PET reconstruction of the posterior image probability distribution, using multimodal data

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Goals

1. Posterior probability distribution of the PET image
   - voxel-wise
   - uncertainty
2. Spatial regularization
   - noise
   - partial volume
3. MRI
   - potential synergy
   - available (PET/MRI)

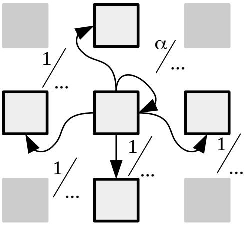
Goals

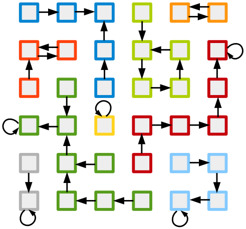
1. Posterior probability distribution of the PET image
   - Bayesian inference model $\rightarrow$ non-parametric
   - MCMC sampling
2. Spatial regularization
   - prior distribution over spatial homogeneities
   - additional information $\rightarrow$ other modalities
3. MRI
   - already reconstructed images
   - one or more

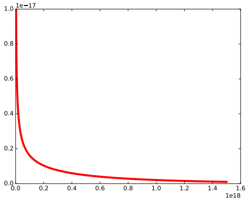
Model : Prior

Distance-dependent Chinese restaurant process (ddCRP)

- distribution over possible clusterings of voxels
- cluster intensity $\sim$ Gamma distribution







Unknown image $\sim$ p (clustering, cluster intensity)

$\Longrightarrow$ Main prior assumption : piece-wise smoothness

Model : Likelihood

Noise of the measured/observed data

- PET projection data

$$\begin{array}{lll} \textit{Poisson} & (& A * \text{image} \quad) \\ \textit{Poisson} & (& E(\text{background signal}) \quad) \end{array}$$

- MRI reconstructed image

$$\mathcal{N}(m, \sigma)$$

PET and MRI data share the (ddCRP) model of voxel clustering

Model : Posterior

- Bayes' theorem

  $$p \quad (\text{clustering, cluster intensity} \quad | \quad \text{PET projection data, MR image})$$

- Unknown, intractable analytically $\implies$ draw samples

Model : Posterior

- Bayes

$$p \quad (\text{clustering, cluster intensity, } n \quad | \quad \text{PET projection data, MR image})$$

n = latent complete PET data as in ML-EM, number of counts detected in projection line i corresponding either to emission from voxel j or to background signal (random/scatter)

Sampling the posterior

Monte Carlo Markov chain sampler (Gibbs)

1 iteration $\implies$ 1 (image) sample of the posterior distribution

1. $p(n|\ldots) \sim$ Multinomial (backprojection)
2. $p(\text{clustering}|\ldots) \sim$ posterior ddCRP
3. $p(\text{cluster intensity}|\ldots) \sim$ Gamma

Overview of the posterior

Summary of the posterior

- an image : average
- uncertainty : 95% credible intervals
- posterior distribution of an ROI SUV mean/peak

RCP-GS : Random Clustering Prior - Gibbs Sampler

M. Filipović et al., "PET Reconstruction of the Posterior Image Probability, Including Multimodal Images," IEEE TMI, July 2019

