Institute of Biomedical Engineering
Department of Engineering

Non-local shape descriptor: A new similarity metric for deformable multi-modal registration

Mattias P. Heinrich, Mark Jenkinson, Manav Bhushan, Tahreema Matin, Fergus V. Gleeson, Sir J. Michael Brady and Julia A. Schnabel

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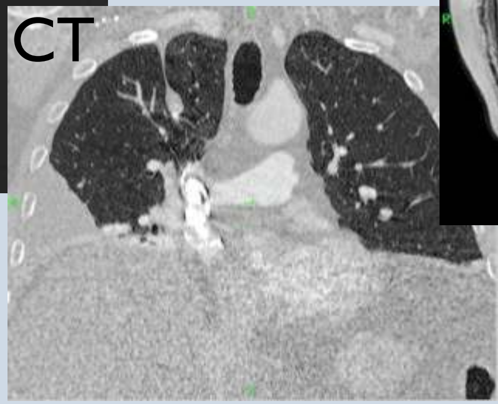
Motivation for multimodal image registration

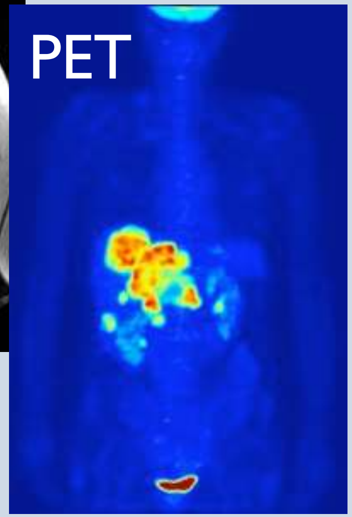
- Combine complementary information from modalities in medical imaging: Ultrasound, CT, MRI, PET, etc…

temporal resolution



spatial resolution
dense tissue contrast

soft tissue contrast

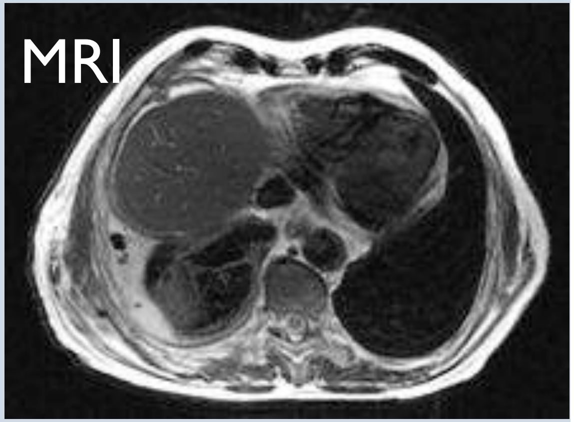


metabolic activity

- Align CT and MRI scans of lung disease patients to improve diagnosis

Similarity in multimodal images

- Features used to derive similarity:
  (needed for registration cost function)
  - Image intensities (iconic) ■
  - Tissue boundaries / gradients ■
  - Corners / point features (geometric) ■
- Challenging to relate features between modalities
  - different types of features relate to corresponding anatomies in different modalities
  - higher-level models of intensity relations (statistical similarity metrics) need large (up to global) support
  - common similarity metrics use only one feature



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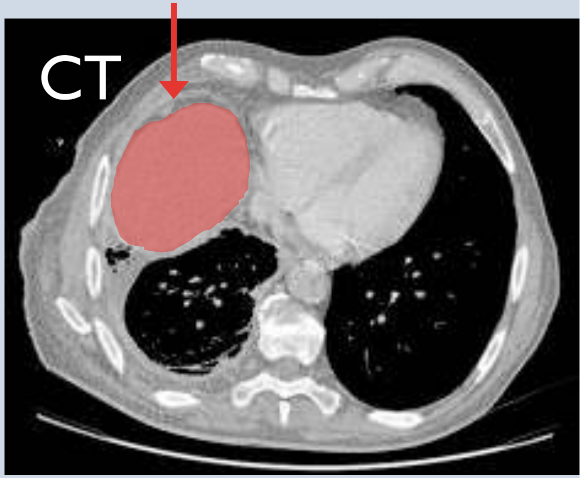

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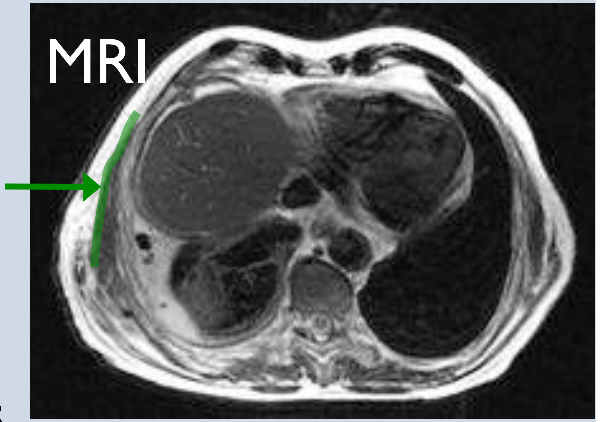

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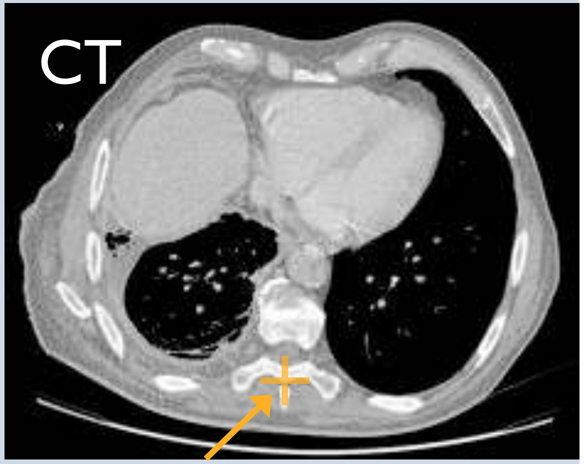

