

## Dual-time-point Patlak estimation from list mode PET data

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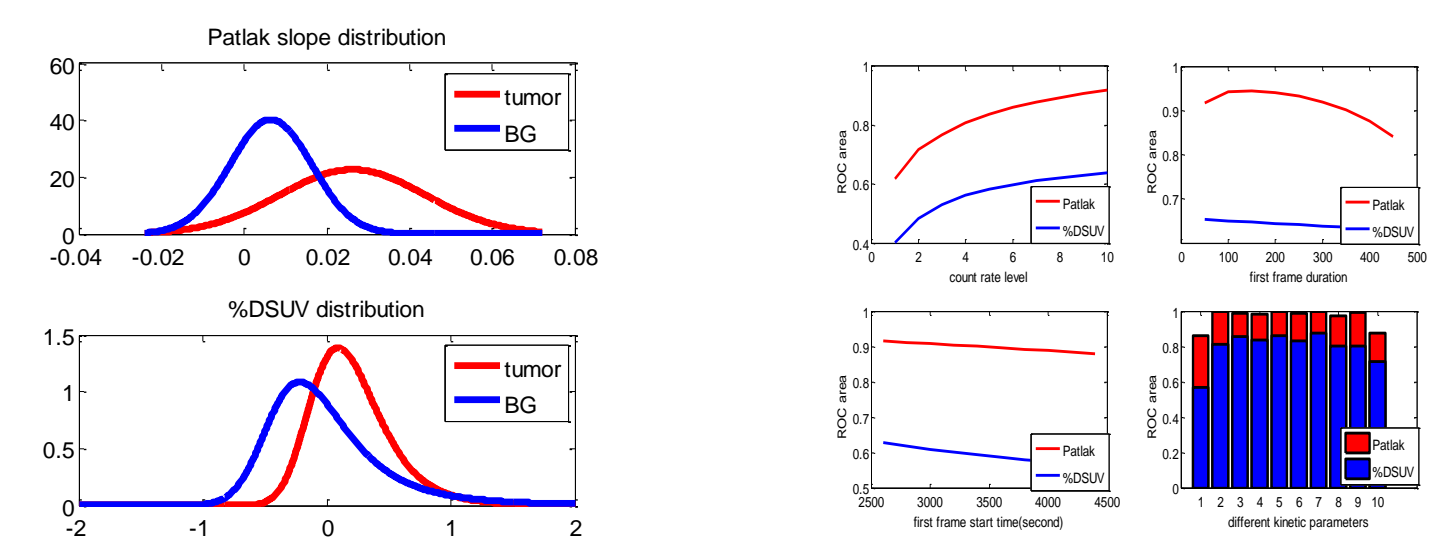
### Motivation & Introduction

We investigate the potential of using dual-time-point PET data to perform Patlak modeling. This approach could be used for whole-body dynamic PET in which we compute voxel-wise estimates of Patlak parameters using two frames of data for each bed position. Our approach directly uses list mode arrival time for each event to compute the Patlak image. We evaluate performance of the method in comparison to percentage changes in SUV values. Both the simulation, the Cramer-Rao analysis and real data test suggest that our dual-time-point Patlak estimation method can achieve superior differentiation of tumor from background in small tumors.

