Deformable Image Registration

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Course overview

- Theory:
  - Rigid/affine + basics — N. Duchateau
  - Non-rigid + advanced concepts — D. Sarrut
    - 20/01/2022 2pm - 5pm
    - 04/02/2022 8am – 9:30am
- Practial exercice
  - Elastix / rigid-affine-nonrigid
  - 04/02/2022 9:30am – 12:30pm

Goals

- Future jobs: engineer, research, application
- Know how/why to read research papers
- Be ready to code
- Understand context
- Understand notation
- Comparison with other works
- Validation

- Previous course: questions ?

Tiny poll …

www.wooclap.com/UIDJAR

Outline

- Introduction, principles
- Method n°1 : Demons
- Evaluation
- Method n°2 : B-Splines
- Method n°3 : TPS (Thin Plate Spline)
- The « sliding » problem
- Spatio-temporal deformable registration
- Conclusion

Outline

- **Introduction, principles**
- Method n°1 : Demons
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- Method n°3 : TPS (Thin Plate Spline)
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- Spatio-temporal deformable registration
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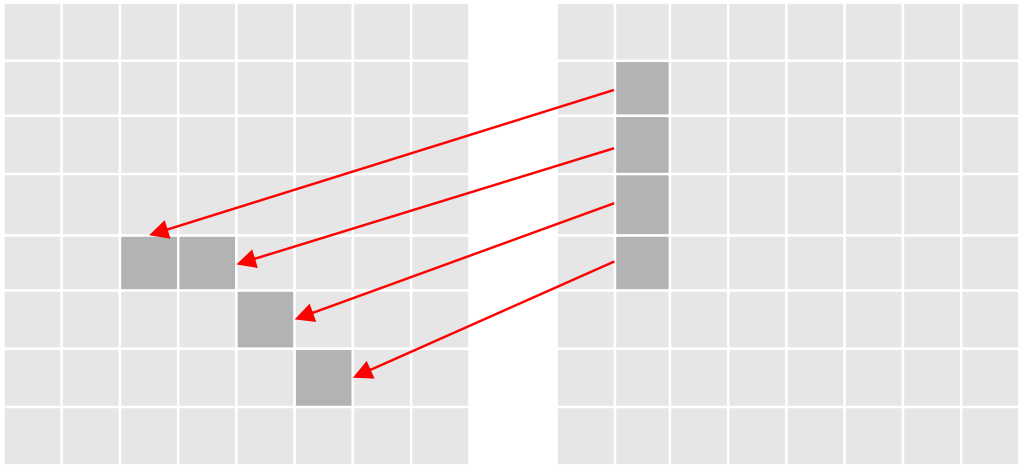
Deformable Image Registration (DIR)