Concept of non-local shape descriptor

- Single-modal similarity formulations are simple
  - multiple features (intensities, boundaries, textures)
    - more general: image patches
  - similarity metric: sum of squared differences (SSD)

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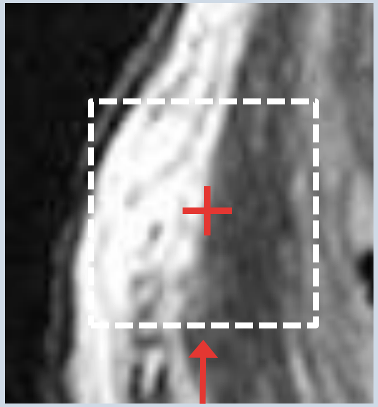
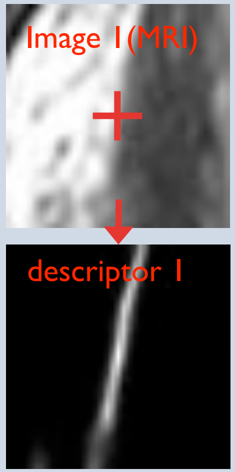
  - define a spatial descriptor for a voxel
    - within non-local search region in the same image
  - based on an intensity difference within modality (SSD)



non-local search region *N*



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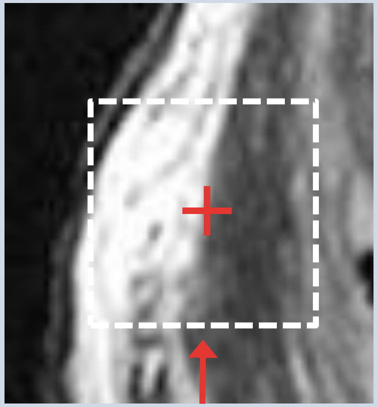
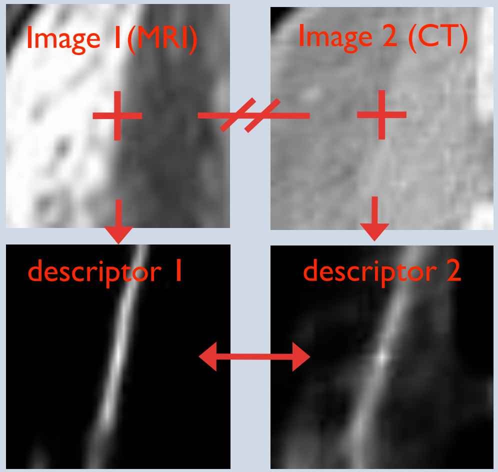
  - define a spatial descriptor for a voxel
    - within non-local search region in the same image
  - based on an intensity difference within modality (SSD)
  - compare descriptors of two multimodal images

- Advantages
  - no global relations of intensities is assumed
  - highly discriminative and robust to noise





Related work: application of internal similarity

- Image denoising: non-local means

- P. Coupe, IEEE Trans Med Imag 2008

- Object detection: self-similarities

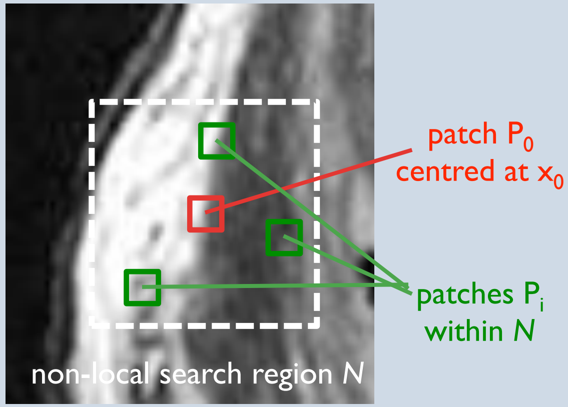
- E. Shechtman: CVPR 2007

<u>Our contribution:</u> Similarity metric for deformable multi-modal registration

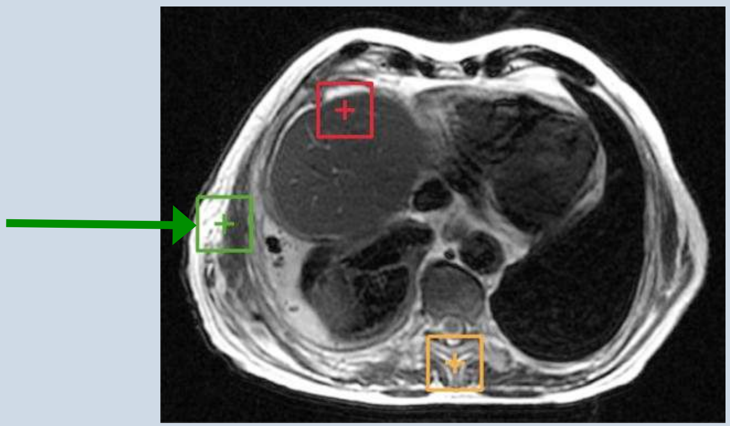
Internal similarity: non-local weights

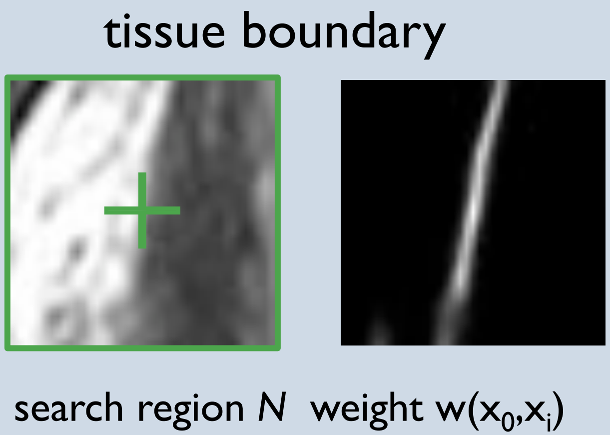
- Uses same principle as non-local means filtering
- (A. Buades, CVPR 2005)
- spatial weight for x_0 is given by distance function between patches P_0 and P_i (within same image)

$$w(\mathbf{x}_0, \mathbf{x}_i) = \exp(-\mathrm{SSD}(P_0, P_i)/\sigma^2)$$



- non-local weights for 3 voxels in MRI slice
- weights are a good measure of shape





