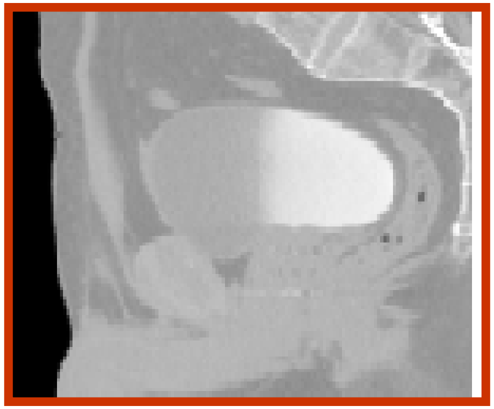 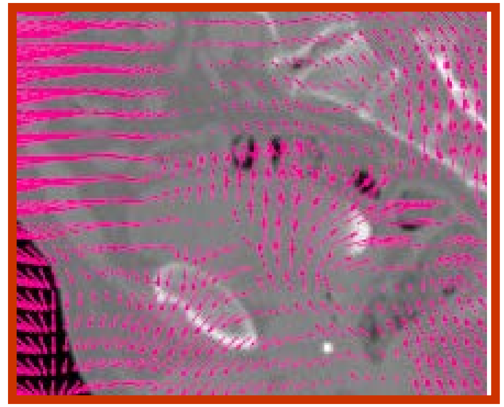 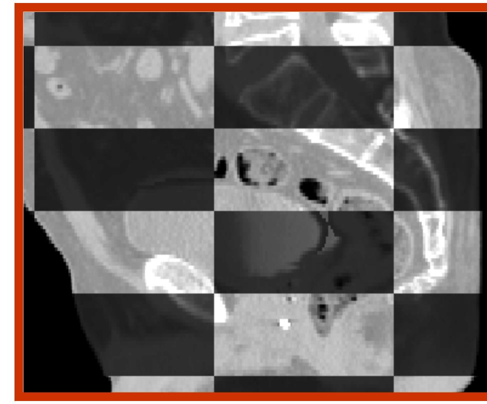

Registration in medical imaging: Principles and applications

Enseignement post-universitaire sur le traitement d'image en physique médicale
Port Bourgenay Octobre 2015

Oscar Acosta,

[1] INSERM, U 1099, Université de Rennes 1, LTSI,

http://blogperso.univ-rennes1.fr/oscar.acosta/index.php/

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Institut national de la santé et de la recherche médicale

Outline

- Registration in medical applications
- Image registration in a nutshell
- Validation
- Conclusions

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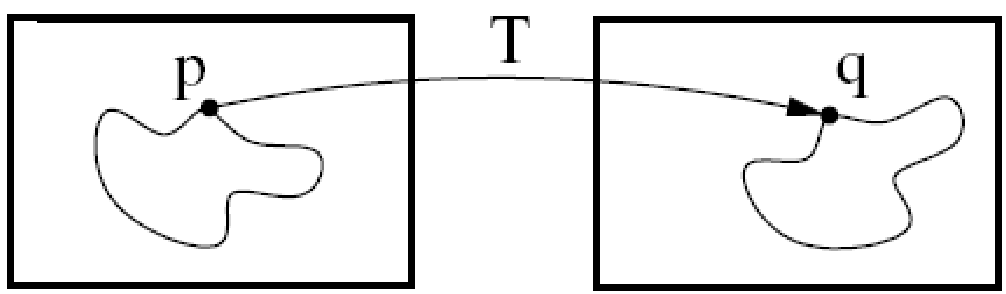
Key idea