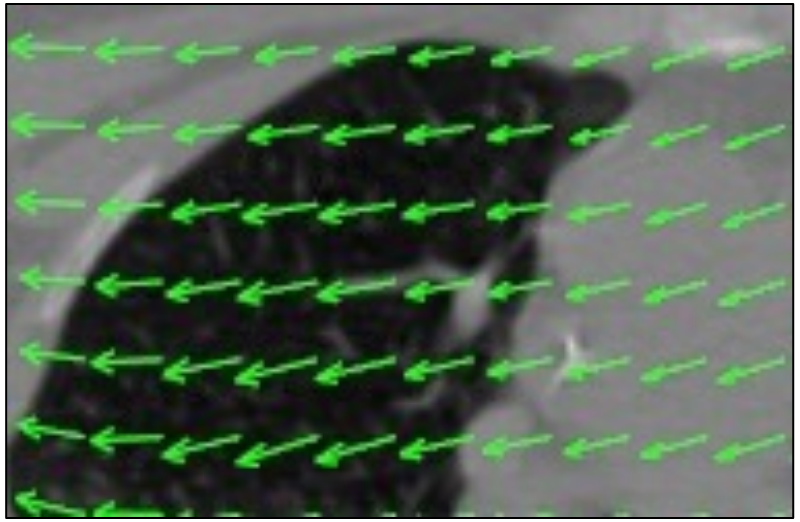
Algorithm

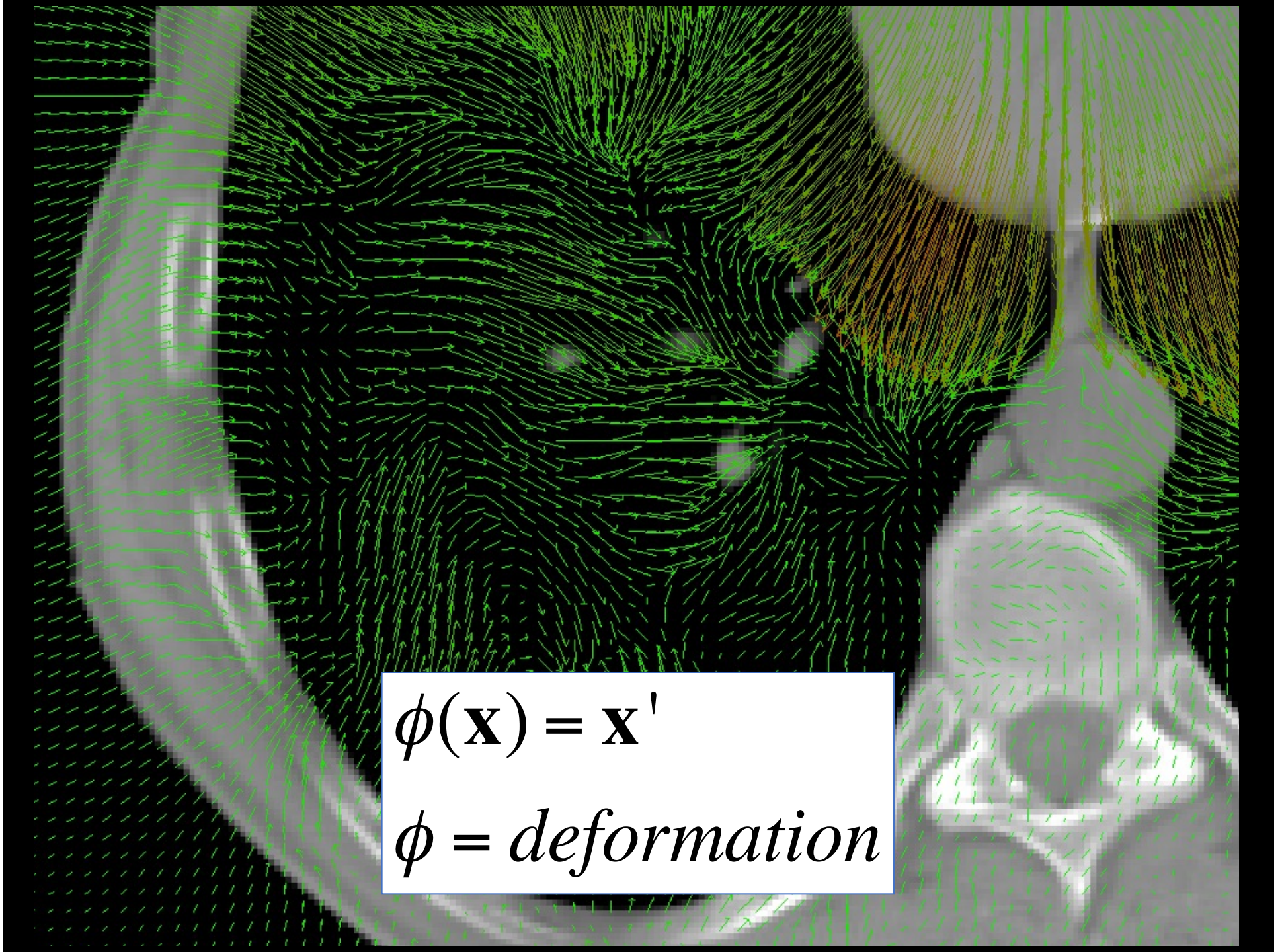
Input = two images
(reference & moving)

Output = deformation map



Fixed Image (reference) Moving Image





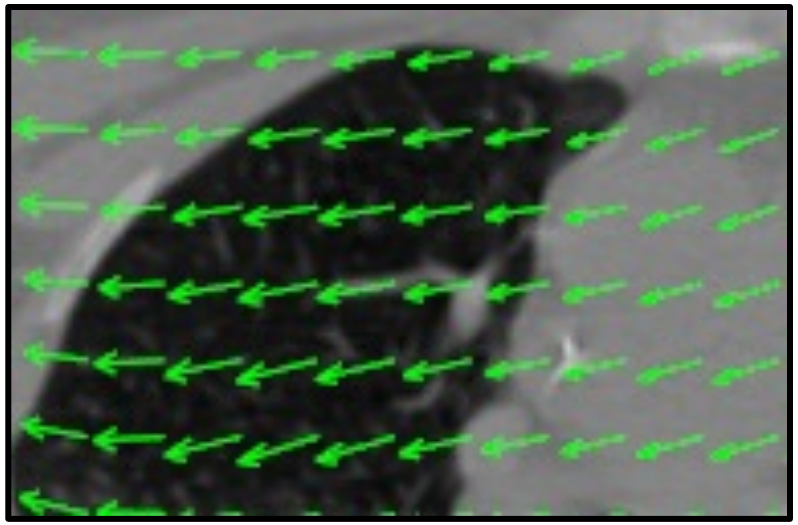
$$\phi(\mathbf{x}) = \mathbf{x}'$$

$$\phi = deformation$$

Deformation Vector Field

DVF is used to :

- To **quantify** the motion in ROIs
- To **deform** an image or a contour



DVF can be stored :

- With one vector by pixel
- With a function : B-Spline, RBF …

$$T(\mathbf{p}) : R^3 \mapsto R^3 = \mathbf{p} + u(\mathbf{p})$$

$$\mathbf{p} = \begin{pmatrix} x \\ y \\ z \end{pmatrix} \quad u(\mathbf{p}) = \begin{pmatrix} dx \\ dy \\ dz \end{pmatrix}$$

