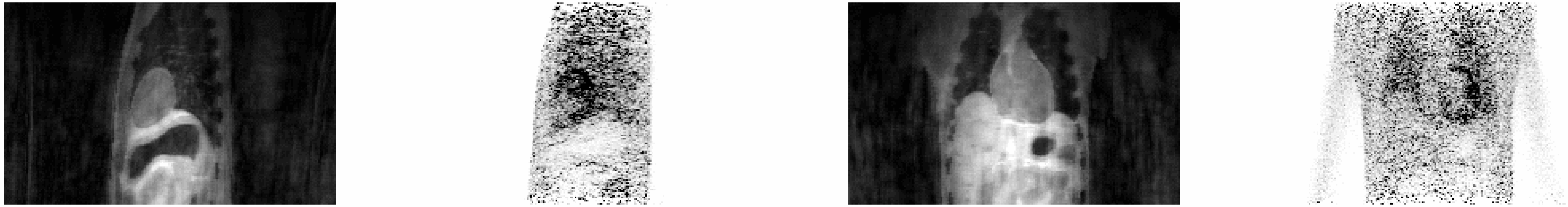
All simulations are based on a segmentation and associated motion model. In this case it is the XCAT.
Image data shown reconstructed from simulated PET rawdata without AC to avoid the imprint of the mu map.
MRI data [containing fat-water chemical shift!] was reconstructed from simulation data in ISMRMRD format.

For respiration 24 sinograms were simulated and binned into 8 respiratory states.
For cardiac motion 16 sinograms were simulated and binned into 8 cardiac states.
Binning was performed based on surrogate signal used as simulation input.

4D cardiac motion

4D respiratory motion



This image data was used to evaluate a registration algorithm.

"Synergistic" registration: cost function for transformation T is computed for similarity metric S which weights the MRI and PET contribution to the registration:

$$\mathcal{C}(T) = (1-\lambda)\cdot\mathcal{S}(I^{move}_{PET}\circ T, I^{ref}_{PET}) + \lambda\cdot\mathcal{S}(I^{move}_{MRI}\circ T, I^{ref}_{MRI})$$

The registration output can be compared to the ground truth motion fields in and ROI which contains the left myocardium only.
The graphs on the left are registration evaluations for 4D resp motion.

The upper graph shows the registration amplitude [black] in comparison to the ground truth [red] and their vectorial deviation [blue] for one choice of lambda. Data points are each the mean value over the ROI [6000 voxels] with error bars one standard deviation.
One can see that this algorithm captures the amplitude well with deviations on ROI average below 1 voxel.

The lower graph shows the maximum of the blue curve in the upper graph [i.e. the maximum error of registration] for different choices of lambda. The minimum is somewhere in the middle, showing how using both PET and MRI information can improve the registration.

Very preliminary