DeepSLM: Image Registration Aware of Sliding Interfaces for Motion-Compensated Reconstruction

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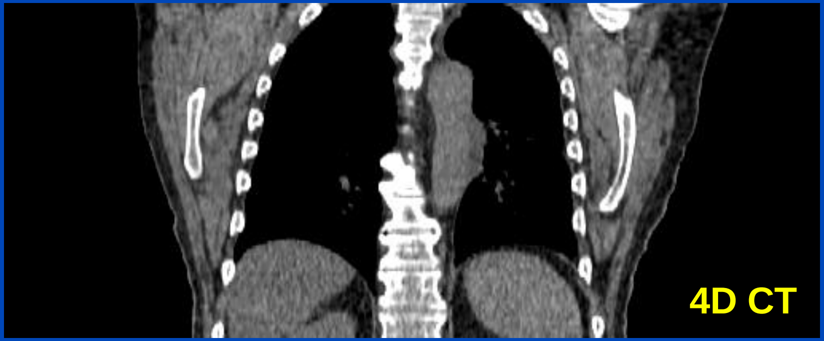
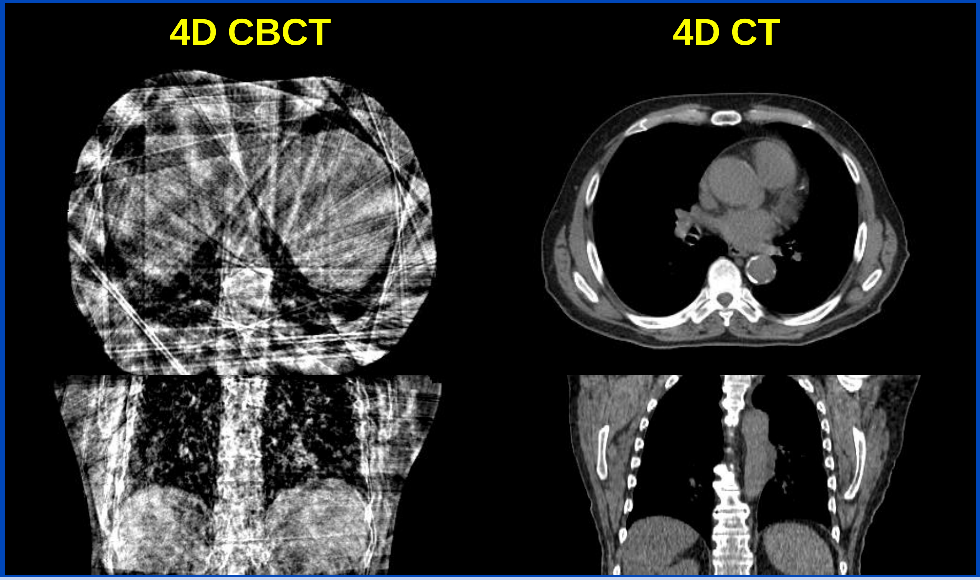
Motivation

- Sliding interface motion appears in patients at the border of different organs, for example at the ventral cavity. We will concentrate at the thoracic cavity and refer to it as sliding lung motion (SLM).
- Motion-compensated (MoCo) reconstruction can introduce non-physiological motion at these anatomical regions.
- This is especially important, when it is used with high regularization, for example in MoCo reconstruction for 4D CBCT.



Motivation II

- Previous work by us has been dealt with MoCo reconstruction on short 4D CBCT scans.
- However, the respiration phase images are sparse and require strong regularization in the Demons image registration algorithm.
- To transfer the knowledge from the conventional image registration, to a deep learning framework, we apply as an intermediate step MoCo on 4D CT.



Aim

- Include sliding lung motion in a deep learning framework for deformable image registration.
- Prevent or suppress non-physiological motion in motion-compensated reconstruction.
- Show the benefit of motion-compensated reconstruction for 4D CT.