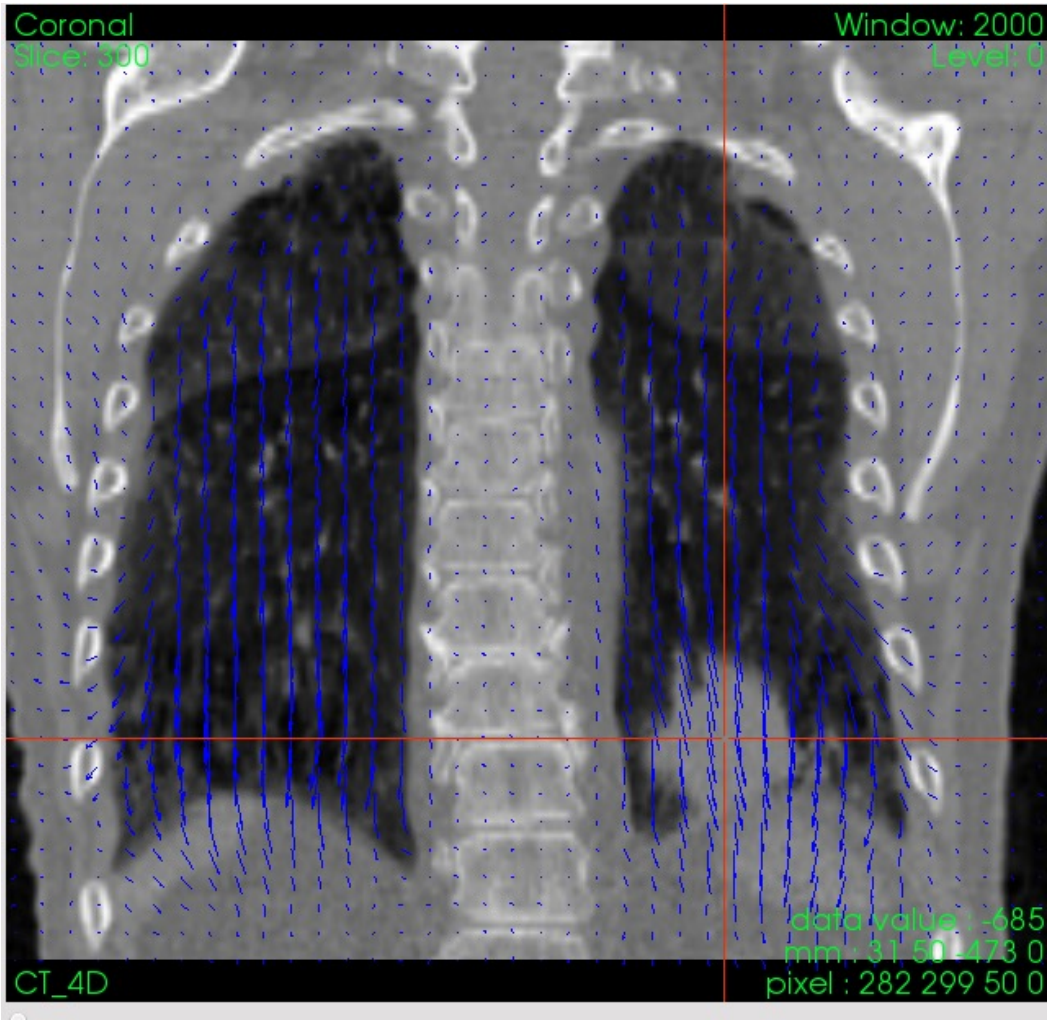
In DIR we trust …

Rigid image registration

- Find rotation and translation
- 6 numbers for 3D images

Deformable image registration

- Find deformation
- Thousand of numbers (even more !)
- One vector at each pixel



Léon Bérard cancer center (CLB)

22 000 patients/year

Radiation Therapy department

- ~3000 patients/year
- Technical facility :
  Linacs, CT scanner, on-board scanners (CBCT), Tomotherapy, Cyberknife

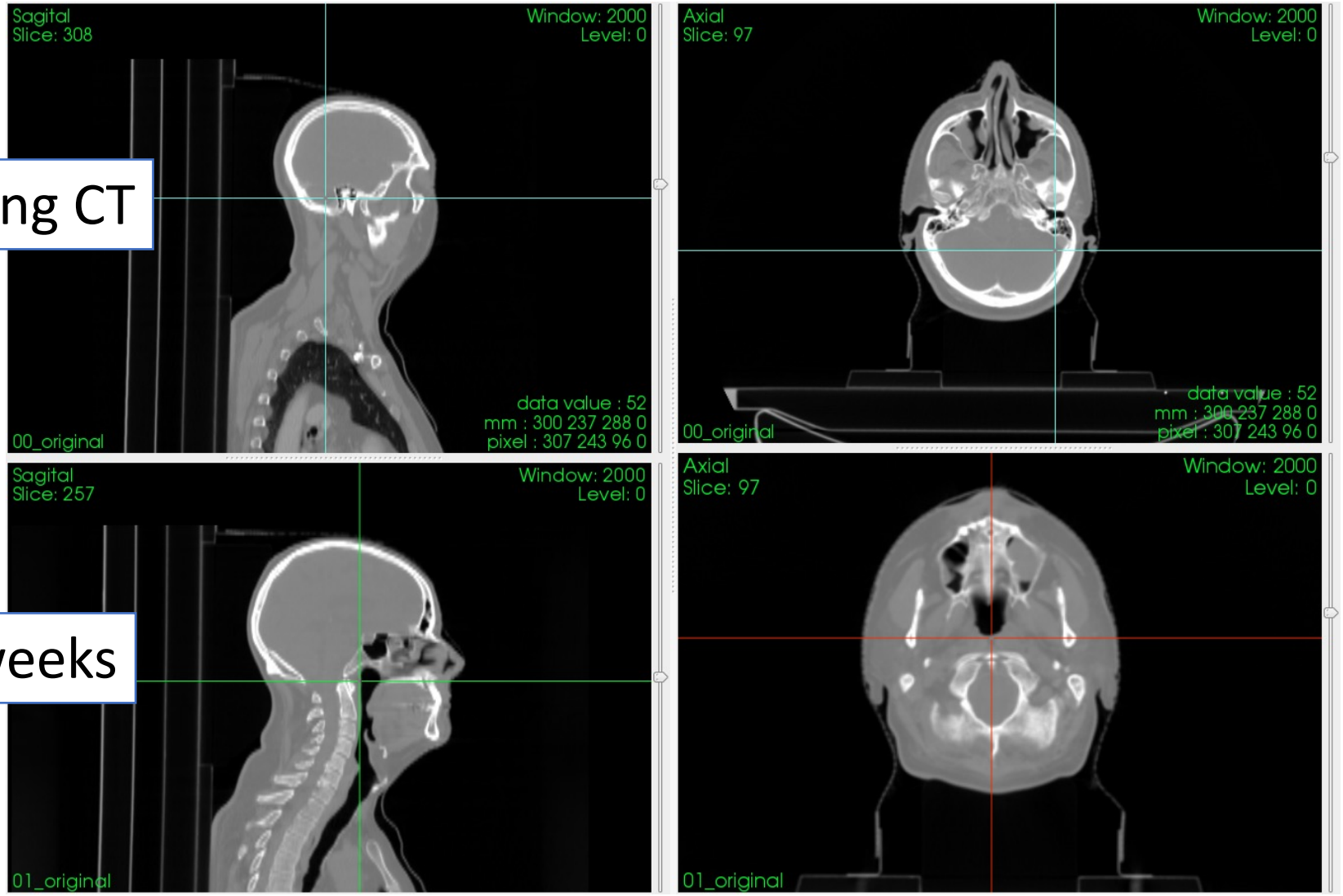
CENTRE DE LUTTE CONTRE LE CANCER LEON BERARD