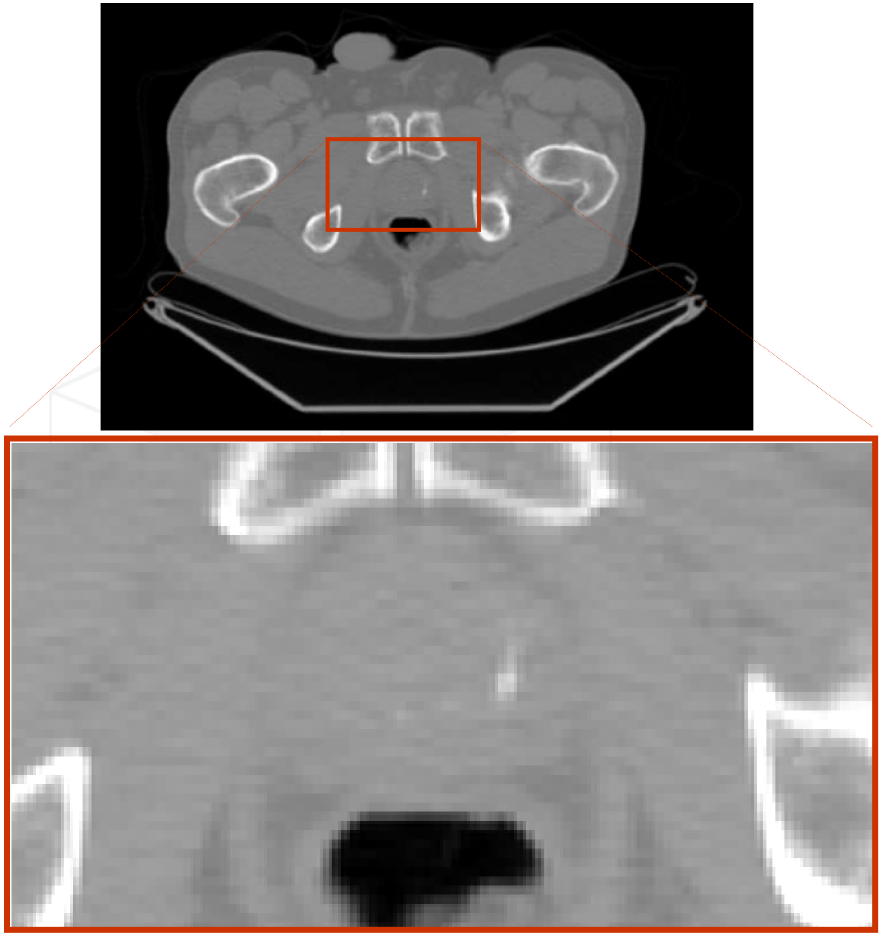
- The registration problem
  - Registration is the task of aligning or defining meaningful correspondences between data. In other words, it is about computing a spatial transformation between two images.



L. Ibanez, W. Schroeder, L. Ng, and J. Cates. *The ITK Software Guide. Kitware, Inc*. ISBN 1-930934-15-7, second edition, 2005.

