UNIVERSITÄT ZU LÜBECK
INSTITUTE OF MEDICAL INFORMATICS

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Estimating Large Lung Motion in COPD Patients by Symmetric Regularised Correspondence Fields

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Motivation and challenges for COPD registration

- 4th **most common cause of death** in US (caused mainly by smoking)
- Diagnosis with spirometry only global, **but air trapping localised**
- Ventilation of tissue quantifiable by **registering exhale to inhale scan**

- **Strong noise in exhale scan** due to ultra low-dose protocol
- **Large volume differences (~100%)** between inhale and exhale
- **Locally varying contrast** due to lung compression

Overview of our registration approach

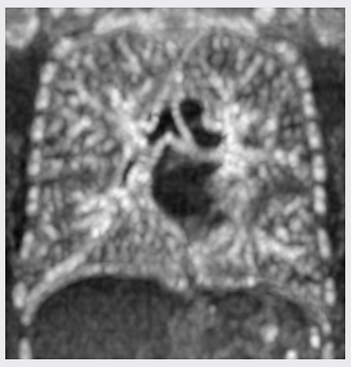
1. **Keypoint extraction** using Förstner operator (interest points)
2. Block-matching with discriminative **self-similarity context [1]**
3. **Parts-based model** [2] for regularisation + symmetry constraint

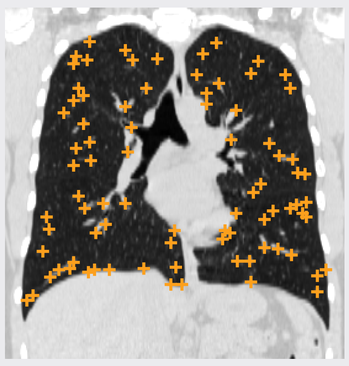
1. Keypoint extraction

- Restrict motion estimation to **interesting points** in image
- Förstner operator **detects high local curvature** (corners)

$$D(x) = 1/\operatorname{trace}\left((G_\sigma * (\nabla F \nabla F^T))^{-1}\right)$$

operator response





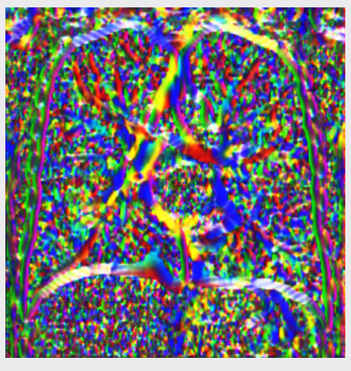
selected keypoints

- **Non-maximum suppression** → well-distributed points within lungs
- Keypoints are **only defined in fixed (inhale) scan,** but dense search

2. Block-matching with self-similarity context

- Convert representation of both scans to **self-similarity descriptors**

example for inhale



RGB-colours 3/12 elements

- Sensitive to edges/orientation and contrast invariant
- Distance of SSC-vectors can be calculated in **Hamming space**

$$\mathcal{D}(\mathbf{k},\mathbf{l}) = 1/|\mathcal{P}| \sum_{p\in\mathcal{P}} \Xi\{SSC_F(\mathbf{k}+p) \oplus SSC_M(\mathbf{l}+p)\}$$

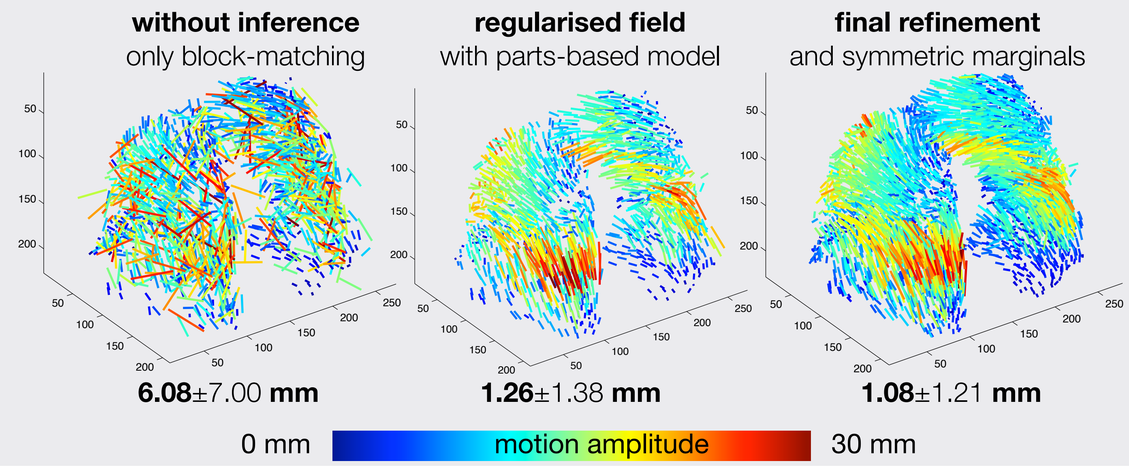
- **Dense sampling of displacements** and storing of all probabilities (block-matching retains only most probable vector)