www.centreleonberard.fr

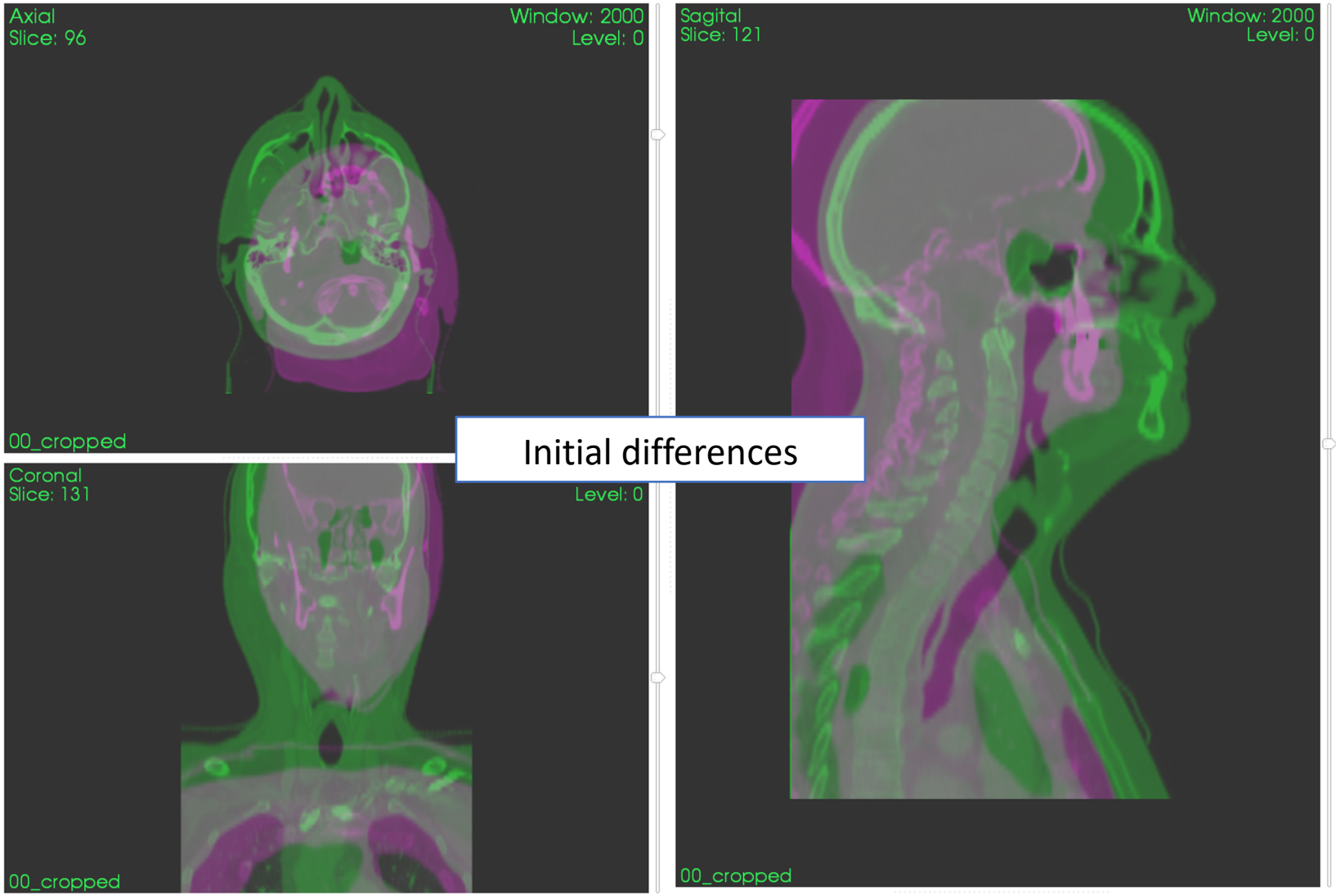
Example 1

Initial planning CT

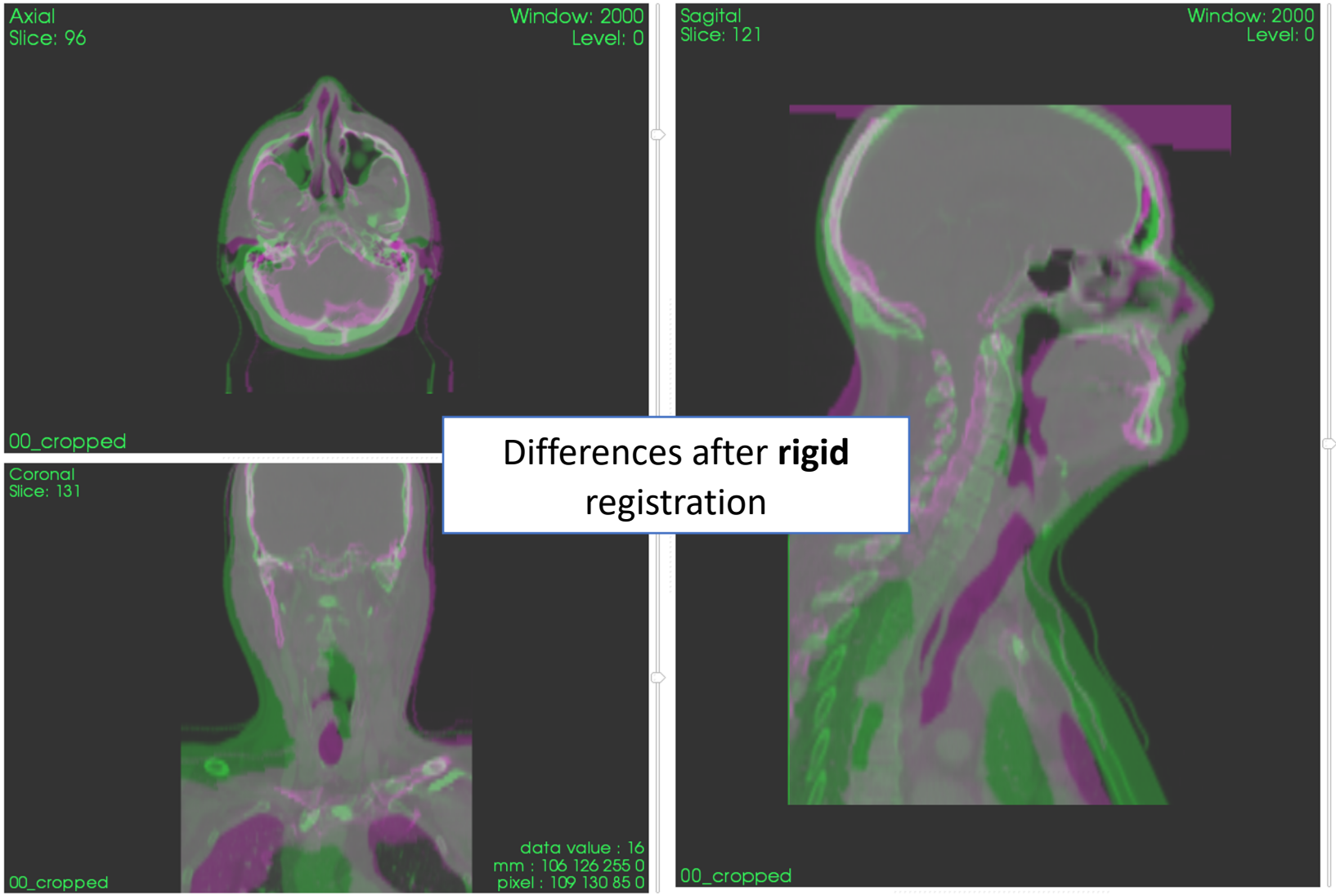
CT after 2 weeks



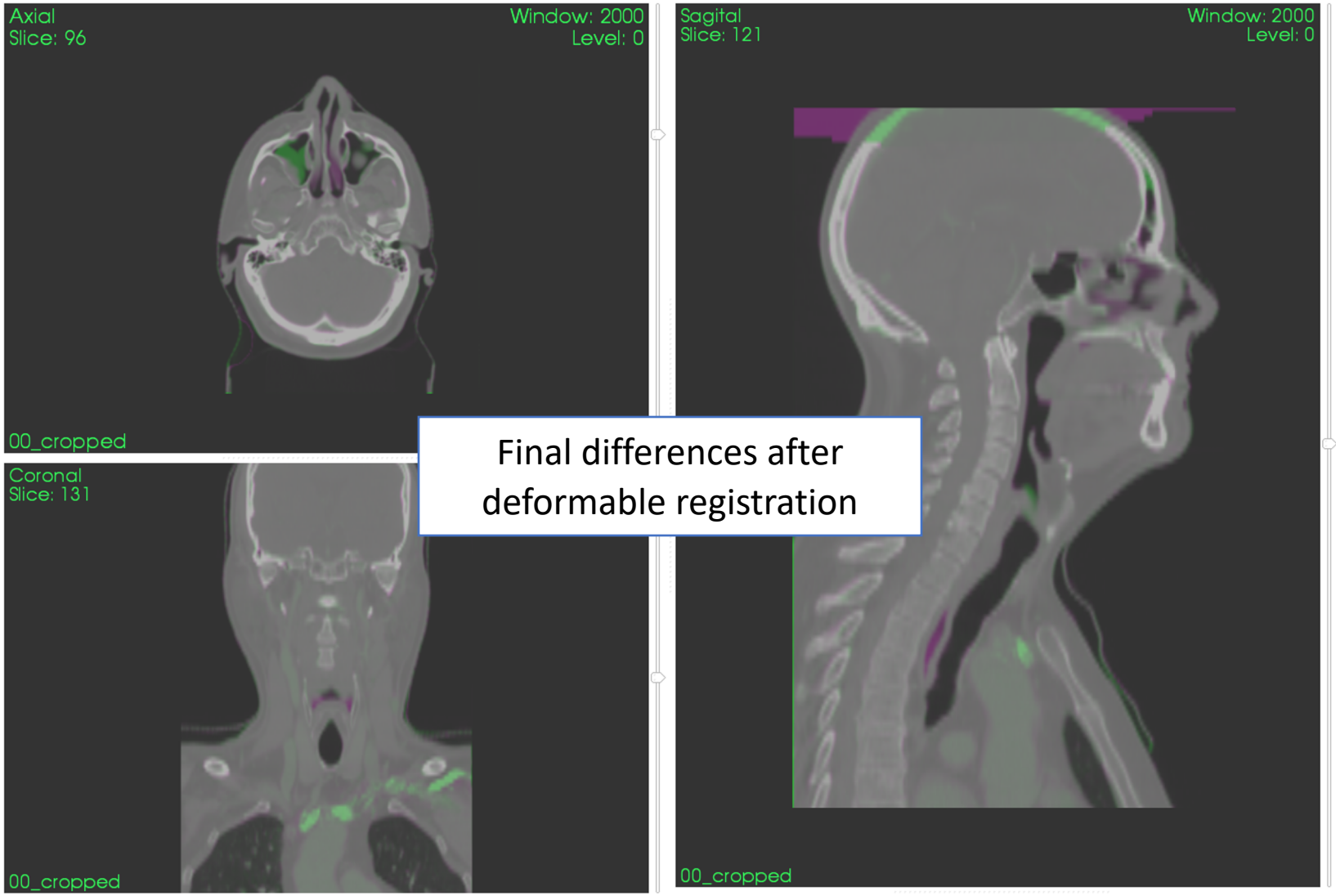
Example 1


Axial
Slice: 96
Window: 2000
Level: 0
00_cropped
Sagital
Slice: 121
Window: 2000
Level: 0
00_cropped
Coronal
Slice: 131
Level: 0
00_cropped
Initial differences