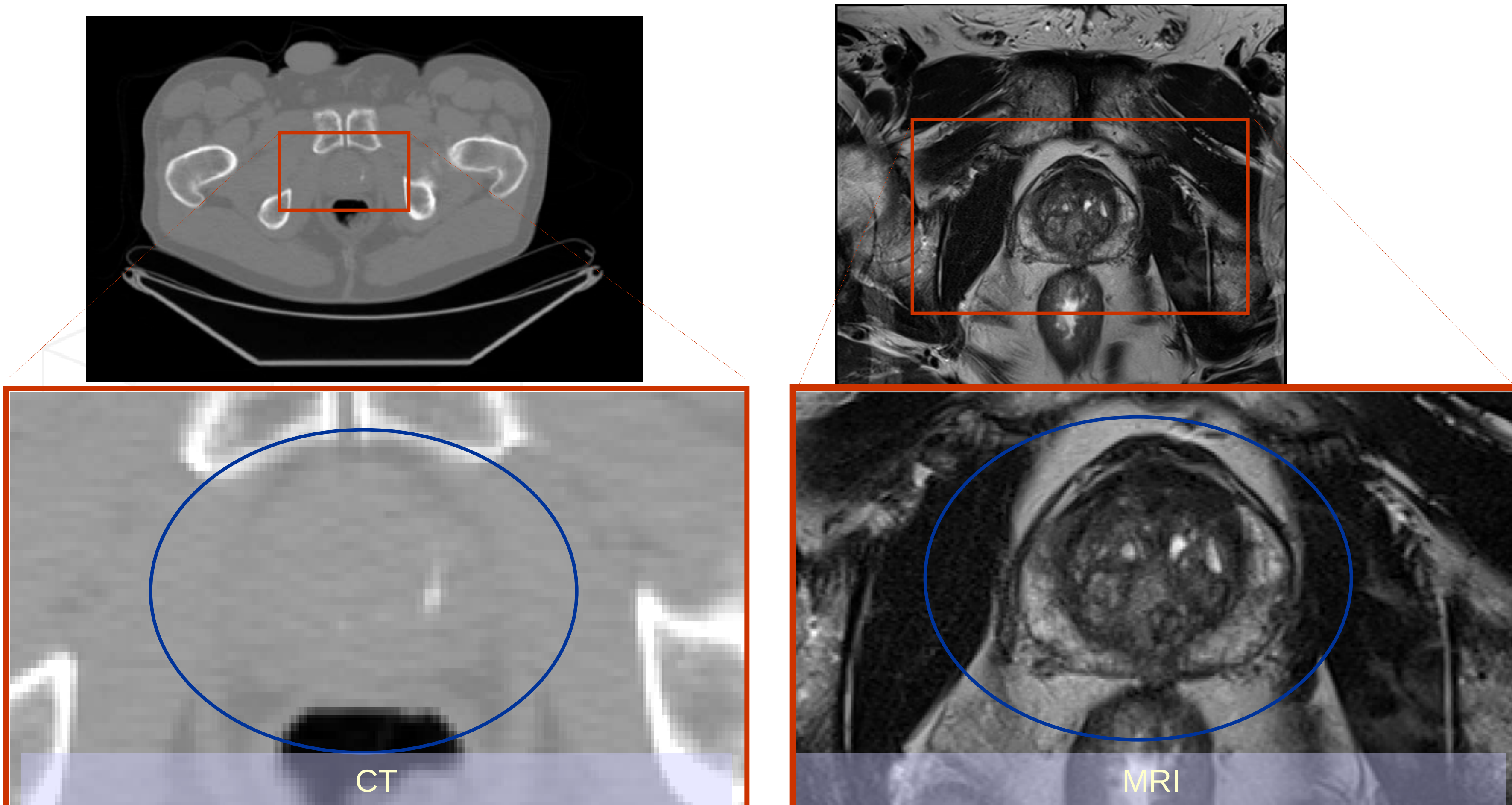
Registration in medical applications

- CT only??
  - Multimodal fusion



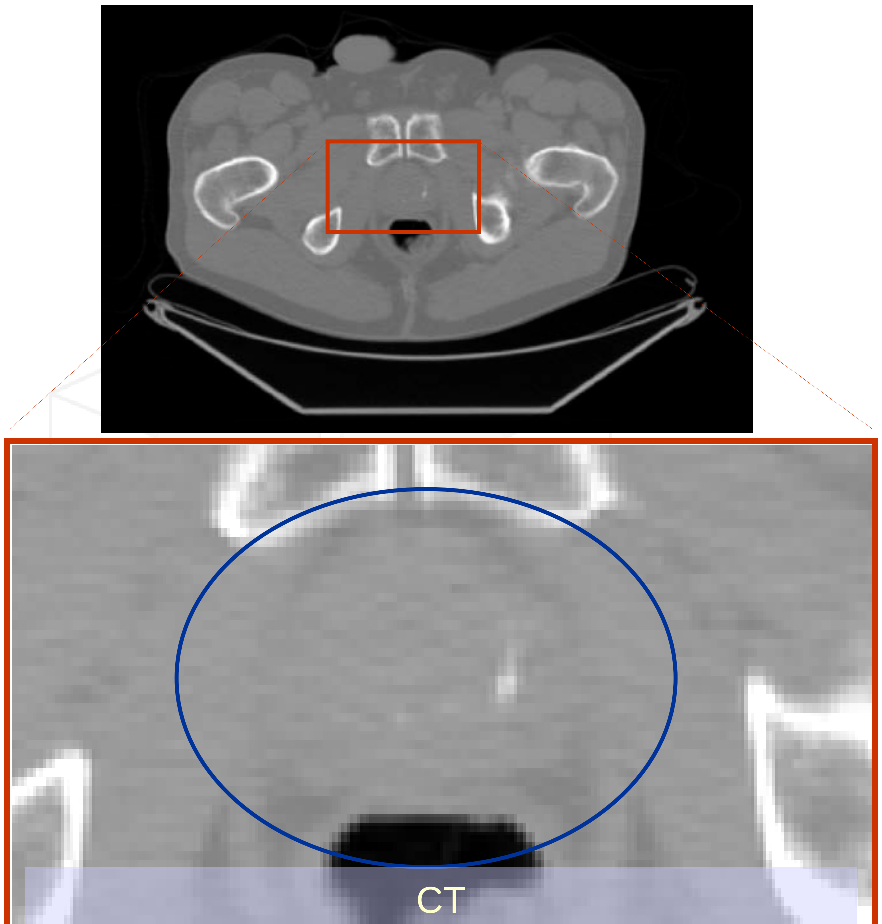
Registration in medical applications

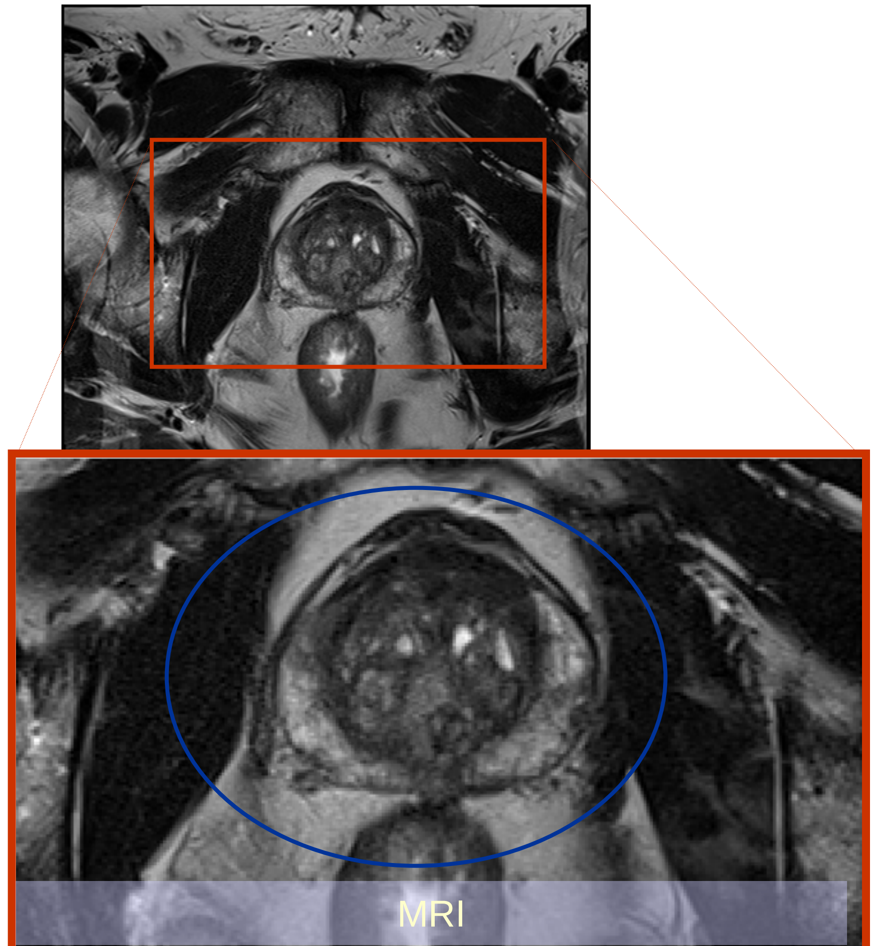
- To align the observed **data** (modality1) with the observed **data in** (modality2)