Deformable Image Registration

- **In deformable image registration, we look for a motion vector field (MVF) *d*, which warps the source image *f* into the destination *g*:**

$$g(\boldsymbol{r}) = f(\boldsymbol{r} + \boldsymbol{d}(\boldsymbol{r}))$$

- **This search is usually conducted by optimizing a loss function, which features an image similarity metric and an MVF regularization:**

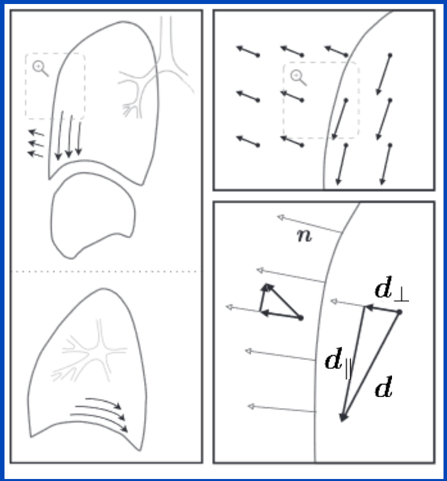
$$\operatorname*{argmin}_{\boldsymbol{d}} \mathcal{L}(f, g, \boldsymbol{d}) = \mathcal{L}_{\mathrm{SIM}}(f(\boldsymbol{d}), g) + \lambda\, \mathcal{L}_{\mathrm{REG}}(\boldsymbol{d})$$

- **Common choices for the similarity loss is the l2 norm of the image differences and for the MVF regularization the l2 norm of the gradient of the MVF:**

$$\mathcal{L}_{\mathrm{SIM}}(f(\boldsymbol{d}), g) = \|f(\boldsymbol{d}) - g\|_2^2$$
$$\mathcal{L}_{\mathrm{REG}}(\boldsymbol{d}) = \|\nabla \boldsymbol{d}\|_2^2$$

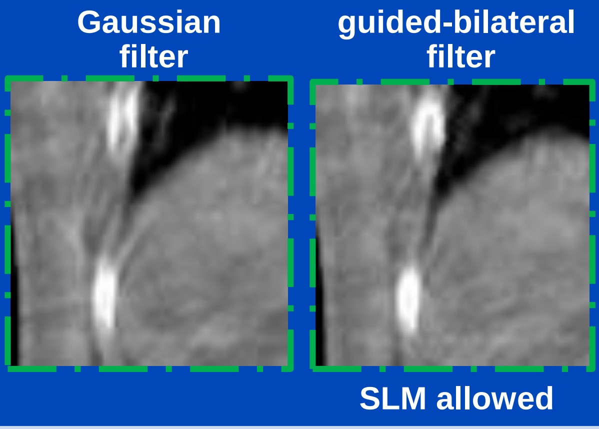
Previous Work

- Alexander Schmidt-Richberg, Jan Erhardt et al., “Estimation of Slipping Organ Motion by Registration with Direction-Dependent Regularization,” Medical Image Analysis 16(1), 150–159 (2012).



$$\mathcal{L}_{\mathrm{REG}} = \sum_{r} \|\nabla \boldsymbol{d}(\boldsymbol{r})\|_2^2 \approx \sum_{r} \|\nabla \boldsymbol{d}_\perp(\boldsymbol{r})\|_2^2 + \sum_{r} \|\nabla \boldsymbol{d}_\|(\boldsymbol{r})\|_2^2$$

- Sebastian Sauppe, Marc Kachelrieß et al., “Demons-Based Sliding Lung Motion Registration with Guided-Bilateral Filter at the Lung Border.”, ECR 2018
- Markus Susenburger, Marc Kachelrieß et al., “4D Segmentation-Based Anatomy-Constrained Motion-Compensated Reconstruction of On-Board 4D CBCT Scans”, CT Meeting 2020



MVF Regularization

- For motion estimation with sliding lung motion constraint, we split the MVF *d* regularization into a part perpendicular $d_\perp$ and tangential $d_\parallel$ to the border of the ventral cavity segmentation *m*.