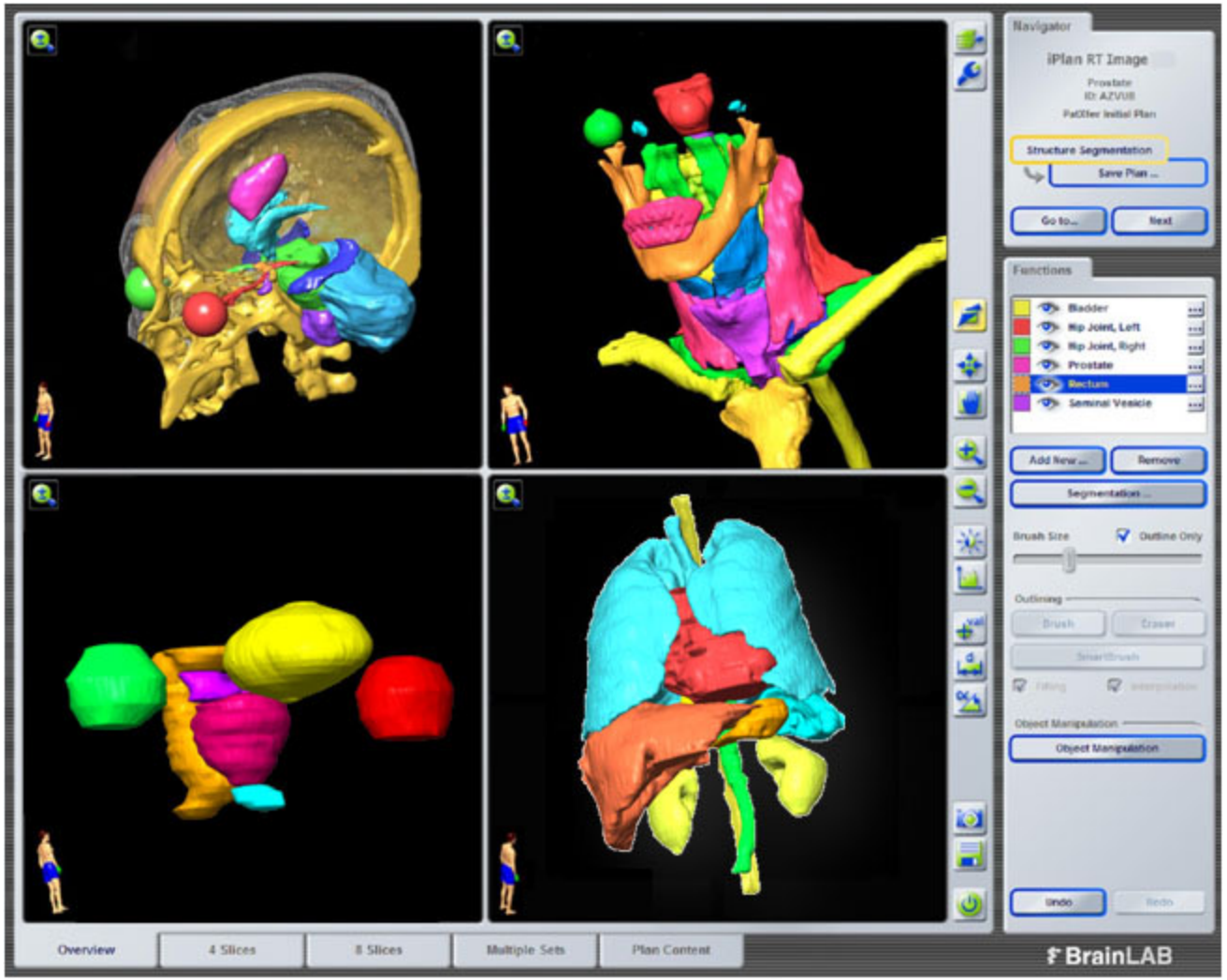
Example 1


Axial
Slice: 96
Window: 2000
Level: 0
00_cropped
Sagital
Slice: 121
Window: 2000
Level: 0
00_cropped
Coronal
Slice: 131
00_cropped
data value : 16
mm : 106 126 255 0
pixel : 109 130 85 0