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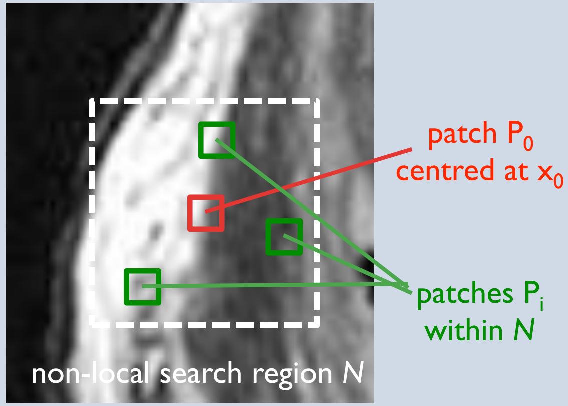

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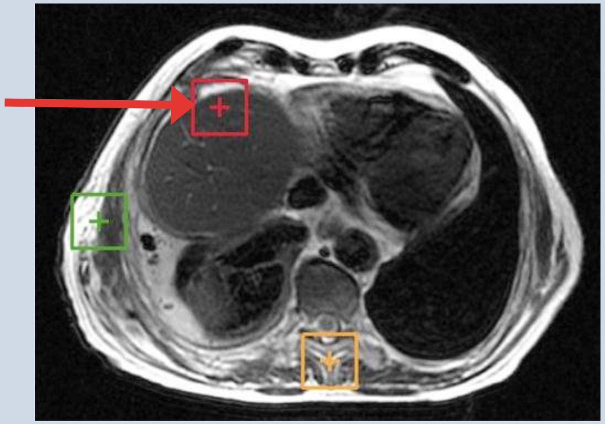
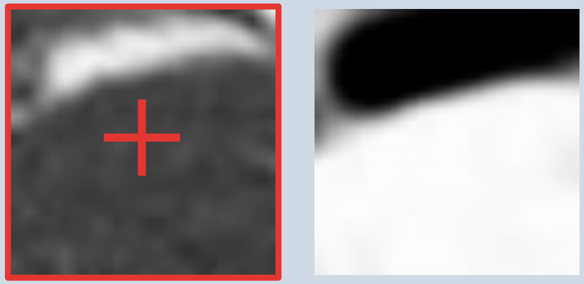


homogeneous region



search region N weight $w(x_0,x_i)$

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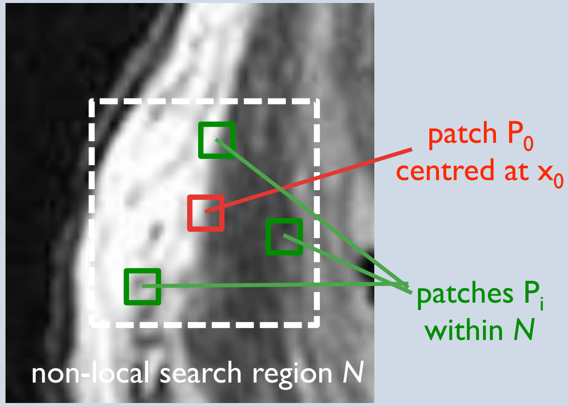

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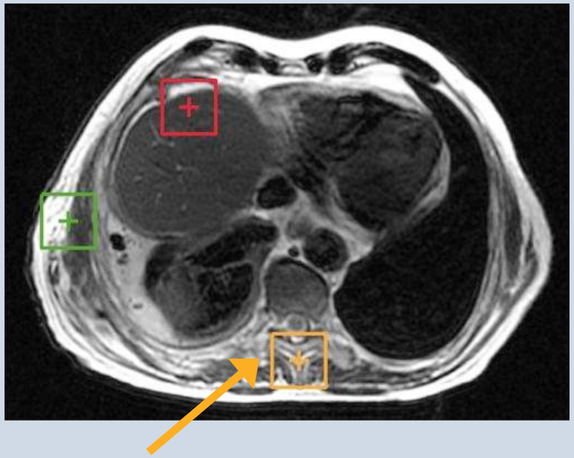
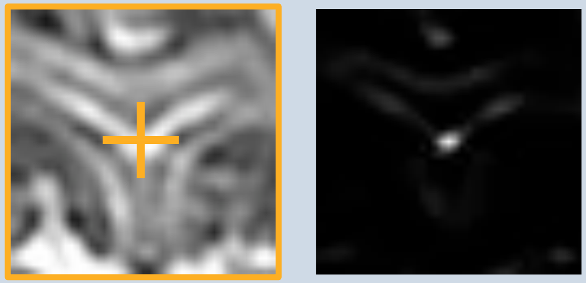