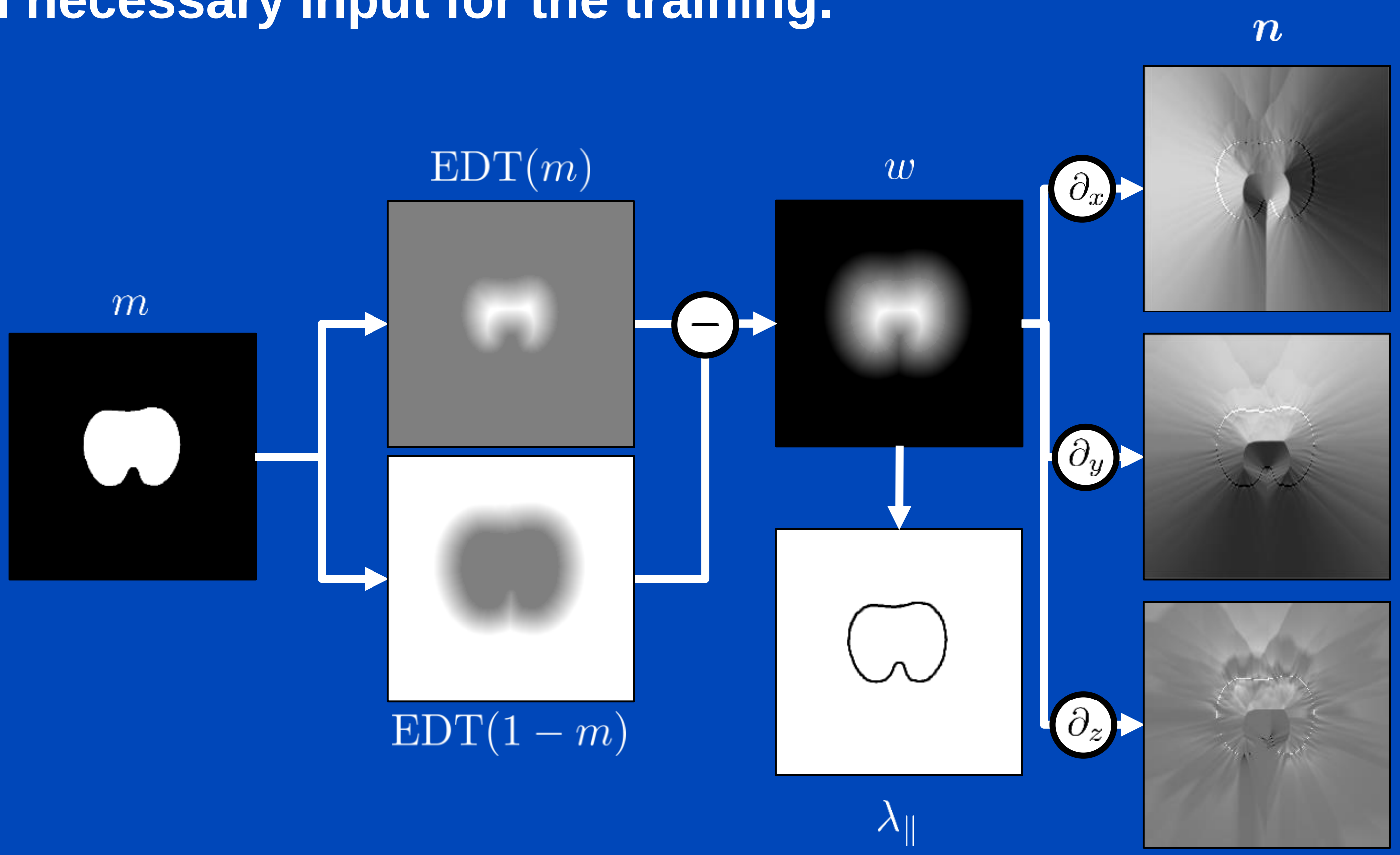
$$\mathcal{L}_{\mathrm{REG}} = \sum_{r} \|\nabla d(r)\|_2^2 \approx \sum_{r} \|\nabla d_\perp(r)\|_2^2 + \sum_{r} \|\nabla d_\parallel(r)\|_2^2$$

$$\text{with } d_\perp = \frac{(n \cdot d)n}{n^2} \text{ and } d_\parallel = d - d_\perp$$

- This approximation becomes an equality, if the normal vector field map *n* is smooth.

