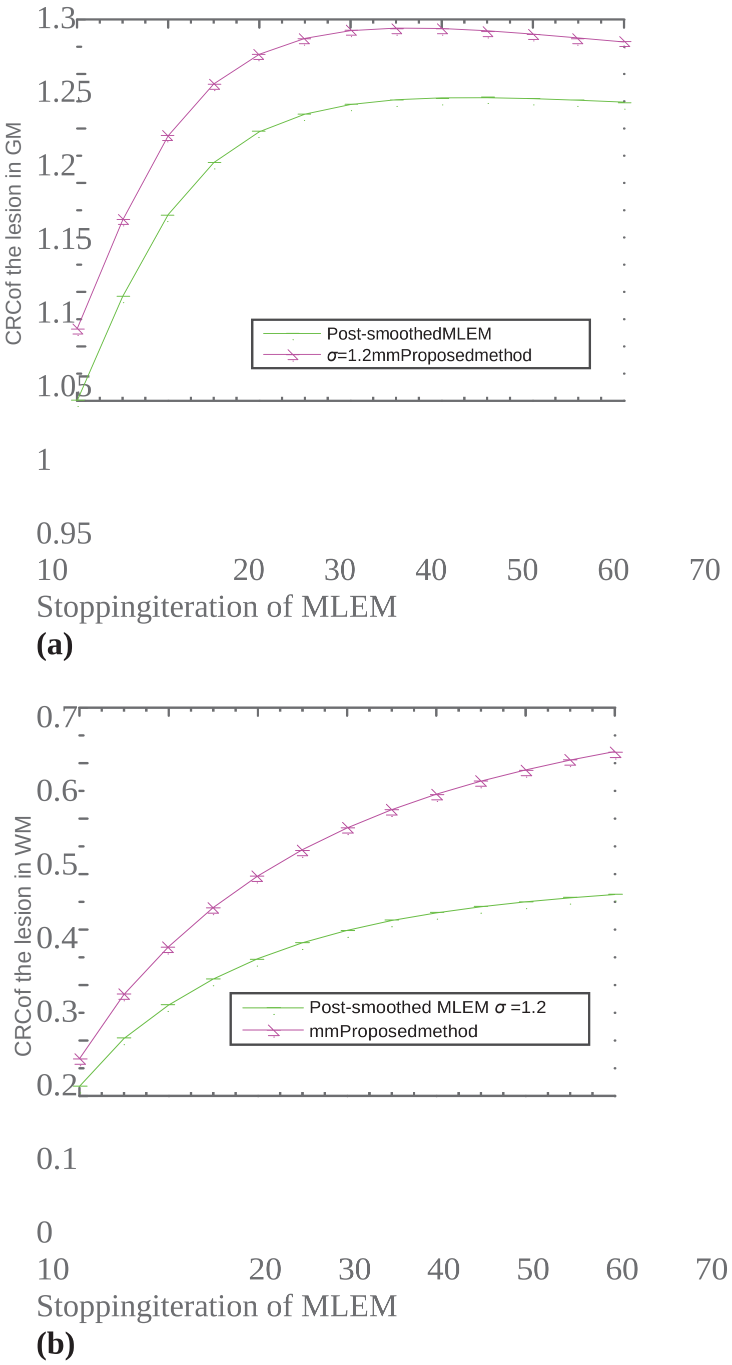
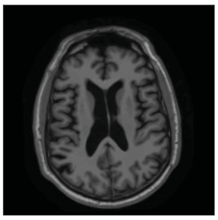
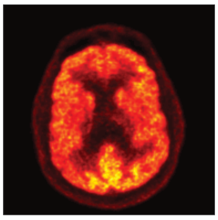


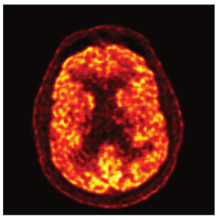
Figure3:Themeancontrastrecoverycoefficientsofthetwolesionsembeddedingrey matter(GM) andwhitematter (WM)across 5realizations.



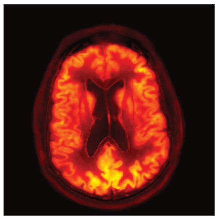
(a)



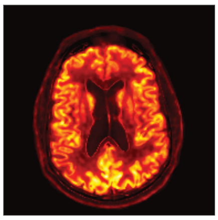
(b)



(c)



(d)



(e)

Figure4:DenoisingresultofabaselineFDGimageofanMCI patientfrom the ADNI dataset. (a) Registered MR image. (b) Noisy reconstructedimage.(c)PVEcorrectedimage.d)denoised.(e)PVE corrected+denoised.

whichdisappearedinstepone(Fig.1(e))becomevisibleafteraddingthedenoisedresidual(Fig.1(f)).

Inordertoevaluatetheabilityoftheproposedmethodin regions where functional anatomy in PET does not agreewith the anatomical information in MR, the contrast recoverycoefficients(CRC)ofthetwolesionswereobtainedandcom-pared to those for Gaussian post smoothing. Fig.3 comparesthemeanCRCofthelesionsacrossmultiplerealizationsfor the proposed method and the Gaussian post-smoothingwiththeσparametervalueleadingtomaximumPSNR(i.e.$\sigma = 1.2mm$). The results indicate that the proposed methodprovidesahighercontrastintheseregionsforalliterationsofMLEM.

APPLICATIONONREALDATA

An FDG image of a subject with mild cognitive impair-ment(MCI)withfour5-minuteco-registeredframeswasobtained from the Alzheimer's Disease Neuroimaging Ini-tiative (ADNI,http://www.adni-info.org/) database. The co-registered frames were then averaged together and the result-ing static image was co-registered to the subject's baselineT1-weightedMRimage.Then,theproposedmethodwasappliedtotheresultingimagewiththesamepar ametersused for the simulation data. In addition, in order to correctforPVE,10stepsoftheRichardson-Lucydeconvolutionalgorithm [4], [6] with FWHM equal to 6.5mm were appliedto the image prior to denoising. The result of the denoisingwithandwithoutPVEcorrectionisshowninFig.4.

3. CONCLUSION

In this study a novel MR-guided PET image denoisingmethodwasproposed.Simulationresultsshowthattheproposed method is able to significantly improve the peaksignal to noise ratio of PET images reconstructed using theMLEM algorithm. Furthermore, we show that the proposedmethod can be applied after the conventional PVE correctionmethod to restore the PET images by both reducing the noiseandrecoveringtheboundaries.

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