corner point

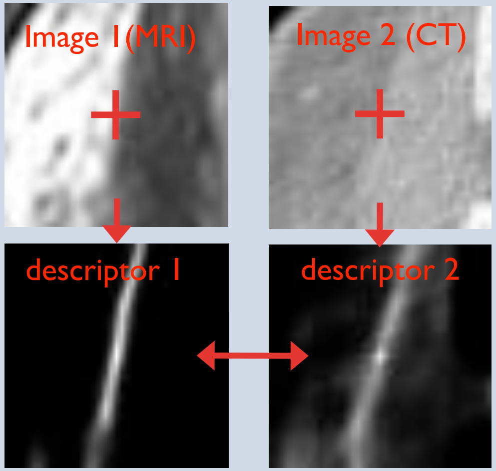


search region N weight $w(x_0,x_i)$

Shape descriptor as similarity metric

- Calculate weights in both modalities for each voxel based on patch similarities
- Similarity is defined as cross-correlation between two weights w_1 and w_2:

$$\mathrm{NLSD}(\mathbf{x}_0) = \mathrm{NCC}(w^1(\mathbf{x}_0, \mathbf{x}_i), w^2(\mathbf{x}_0, \mathbf{x}_i))$$



- weights are almost independent of contrast in different modalities
- using cross-correlation allows to compare regions with different local noise magnitude
  - global noise variance σ is estimate from data
- fast implementation using convolution filter

Comparison to mutual information

- Popular similarity metric *Viola et al., IJCV 1997* and *Maes et al., TMI 1997*
- Measures the mutual dependency of two image intensity distributions

- Difficult local estimation (MI is global measure)
  - Local normalized mutual information (based on global histogram)

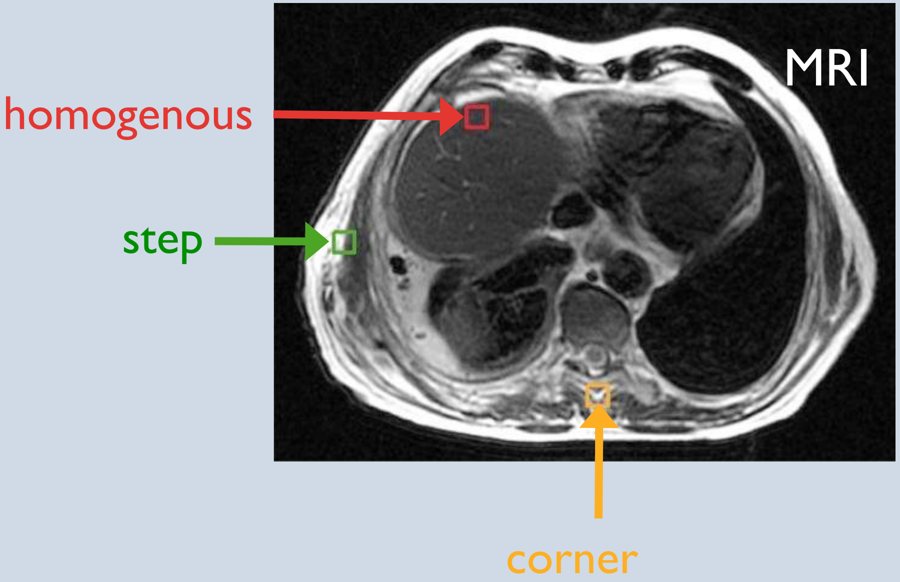
$$\mathrm{LNMI}(\mathbf{x}) = \log\left(\frac{p_{12}(I_1(\mathbf{x}), I_2(\mathbf{x}))}{p_1(I_1(\mathbf{x}))\cdot p_2(I_2(\mathbf{x}))}\right)\frac{1}{\int_{\mathbf{x}} p_1(I_1(\mathbf{x}))\log(p_1(I_1(\mathbf{x})))d\mathbf{x}}$$

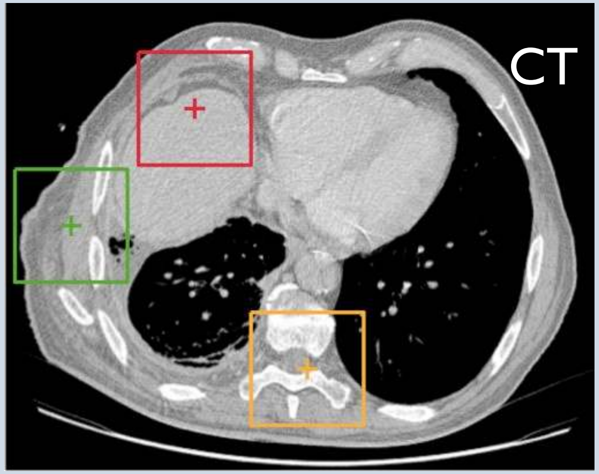
Hermosillo et al., IJCV 2002 and *Rogelj et al., CVIU 2003*

- Converges to local minima if initialisation is far away
- Sensitive to varying contrast (bias field) and noise

Similarity maps of both metrics

- Comparison of similarity metrics for three different image features in MRI (step, homogenous, corner) over large search region in CT slice



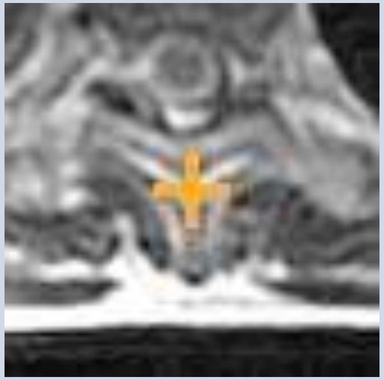


search within bounding boxes

Similarity maps of both metrics

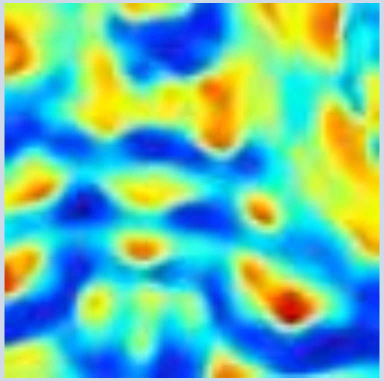
- Feature: Corners / point feature

Point feature in MRI

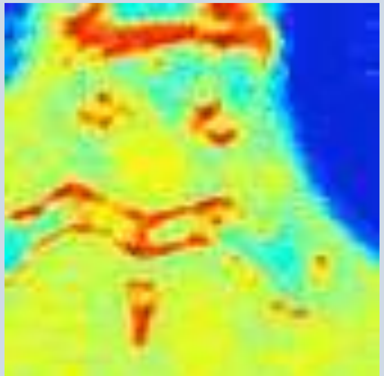


CT search region

NLSD (non-local shape descriptor)