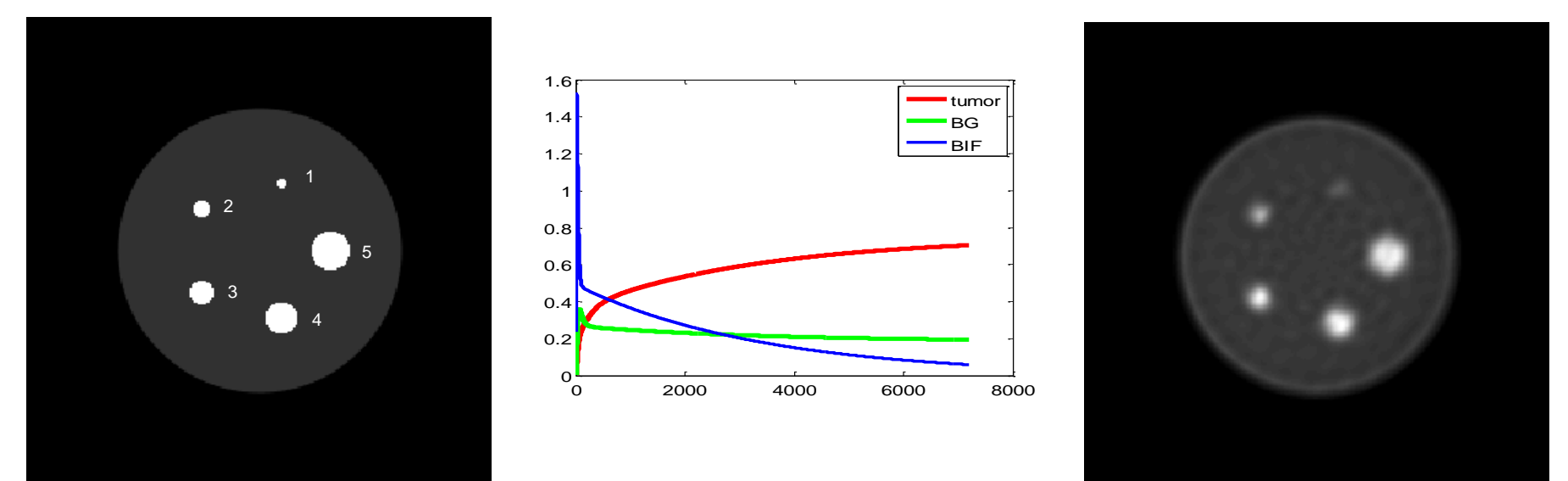
### Experiments

We simulated a small scale 3D PET system (diameter: 148.4mm, detector size: 2.423mm x 2.423mm; number of rings: 4) with a total of 13 sinograms with 84 angles of view by 96 radial lines of response (LORs). A uniform cylindrical phantom of diameter 31.4mm was centered and contained 5 cylinders (“tumors”) of diameter 1.0, 1.8, 2.6, 3.4, and 4.2mm.