  - Multimodal fusion



Registration in medical applications

- **Multimodal fusion:** to improve diagnosis, delineations or finding biomarkers (intra/inter-individual)





Registration in medical applications

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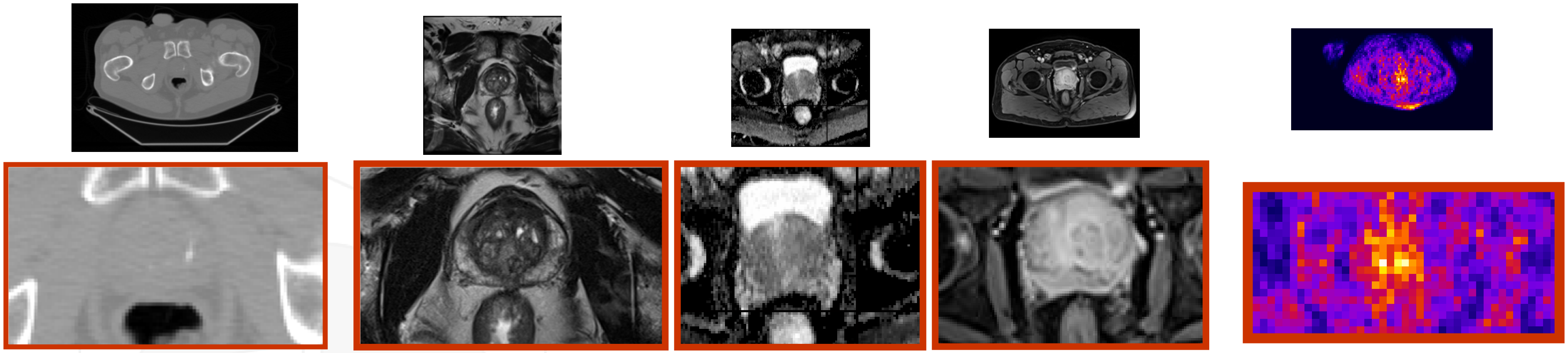