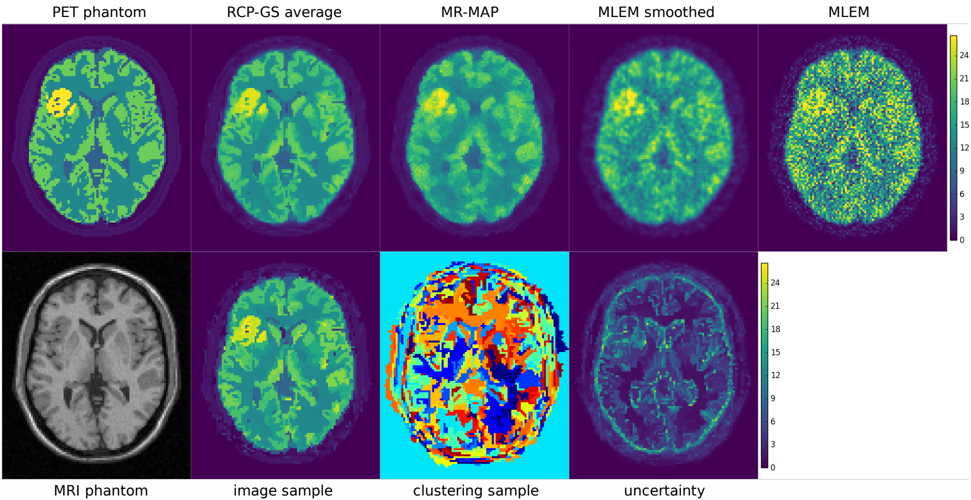
CASToR

Customizable and Advanced Software for Tomographic Reconstruction

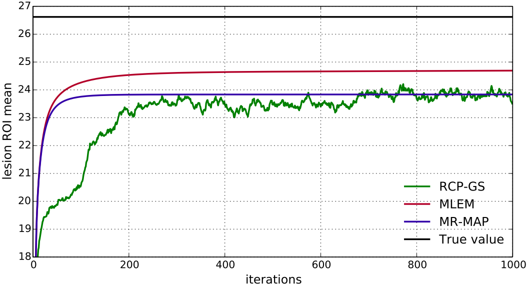
- open source
- generic
- C++

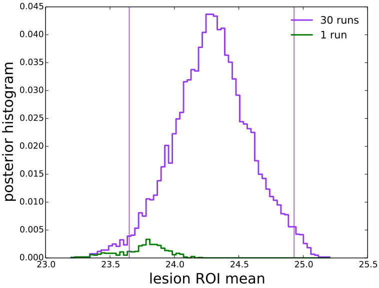
www.castor-project.org

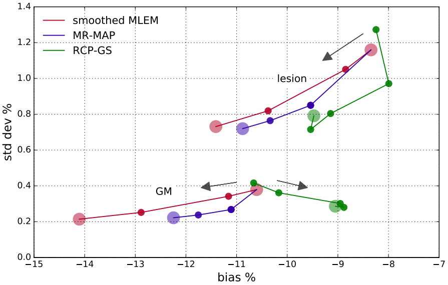
Results : Simulation



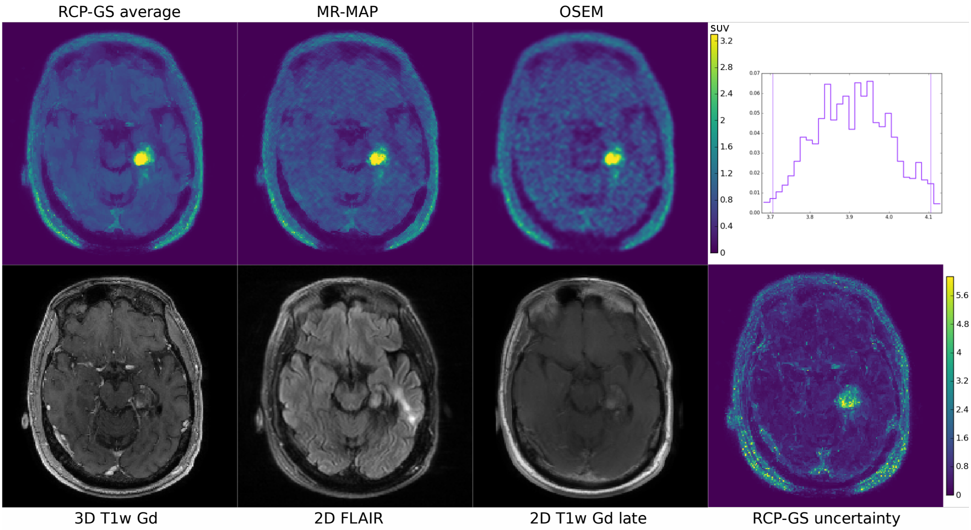
Results : Simulation







Results : Real data (GE PET/MRI scanner)



Discussion

Applying the model

- hyperparameters
- choice of multimodal data: task, resolution

Technical issues

- sampler convergence to the posterior
- PSF

Using the results

- interpretation of the uncertainty
- diagnostic task

Conclusion

Uncertainty is everywhere

Algorithms $\leftrightharpoons$ Medical application