Differences after **rigid** registration

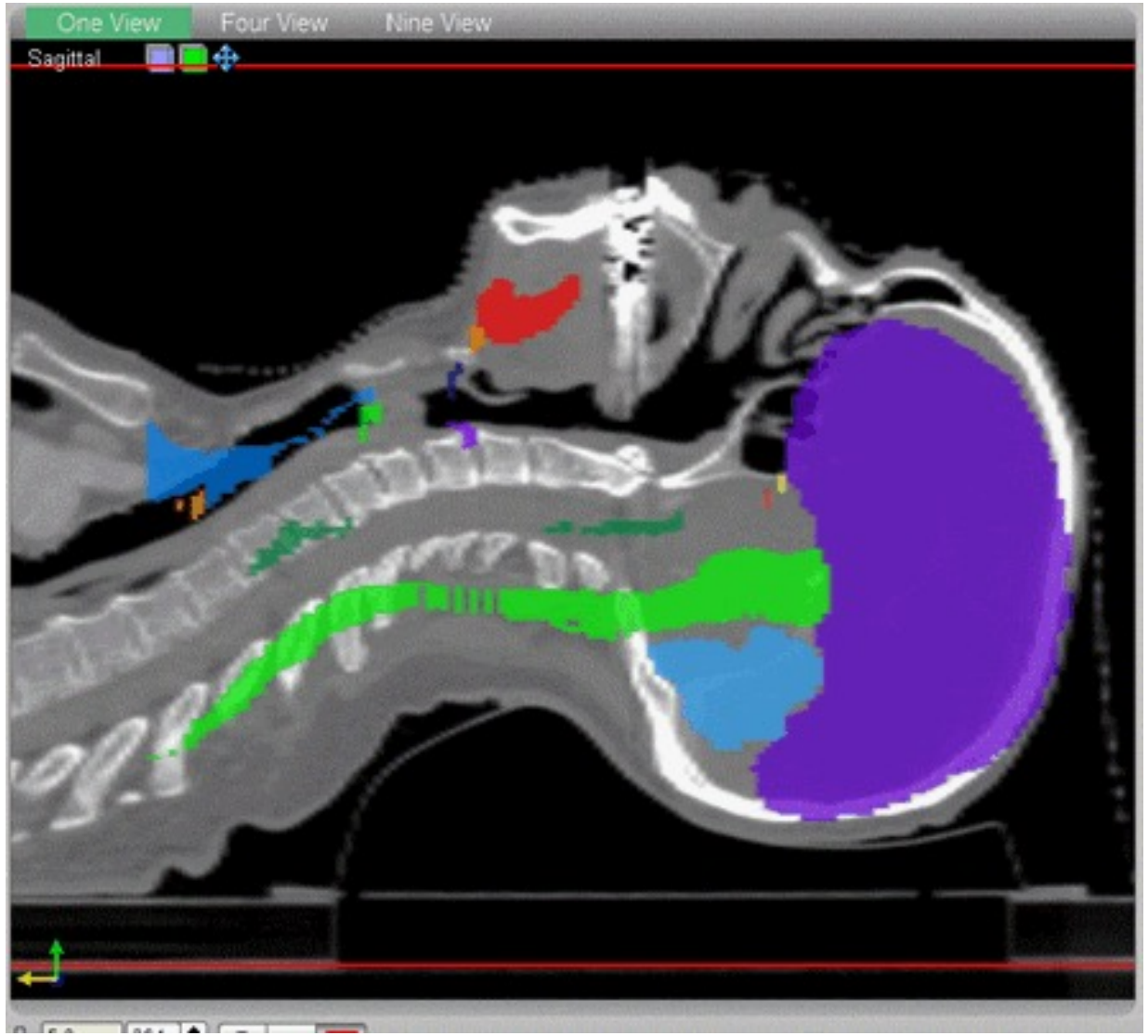
Example 1


Axial
Slice: 96
Window: 2000
Level: 0
00_cropped
Coronal
Slice: 131
00_cropped
Sagital
Slice: 121
Window: 2000
Level: 0
00_cropped
Final differences after deformable registration