LNMI (local normalized mutual information)



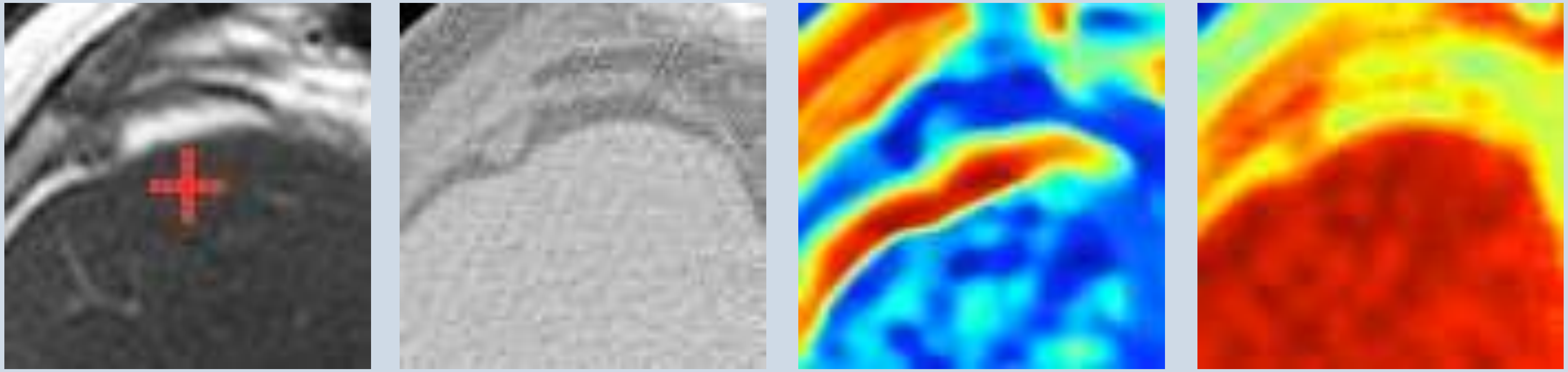
- Both metrics show local maxima at correct location

high local similarity   low local similarity

Similarity maps of both metrics

- Feature: Image intensities / homogenous region ■

Homogenous region in MRI | CT search region | NLSD (non-local shape descriptor) | LNMI (local normalized mutual information)



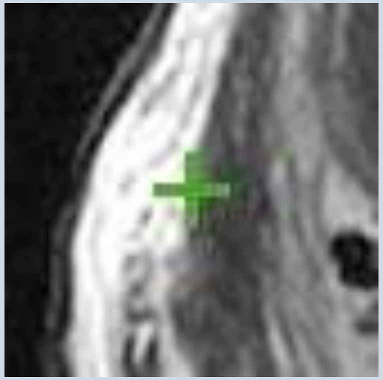
- The maximum for NLSD in homogenous area is more informative than for mutual information

high local similarity   low local similarity

Similarity maps of both metrics

- <u>Feature</u>: Tissue boundaries / step feature ■

Tissue boundary in MRI



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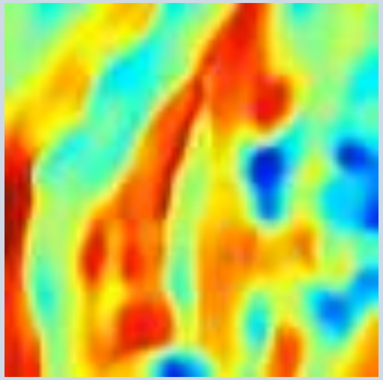
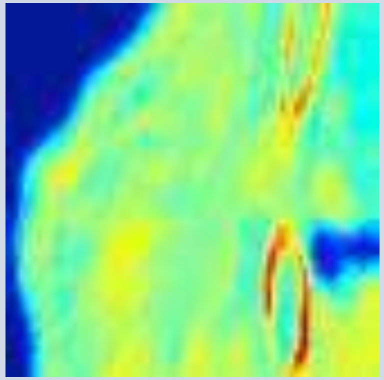


LNMI (local normalized mutual information)