SLM Training Input Generation
Weight and Normal Vector Field Map

- **From an initial ventral cavity segmentation m, we can generate all necessary input for the training.**

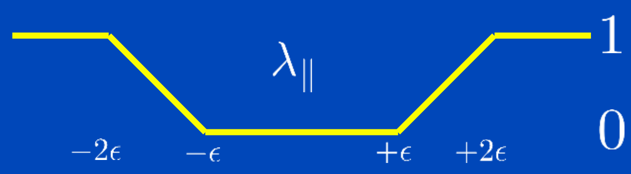


DeepSLM Loss Function

- The loss function can be constructed as

$$\mathcal{L} = \mathcal{L}_{\text{SIM}} + \lambda\,\mathcal{L}_{\text{REG}} = \text{MSE} + \lambda\,\mathcal{L}_{\text{REG}}$$

- The choices for the motion vector field regularization loss are given by:



VoxelMorph $$\mathcal{L}_{\text{REG}} = \frac{1}{3N}\sum_{\boldsymbol{r}} ||\nabla \boldsymbol{d}||_2^2$$

global DeepSLM $$\mathcal{L}_{\text{REG}} = \frac{1}{3N}\sum_{\boldsymbol{r}} (||\nabla \boldsymbol{d}_\perp||_2^2 + \lambda_{||}||\nabla \boldsymbol{d}_{||}||_2^2)$$

local DeepSLM $$\mathcal{L}_{\text{REG}} = \frac{1}{3N}\sum_{\boldsymbol{r}} \begin{cases} ||\nabla \boldsymbol{d}||_2^2 & \text{if } \lambda_{||} = 1 \\ ||\nabla \boldsymbol{d}_\perp||_2^2 + \lambda_{||}||\nabla \boldsymbol{d}_{||}||_2^2 & \text{else.} \end{cases}$$

strict DeepSLM $$\mathcal{L}_{\text{REG}} = \frac{1}{3N}\sum_{\boldsymbol{r}} \lambda_{||}||\nabla \boldsymbol{d}||_2^2$$

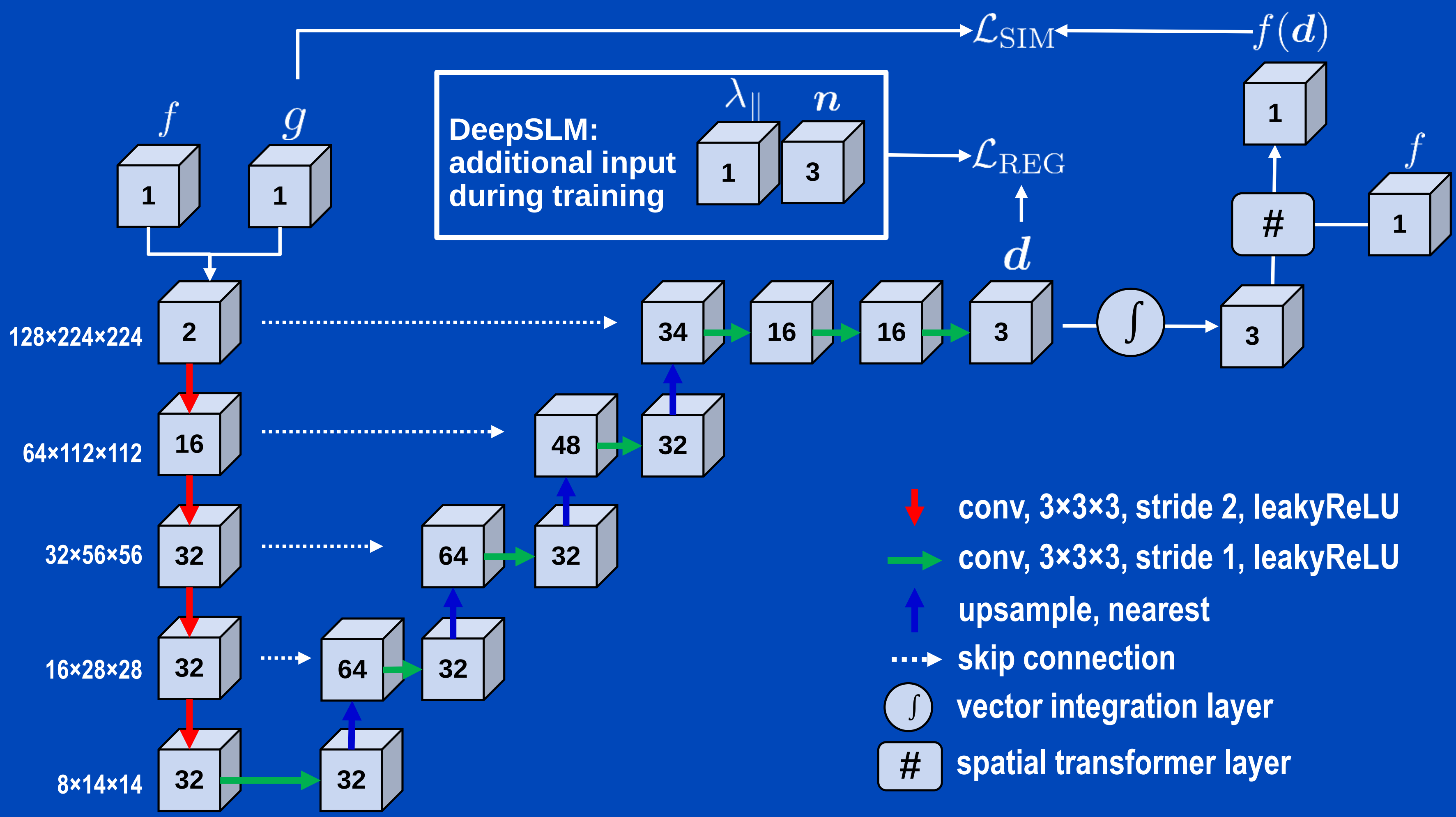
Guha Balakrishnan, Adrian V. Dalca et al., “VoxelMorph: A Learning Framework for Deformable Medical Image Registration,” IEEE Trans. Med. Imaging 38(8), 1788–1800 (2019).