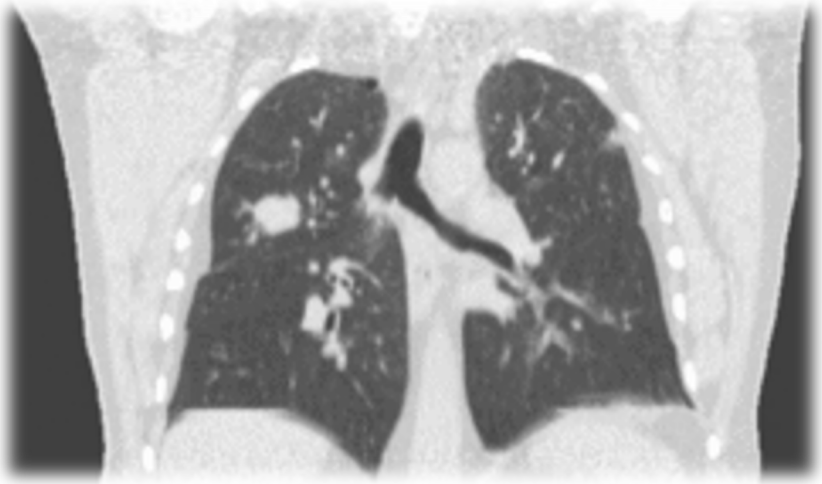
DIR for atlas-based segmentation

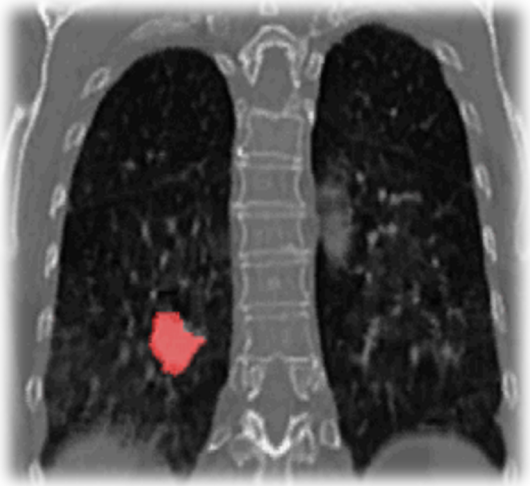


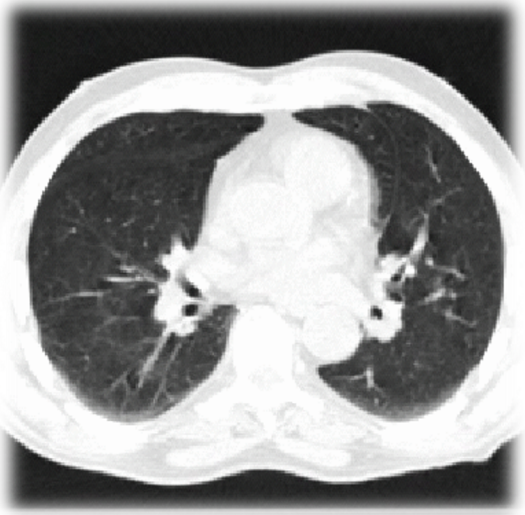
DIR for atlas-based segmentation

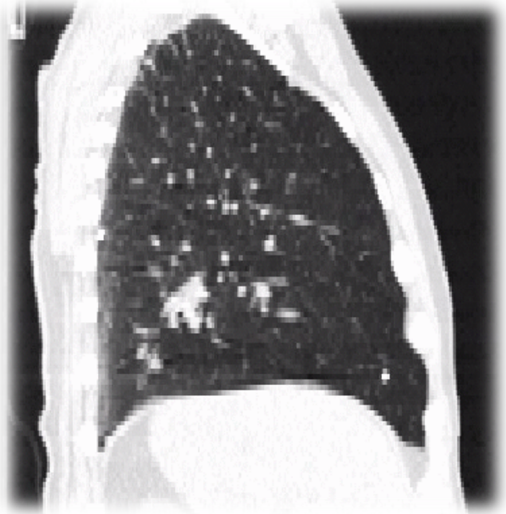


4D CT – breathing motion









Deformable image registration

It is an **ill-posed** problem

- Well-posed = solution exists + the solution is unique + the solution depends continuously on the data
- Hard to solve, tradeoff

Tradeoff :

- Image similarity : can always match any pixel to any other one
  (Mutual Information, correlation coefficient, correlation ratio …)
- Transformation regularity : is the deformation plausible ?

Generic model: optimisation

$$T_{opt} = \arg_T \max \left[\alpha E_{sim}(A, B, T) + (1-\alpha) E_{reg}(T) \right]$$

A, B = the two images to register (reference & moving)

T_{opt} = the sought optimal transformation

E_{sim} = similarity measure

E_{reg} = regularization measure of T

α = tradeoff parameter

$\arg_T \max$ = optimization algorithm

Deformable Image Registration (DIR)

Image Similarity $E_{sim}(A, B, T)$

- Quantify the similarity between I and J deformed by T
- Allow to compare different deformations T

Regularization $E_{reg}(T)$

- T should be smooth enough (no trajectory crossing, …)
- T should be *diffeomorphic* (one-to-one, continuous, inverse continuous)

Optimization procedure: $\arg_T \max$

- How to find the best T ?
- Iterative process ; strategy to search + stopping criteria

Deformable Image Registration (DIR)

Numerous algorithms

- Demons *[Thirion 1998]*
- B-Spline free form deformation *[Rueckert 1999]*
- Linear Elastic *[Christensen 2001]*
- … tens others methods or developments (still continuing)

Conclusion

- Hard, useful, numerous algorithms
- No “general” solution (such as in rigid), application dependent