COMPLEX LUNG MOTION ESTIMATION VIA ADAPTIVE BILATERAL FILTERING OF THE DEFORMATION FIELDS

Bartlomiej W. Papież[1], Mattias P. Heinrich[1], Laurent Risser[2], Julia A. Schnabel[1]

[1]Institute of Biomedical Engineering, Department of Engineering Science, University of Oxford, UK

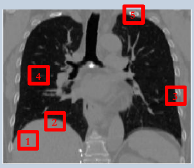
[2]CNRS, Institut de Mathématiques de Toulouse (UMR5219), France

Aims of this work

- Fast and automated image registration framework for entire thoracic cage
- Modelling plausible lung-specific motion patterns (e.g. sliding motion) without prior segmentation

Challenges of lung registration

- Complex motion of organs:
  - Motion discontinuities in the cavity of the pleura
  - Smooth deformation field inside the lungs



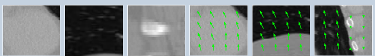
- Various organs/tissue properties:
  - Deformable structures
  - Rigidity of chest bones and spine

Adaptive filtering of deformation

- We propose an adaptive filtering approach based on bilateral filtering [1] to regularise three different aspects of lung motion: **spatial smoothness**, **local image intensity similarity** and **local deformation field similarity**:

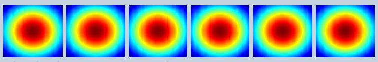
$$\boldsymbol{u}_{new}(\boldsymbol{x}) = \frac{1}{W}\sum_{\boldsymbol{y}\in N} G_x(\boldsymbol{x},\boldsymbol{y})\, G_r(I(\boldsymbol{x}), I(\boldsymbol{y}))\, G_u(\boldsymbol{u}(\boldsymbol{x}), \boldsymbol{u}(\boldsymbol{y}))\, \boldsymbol{u}_{old}(\boldsymbol{y})$$

- The exemplar kernels of typical local intensities and deformation field combinations are



- **spatial smoothness: (classic Demon)**

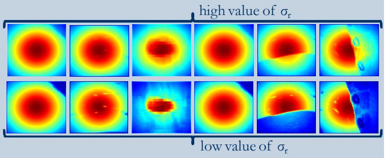
$$G_x(\boldsymbol{x},\boldsymbol{y}) = \exp\left(\frac{(\boldsymbol{x}-\boldsymbol{y})^T \cdot (\boldsymbol{x}-\boldsymbol{y})}{2\sigma_x^2}\right)$$



  - keep smooth deformation across whole image domain
  - does not preserve motion discontinuities (e.g. sliding motion)

- **spatial and intensity smoothness:**

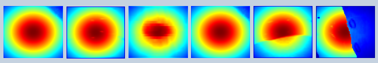
$$G_r(I(\boldsymbol{x}), I(\boldsymbol{y})) = \exp\left(\frac{(I(\boldsymbol{x})-I(\boldsymbol{y}))^T \cdot (I(\boldsymbol{x})-I(\boldsymbol{y}))}{2\sigma_r^2}\right)$$



  - does not allow for smoothing when neighbourhood intensity values are different
  - generates several deformation field discontinuities (depended on σ_r)

- **spatial, intensity and deformation smoothness**

$$G_u(\boldsymbol{u}(\boldsymbol{x}), \boldsymbol{u}(\boldsymbol{y})) = \exp\left(\frac{(\boldsymbol{u}(\boldsymbol{x})-\boldsymbol{u}(\boldsymbol{y}))^T \cdot (\boldsymbol{u}(\boldsymbol{x})-\boldsymbol{u}(\boldsymbol{y}))}{2\sigma_u^2}\right)$$



  - satisfies all presented combinations of local intensity and deformation field changes: smoothness inside lung and sliding at lung boundaries.

Deformable registration

A classic non-linear image registration with a diffusion regularisation [2]:

$$e(\boldsymbol{u}) = \int_\Omega (I_R(\boldsymbol{x}) - I_S(\boldsymbol{x}+\boldsymbol{u}(\boldsymbol{x})))^2 d\boldsymbol{x} + \sum_d \int_\Omega \|\nabla \boldsymbol{u}\|^2 d\boldsymbol{x}$$

The diffusion regularisation can be performed as Gaussian smoothing of the deformation field, and therefore solving the Euler-Lagrange equations can be seen as an iterative two-step procedure [2]:

1. Find an update: $d\boldsymbol{u}(\boldsymbol{x}) = \nabla Sim(T(\boldsymbol{x}), M(\boldsymbol{x}+\boldsymbol{u}(\boldsymbol{x})))$
2. Smooth the estimated deformation field: $\boldsymbol{u}_{new}(\boldsymbol{x}) = \boldsymbol{G} * [\boldsymbol{u}_{old}(\boldsymbol{x}), d\boldsymbol{u}(\boldsymbol{x})]$