- NLSD distinguishes step features clearly better than LNMI

high local similarity — low local similarity

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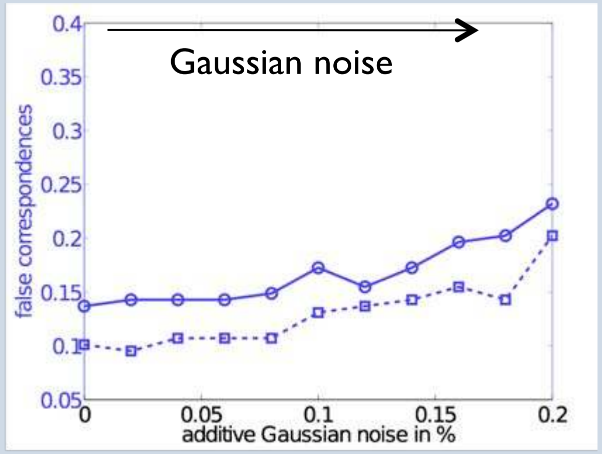
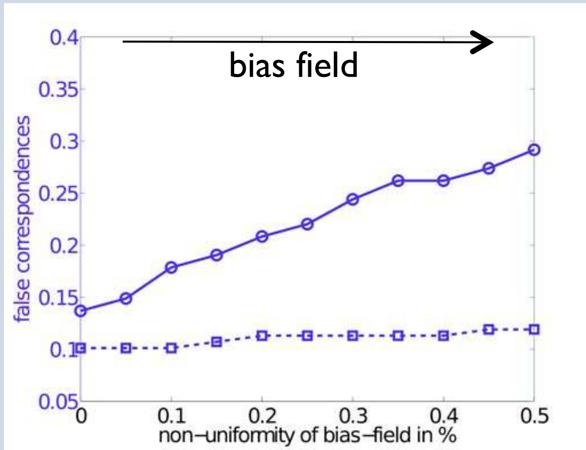
Saliency and robustness of correspondences

- 2D multimodal test images (intrinsically aligned)
  - two colour channels of cryosection (Visible Human)
  - 220 automatic landmarks (Harris corner detector)
- False correspondences (robustness)





— ○ local normalised mutual information (LNMI)

---- □ non-local shape descriptor (NLSD)

- NLSD shows better robustness
  - with increasing noise and bias field

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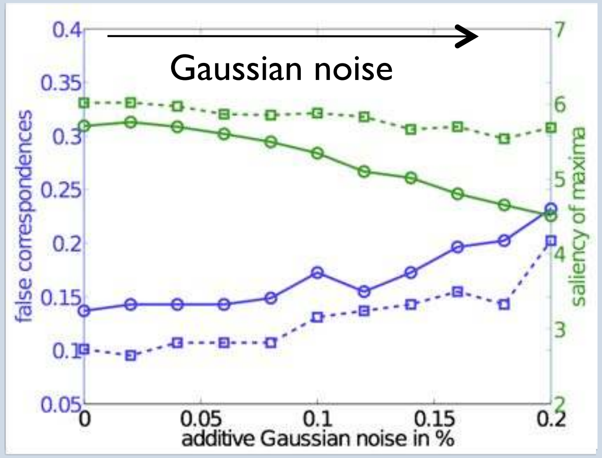
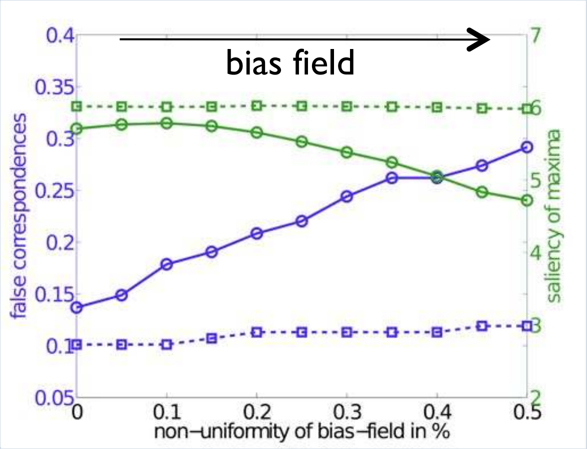
- Saliency of maxima (discrimination)





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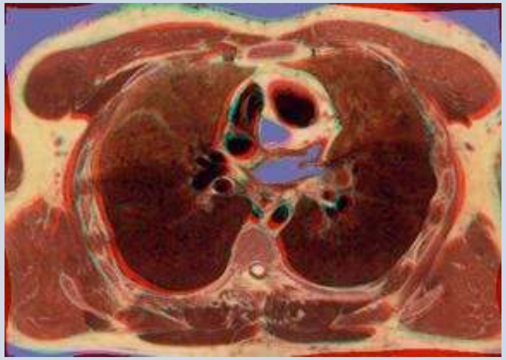
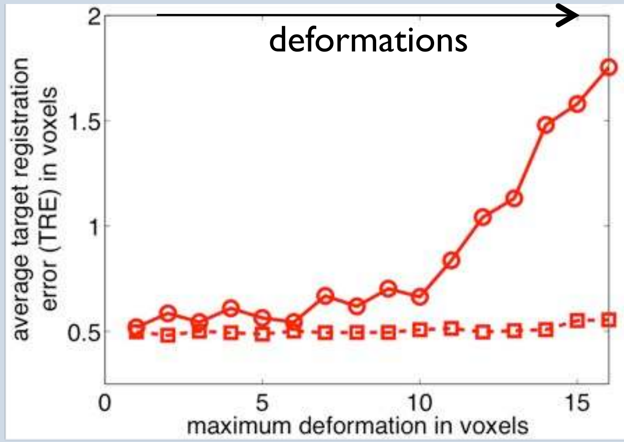
- NLSD shows better robustness and discrimination
  - with increasing noise and bias field

Saliency and robustness of correspondences

- 2D multimodal test images (intrinsically aligned)
  - two colour channels of cryosection (Visible Human)
  - Synthetic B-Spline deformation of one channel
- Non-rigid deformations (average target error)





— O local normalised mutual information (LNMI)
---- □ non-local shape descriptor (NLSD)