CT Multi parametric MRI PET

Registration in medical applications

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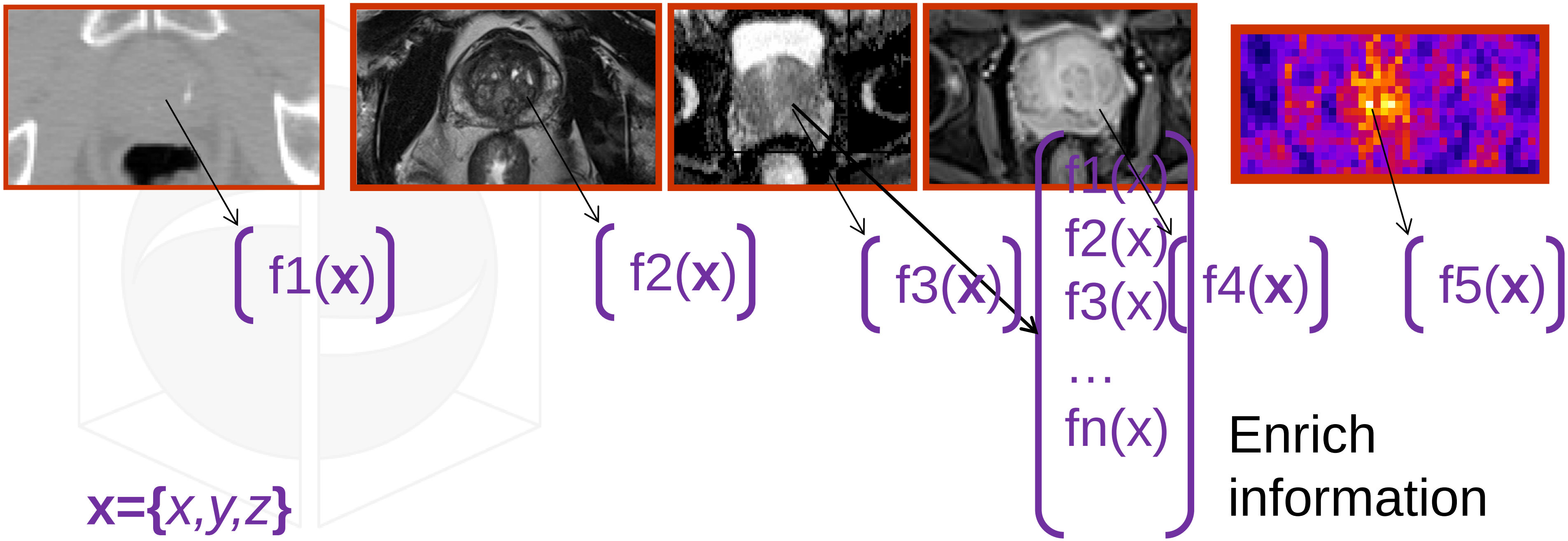

Registration in medical applications

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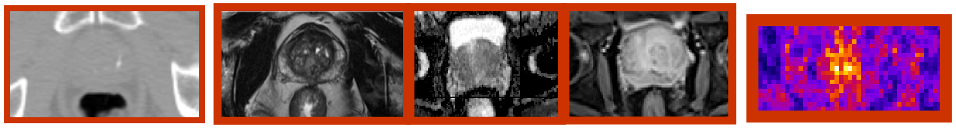
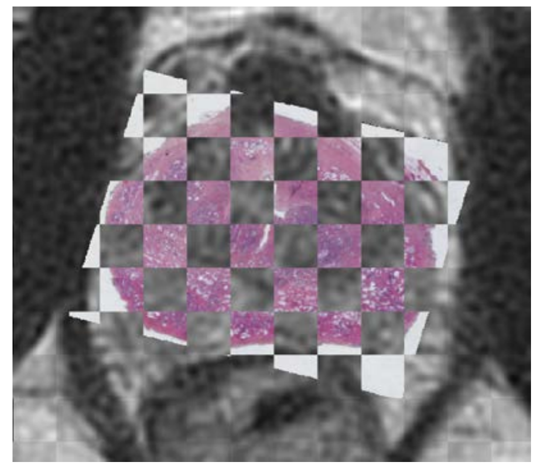