Unsupervised Deep Learning of Deformable Image Registration

- **Deformable image registration with unsupervised deep learning can be closely related to conventional registration algorithms. One such architecture is VoxelMorph, the basis for our networks.**

	Demons-based with Guided Bilateral Filter	**VoxelMorph**
type	conventional	unsupervised deep learning
input	image pair, ventral cavity segmentation	image pair, ventral cavity segmentation only during training
output	MVF and deformed source	MVF and deformed source
multiresolution	yes	yes
diffeomorphic	yes	yes
cost function	MSE and L2 norm of MVF gradient	MSE and L2 norm of MVF gradient

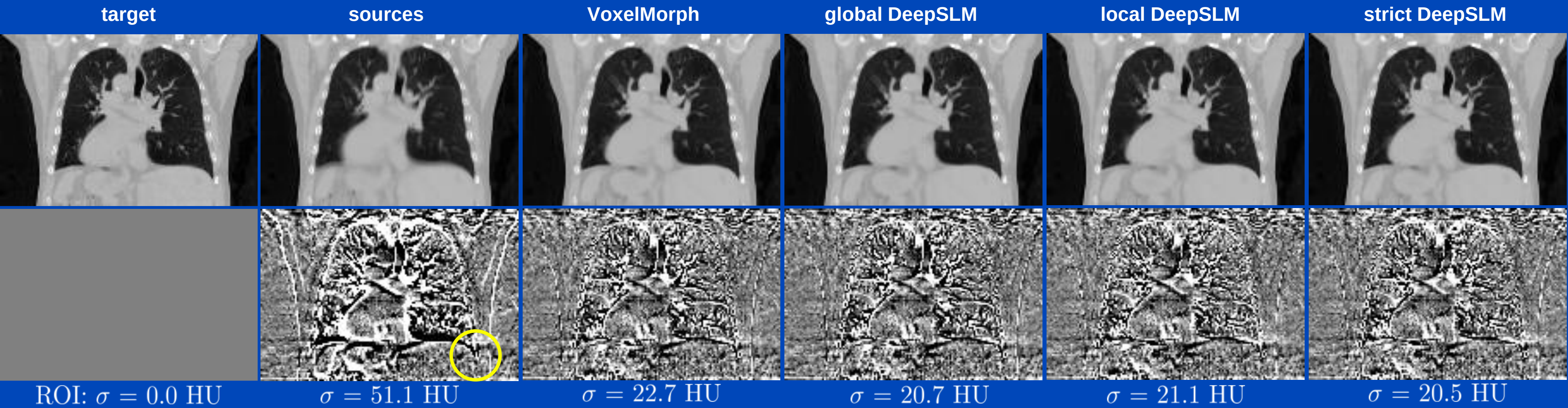
Network Architecture



Data, Preparation and Training

- Clinical 4D CT, 10 respiration phases, all phases include a ventral cavity segmentation (70 training patients, 15 test patients)
- The data preprocessing:
  - Resample to cubic voxels ($3 \times 3 \times 3$ mm^3).
  - Move center of mass of ventral cavity segmentation to center of volume.
  - Crop (x and y) or pad (z) volume to $224 \times 224 \times 128$.
  - Offset and scale images individually into range [0,1].
- 150,000 registrations per training, each registration is a random selection of two phases from one random patient.