- Registration accuracy is higher for NLSD
  - for larger non-rigid deformations

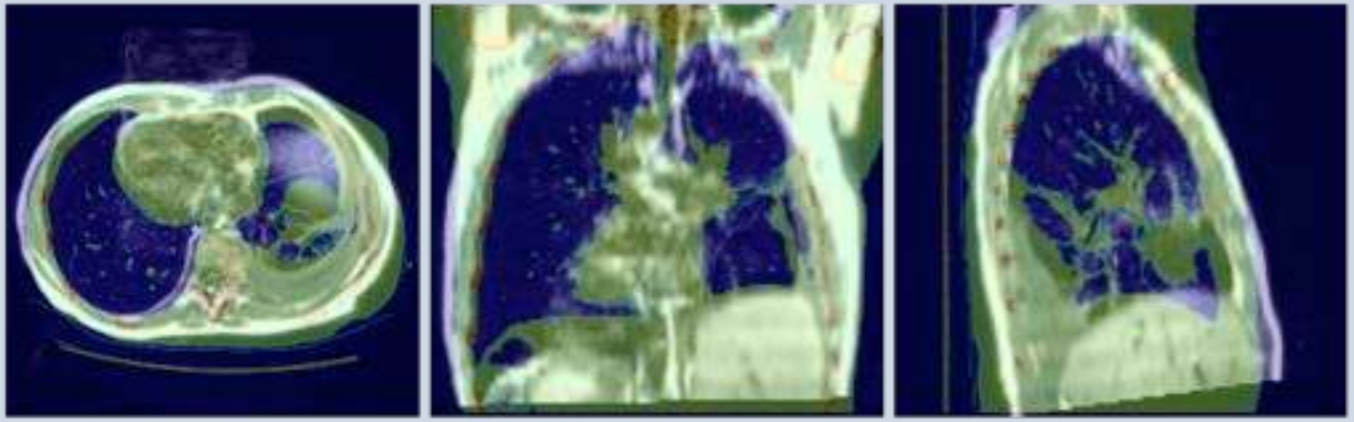
Application to clinical 3D CT/MRI fusion

- Diagnostic scans (CT and MRI) for patients with lung disease
- Challenges for registration
  - large deformations (collapsed lungs)
  - low z-resolution (up to 8 mm) in MRI
  - bias field in MRI
  - lower soft tissue contrast in CT
- Example of registration outcome

- Deformable registration framework
  - initial rigid alignment
  - diffusion regularized Gauss-Newton optimization
  - multi-resolution scheme (3 levels)
    - more details: please see poster

rigidly aligned

CT colour
MRI gray



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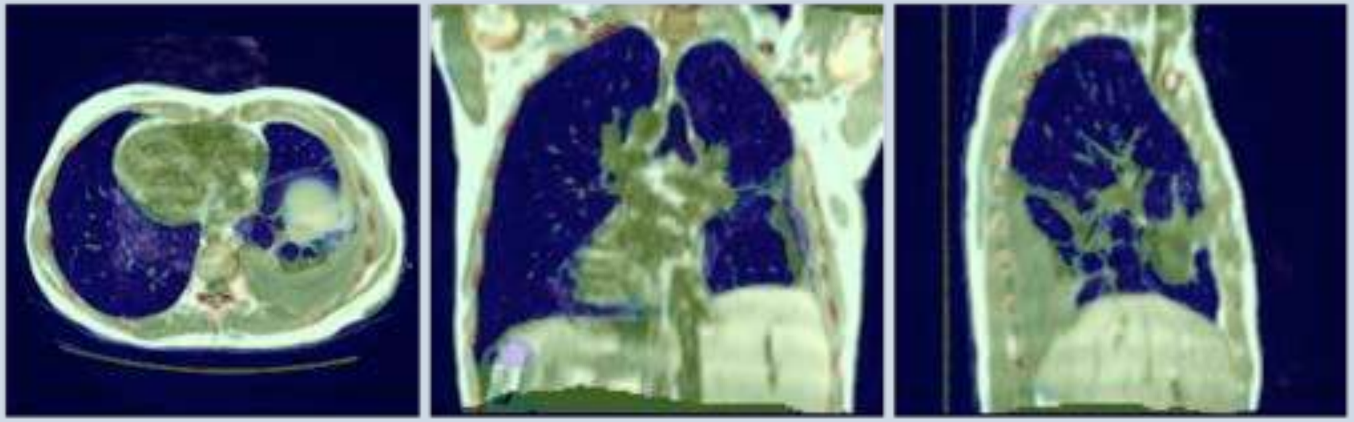
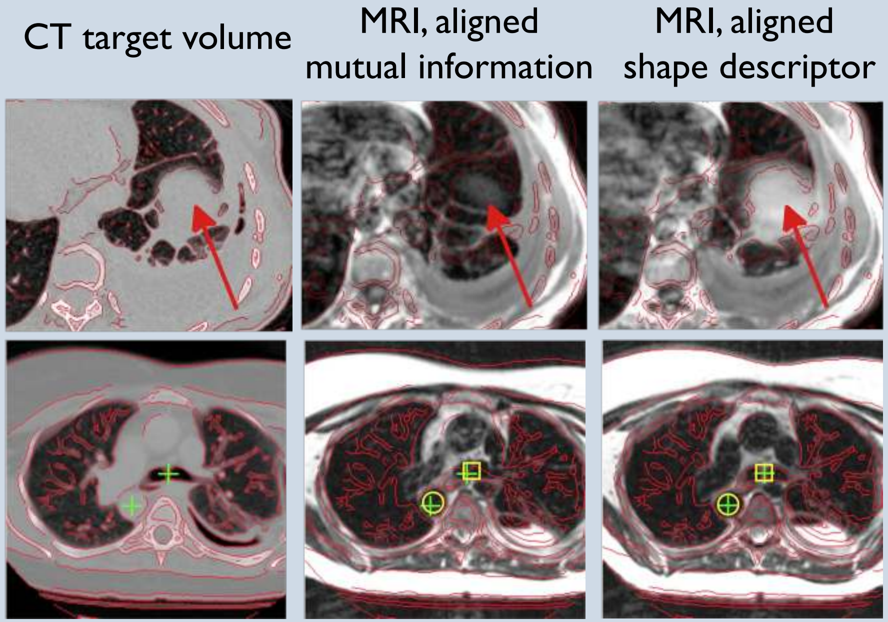
nonrigidly aligned using NLSD