Simultaneous affine registrations of the HES blocks to the MRI

In-vivo/*ex-vivo* comparison
MRI biomarkers vs Histology



HES (Gleason)
Ki67 (Proliferation)
VEGFA (Angiogenesis, hypoxia)
CD31 (Endothelial cells)

Commandeur et al. IEEE EMBC 2015

Registration in medical applications

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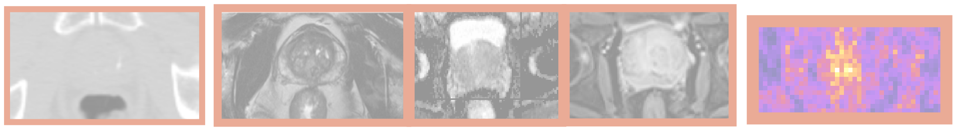
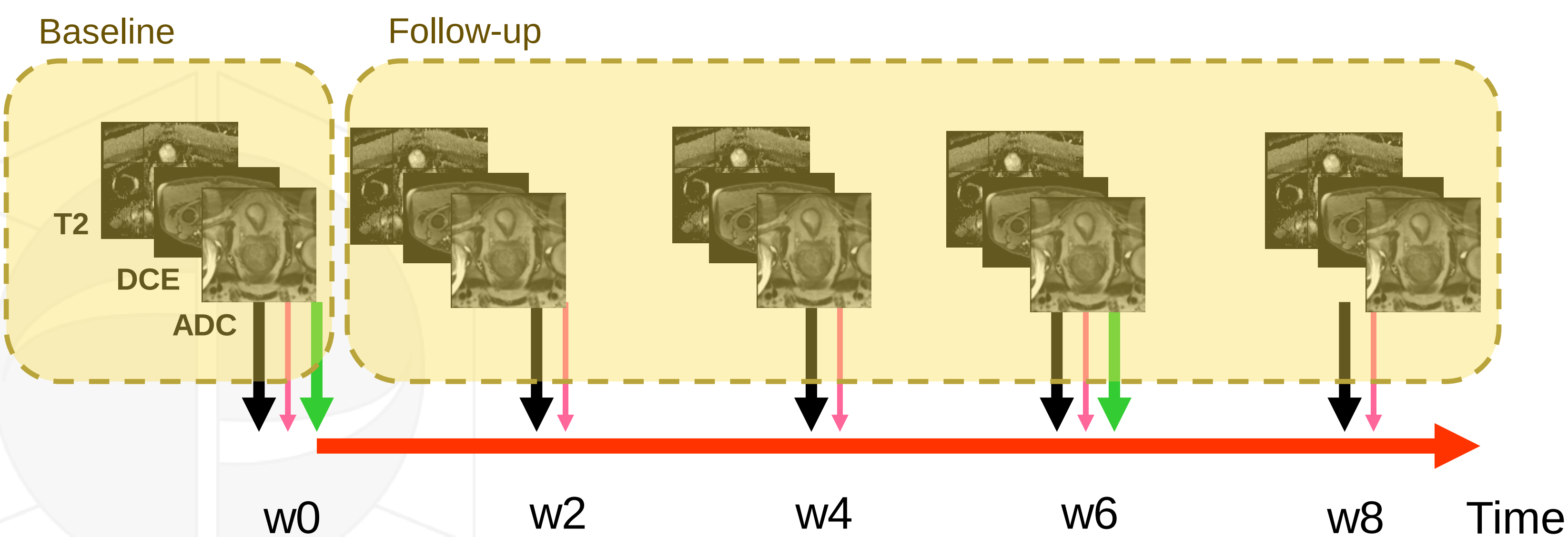


- Follow-up studies: to quantify changes over time (intra-individual)



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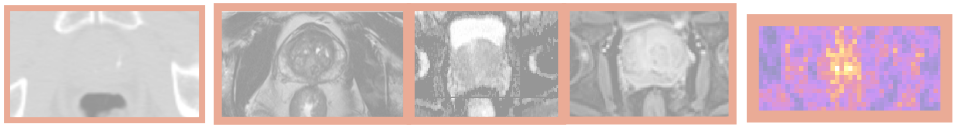