- Training parameters are similar to the ones used in VoxelMorph.

Results – Registration
Register All Phases to One Phase



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all phases average

All phases deformed to the target phase and average of the results. With a perfect registration, there would be no difference to the target phase.

mean volumes: *C* = -250 HU, *W* = 1500 HU
difference volumes: *C* = 0 HU, *W* = 50 HU

Evaluation Metrics

- The methods are evaluated against local normalized cross correlation, root mean square error and DICE:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{\boldsymbol{r}} ||f(\boldsymbol{d}) - g||_2^2}$$

$$\mathrm{NCC} = \frac{1}{Q}\sum_{q} \frac{(\sigma_{f(\boldsymbol{d}),q} - \mu_{f(\boldsymbol{d}),q})(\sigma_{g,q} - \mu_{g,q})}{\sigma_{f(\boldsymbol{d}),q}\sigma_{g,q}}$$

$$\mathrm{Dice} = \frac{2|S_{f(\boldsymbol{d})} \cap S_g|}{|S_{f(\boldsymbol{d})}| + |S_g|}$$

Evaluation Losses

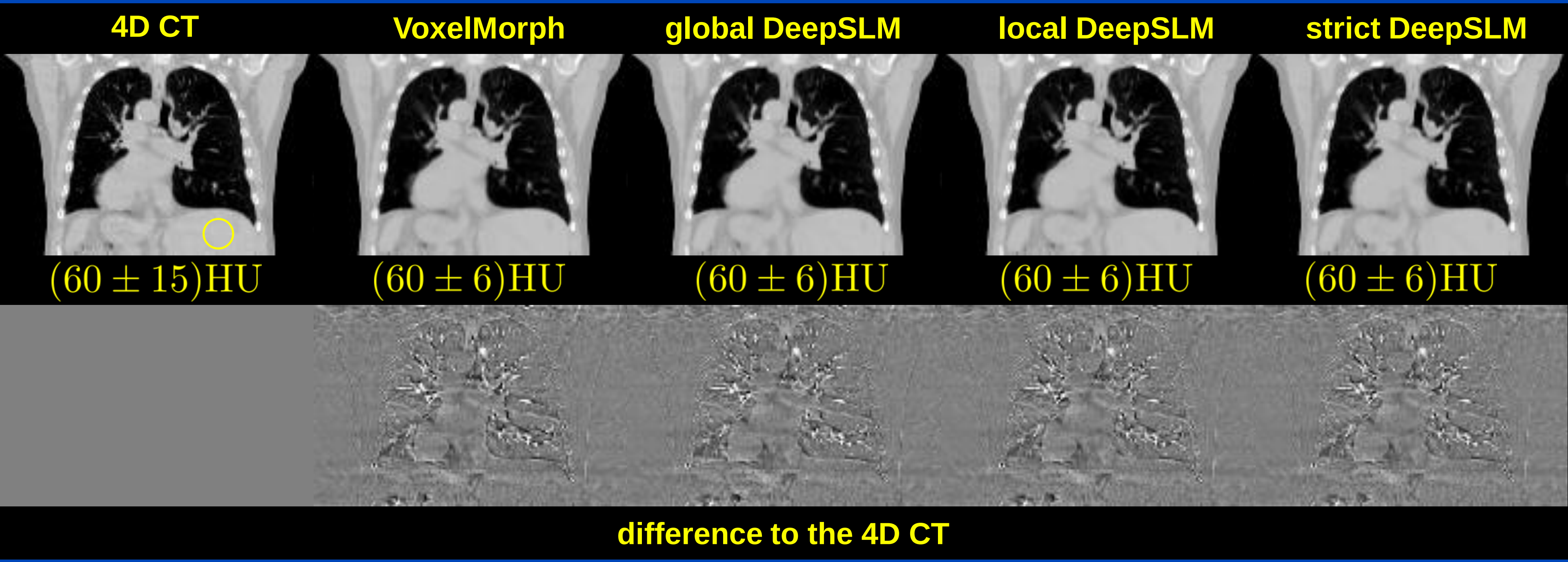
Test loss	unregistered image pairs	VM	global DeepSLM	local DeepSLM	strict DeepSLM
RMSE	0.013 ± 0.009	0.005 ± 0.002	0.005 ± 0.002	0.005 ± 0.002	0.005 ± 0.002
NCC	0.428 ± 0.081	0.464 ± 0.042	0.465 ± 0.036	0.464 ± 0.035	0.428 ± 0.081
Dice	0.989 ± 0.005	0.988 ± 0.003	0.987 ± 0.003	0.987 ± 0.003	0.989 ± 0.005