CT colour
MRI gray



Landmark results for 3D CT/MRI fusion

- Comparison of gold standard with registration outcome (examples)
  - CT contours shown for guidance (red)
  - top row: descending aorta ◦ carina ☐
  - bottom row: dome of the diaphragm ➜



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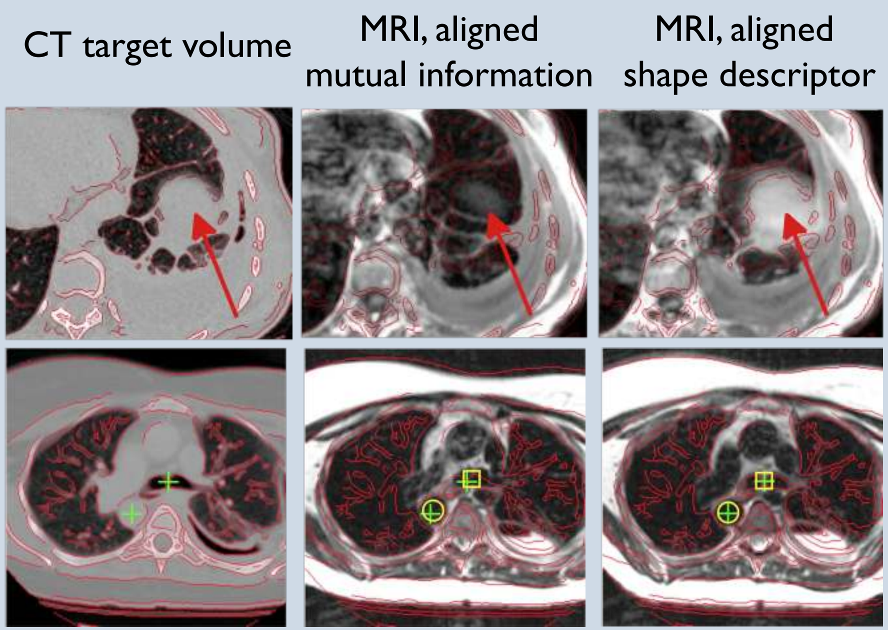
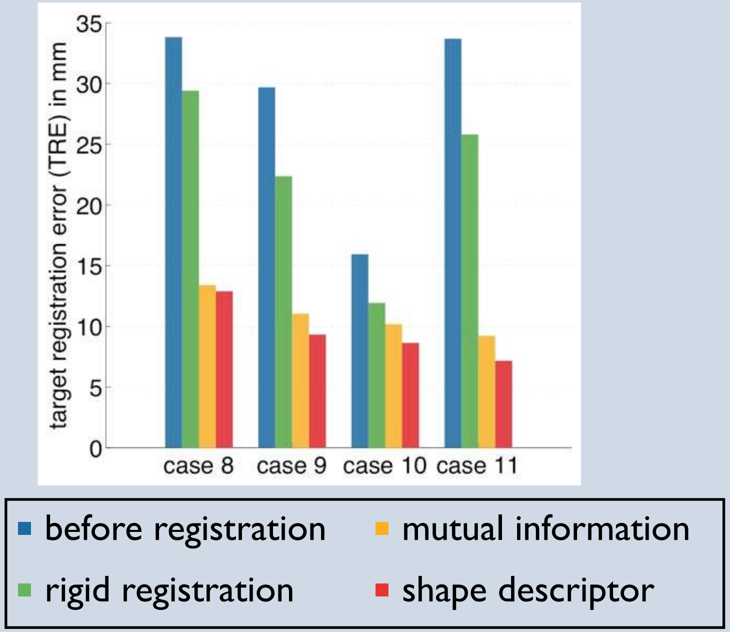
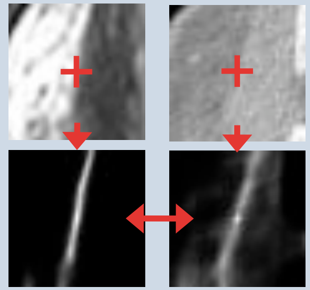


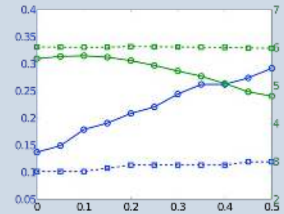
- Manually selected 15 corresponding anatomical landmarks (per case)
  - Evaluation of target registration error
  - Difficult selection of landmarks for expert

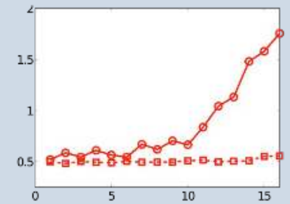


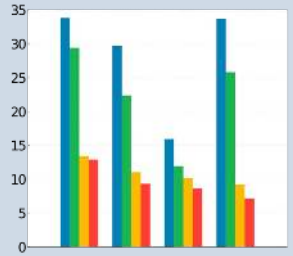
Conclusion

- Non-local shape descriptor
    - based on intrinsic similarity of image patches
    - sensitive to several image features
        - intensities, gradients, points
- Advantages compared to mutual information
    - robust against: noise, varying contrast, bias fields ..
    - reduces number of (false) local minima
    - can recover larger deformations
    - lower landmark error for 3D CT/MRI fusion









- Thank you for your attention!

- Acknowledgements

  - We would like to thank EPSRC and Cancer Research UK for funding this work within the Oxford Cancer Imaging Centre.
  - JAS also acknowledges funding from EPSRC EP/H050892/1.
  - We thank the MICCAI society for supporting us with a Student Travel Award.

- Poster presentation
  - P8 – 102 – T (Registration I)
  - Tuesday 13:15 – 14:30