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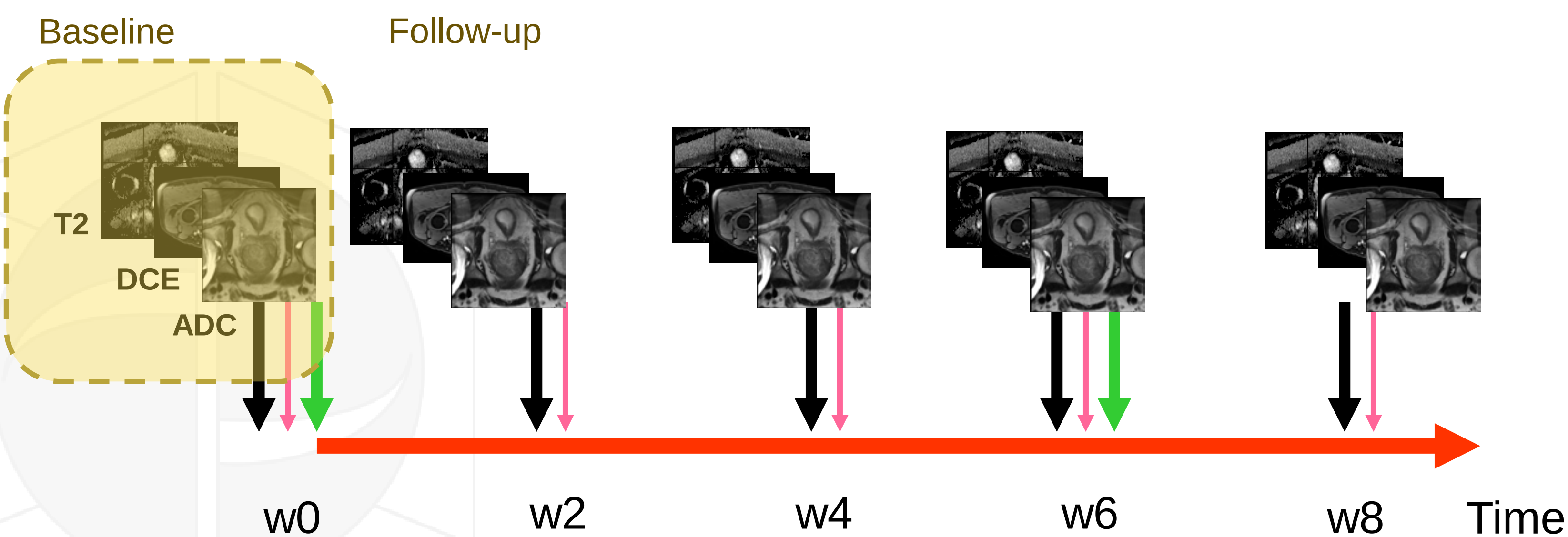

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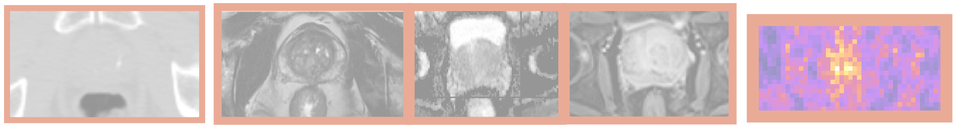

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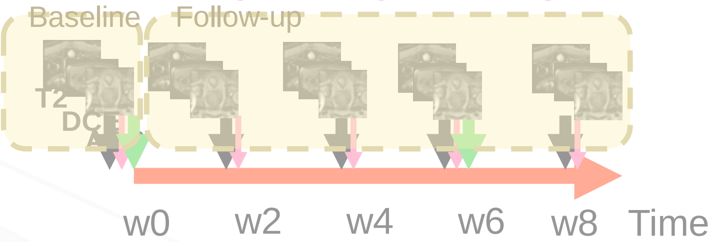

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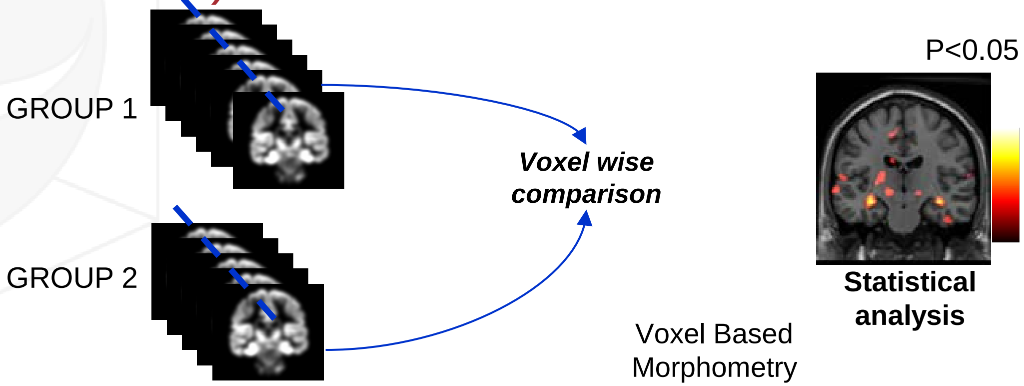