Motion-Compensated Reconstruction of 4D CT Images

- In motion-compensated reconstruction, we can use the full dose information and warp it into other phases. This results in 100% dose usage for each phase. Therefore, we just need to register each phase to all other phases:

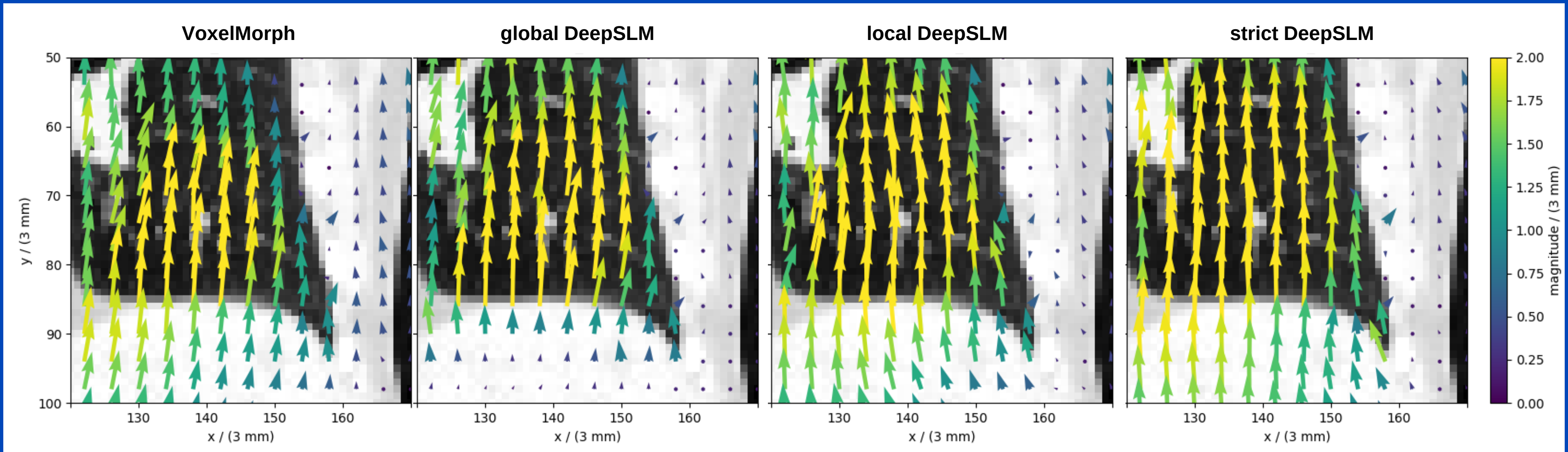
$$f_{\mathrm{MoCo}}(i) = \sum_j f(\boldsymbol{d}_j^i)$$

Results Motion-Compensated Reconstruction (4D CT)



C = -250 HU, *W* = 1500 HU
15 respirations per minute

Motion Vector Field Representation



Conclusions

- The vector field representation indicates that the network can apply the segmentations learned in the training during inference.
- The loss function from VoxelMorph can be adapted to match the loss function of the Demons-based SLM registration approaches.
- The regularization needed for registration in 4D CT is too small to show a significant improvement. A next step is to transfer the learned knowledge into the more complicated case of sparse 4D CBCT.

Thank You!

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