References

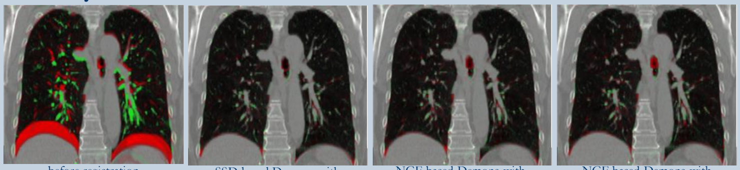
[1] Tomasi C., et al.: Bilateral filtering for gray and color images. ICCV (1998)
[2] Vercauteren T., et al.: Diffeomorphic Demons: Efficient non-parametric image registration. NeuroImage (2009)
[3] Xiao J., et al.: Bilateral filtering-based optical flow estimation with occlusion detection. ECCV (2006)
[4] Zimmer H., et al.: Optic Flow in Harmony. Int. J. Comput. Vision (2011)
[5] Segars W.: Development and application of the new dynamic NURBS-based cardiac-torso (NCAT) phantom (2001)
[6] Amelon R., et al.: A measure for characterizing sliding on lung boundaries, Ann Biomed Eng (2013)

Contributions

- Novel procedure of deformation fields filtering for deformable registration of lung data based on three basic components: **spatial smoothness**, **local image intensities** and **deformation field similarity**.
- Significant improvement (p-value<0.05) of registration accuracy (TRE=1.95mm) compared to the state-of-the-art methods, and comparable registration accuracy with the approaches that require segmentation for challenging 4D CT data.
- Potentially applicable for other medical image registration problems.

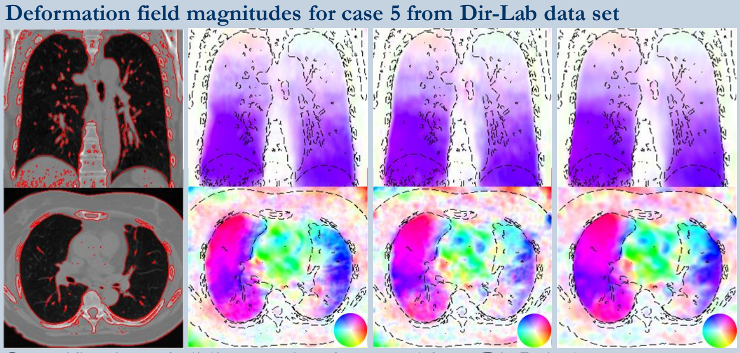
Validation

Intensity Differences for case 5 from Dir-Lab data set



before registration | SSD-based Demons with regularisation using spatial smoothness | NGF-based Demons with regularisation using spatial smoothness | NGF-based Demons with regularisation using spatial, intensity and deformation smoothness

Deformation field magnitudes for case 5 from Dir-Lab data set

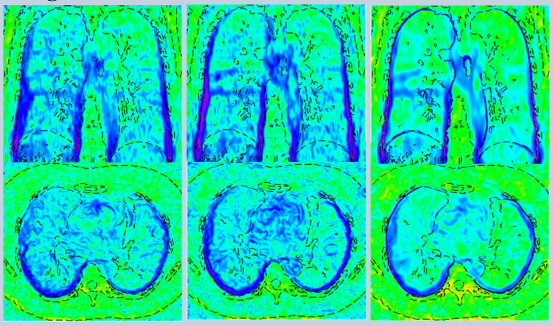


Quantification of sliding motion for case 5 from Dir-Lab data set

To quantify the locations and level of detected sliding motion during evaluation of the presented framework, we use a sliding motion measure (proposed in [6]) which calculates the maximum shear stretch of the estimated deformation field:

$$\gamma_{max} = \frac{\gamma_1 - \gamma_3}{2}$$

where γ_1, γ_3 are the maximal and minimal principal stretch components obtained from eigenvalue decomposition of the deformation field gradients



Discussion and Conclusion

- Bilateral filtering derived from both intensity and deformation field similarity preserves discontinuity between the lungs and the pleura, while satisfying smoothness of the deformation field inside lungs.
- Bilateral filter based only on intensities generates several discontinuities inside and outside the pleural cavity (compare magnitudes of deformation fields depicted by blue arrows, especially close to the lung boundaries).
- The lower target registration error also correlates with visual inspection of the estimated deformation fields.

See more: Papież et al. MICCAI 2013, Papież et al. Medical Image Analysis 2014

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bartlomiej.papiez(at)eng.ox.ac.uk   www.ibme.ox.ac.uk/research/biomedia/people/bartlomiej-papiez