3. Parts-based model for regularisation

- **Infer regularity** over all displacement probabilities with **MST** model

$$\mathcal{R}(\mathbf{d}_i,\mathbf{d}_j) = \frac{||\mathbf{d}_i - \mathbf{d}_j||^2}{\sqrt{||\mathbf{x}_i - \mathbf{x}_j||^2 + |I(\mathbf{x}_i) - I(\mathbf{x}_j)|/\sigma_I}}$$

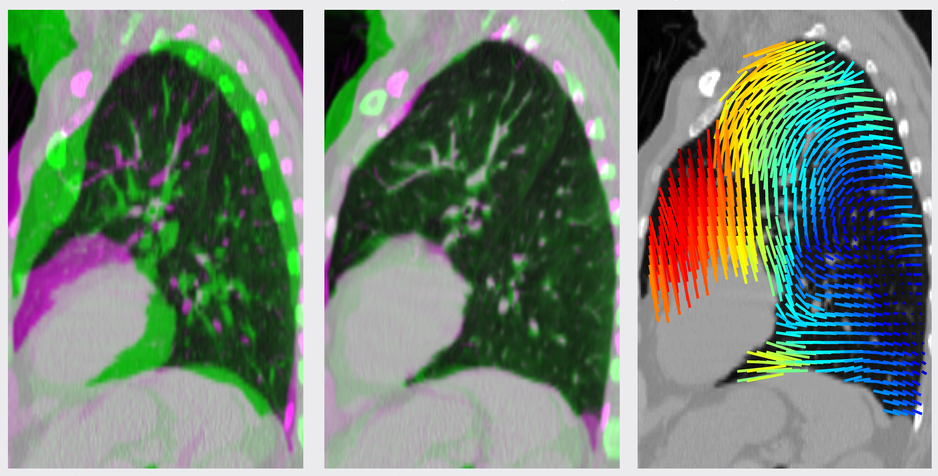
- Regularisation and symmetry constraint improve registration drastically



Visual example of thin-plate spline fit

- Reconstructed dense motion field with thin-plate spline

inhale scan
exhale scan

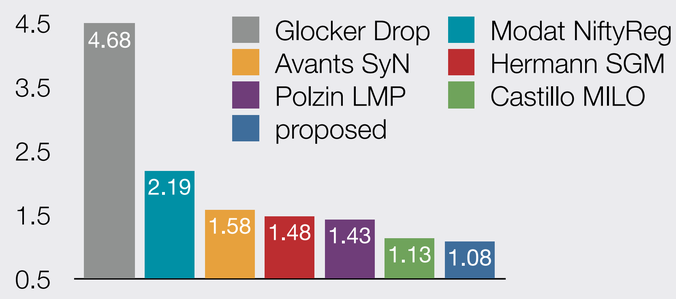


before alignment | after alignment | motion vectors

- Overlay demonstrates well-aligned lung structures
- Diffeomorphisms cannot be directly guaranteed *std*(*Jac*)=0.26

Validation, Results and Comparison

- Evaluation on public COPDgene dataset of dir-lab.com [3]



fast run-time of ~2 min.
publicly available code:
mpheinrich.de/software.html

- Target registration error of **1.08mm** over 3000 landmarks

Outlook and Future Work

- Surface keypoints for (multi-modal) whole-body registration
- Remove topology-changing correspondences → diffeomorphisms
- **Initialise any continuous registration** tool with correspondence field

References

[1] Heinrich et al.: "Towards realtime multimodal fusion … using self-similarities", MICCAI (2013)
[2] Felzenszwalb & Huttenlocher: "Pictorial structures for object recognition" IJCV (2005)
[3] Castillo et al: "A reference dataset for deformable image registration …" Phys. Med. Biol. (2013)

short oral presentation:

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