- Cramer-Rao bound
  - Value distribution and parameter variation

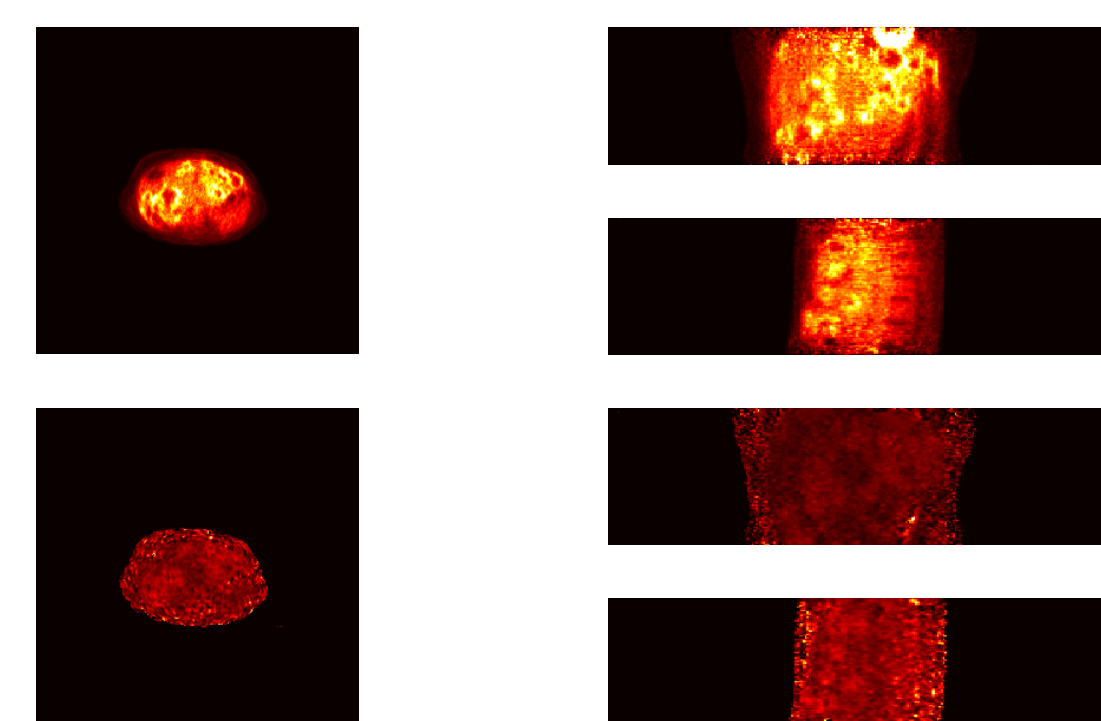


- NEMA phantom simulation
  - Reconstruction and Patlak v.s. %DSUV



ROI	Patlak		%DSUV	
	Tumor	BG	Tumor	BG
1	0.0106±8.35 e-4	0.0064±6.51 e-4	0.0809±0.1300	-0.0935±0.1400
2	0.0190±9.58 e-4	0.0065±4.73 e-4	0.1513±0.0720	-0.0904±0.0926
3	0.0229±7.77 e-4	0.0065±3.87 e-4	0.1527±0.0380	-0.0881±0.0624
4	0.0262±5.22 e-4	0.0064±2.93 e-4	0.1539±0.0265	-0.0898±0.0425
5	0.0264±4.59 e-4	0.0065±2.30 e-4	0.1570±0.0216	-0.0901±0.0338
True value	0.0263	0.0065	0.1640	-0.0903

- Patient with necrosis. Patlak v.s. %DSUV



### Algorithms

- We incorporate the Patlak model into the image reconstruction framework, where we use the blood-input-function as basis to represent the rate function. Inhomogeneous Poisson model is then applied to construct the likelihood function of phantom arrival times.

- Patlak equation  $\eta(t) = \kappa \int_0^t C(\tau) d\tau + qC(t)$

- Rate function  $\lambda_i(t) = e^{-t/\tau} \sum_{j=1}^{n_p} \sum_{k=1}^2 p_{ij} \omega_{jk} B_i(t)$

$$\omega_{j1} = \kappa_j, \omega_{j2} = q_j, B_1(t) = \int_0^t C(\tau) d\tau, B_2(t) = C(t)$$

- Cost function  $L(W) = - \sum_{i=1}^{n_p} \sum_{k=1}^{x_i} \log \lambda_i(a_{ik}) + \sum_{i=1}^{n_p} \int_{T^*}^T \lambda_i(t) dt$

- Dual frame  $L(W) = - \sum_{i=1}^{n_p} \sum_{k=1}^{x_i} \log \lambda_i(a_{ik}) + \sum_{i=1}^{n_p} \left( \int_{t_1}^{t_2} \lambda_i(t) dt + \int_{t_3}^{t_4} \lambda_i(t) dt \right)$

- Cramer-Rao  $\frac{\partial L^2(W)}{\partial \omega_{mj} \partial \omega_{nl}} = \sum_{i=1}^{n_p} \sum_{k=1}^{x_i} \left\{ \frac{e^{-\frac{2a_{ik}}{\tau}} p_{im} p_{in} B_j(a_{ik}) B_l(a_{ik})}{\lambda_i^2(a_{ik})} \right\}$

### Discussion & Future Work

- For the two smaller tumors, the areas under the ROC curve are lower for percentage SUV than for Patlak estimation.
- We have seen performance consistent with that reported above when we varied these parameters.
- The Cramer-Rao analysis reveals similar behavior, albeit in a simplified setting.
- The simulation and real clinical data suggest that dual-time-point Patlak analysis has better performance than %DSUV.
- In future we plan to apply our work to longitudinal PET studies and make better predications of liver lesions.