Ashburner, J., Friston, K.: Voxel-based morphometry–the methods. Neuroimage 11(6 Pt 1) (Jun 2000) 805–821

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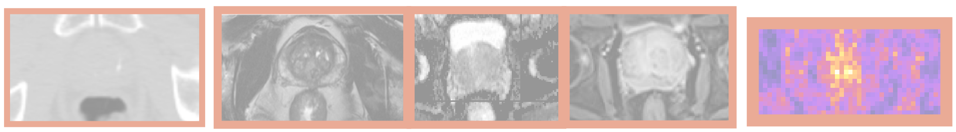

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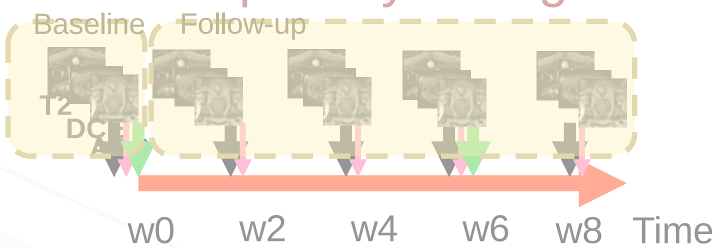

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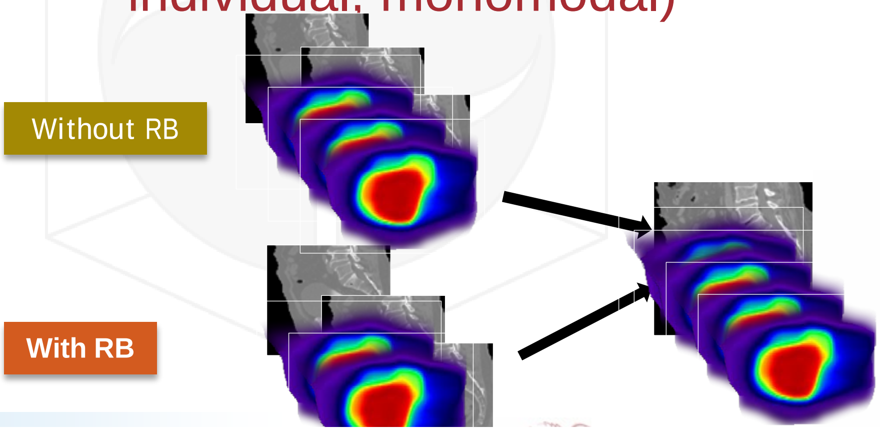

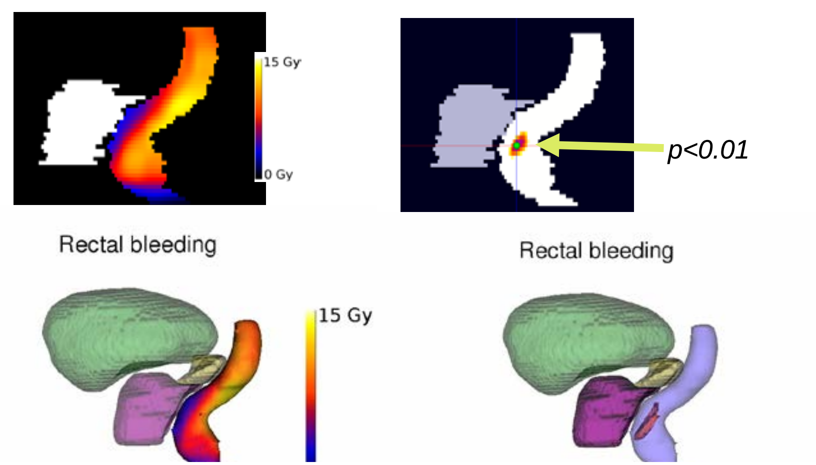

Acosta O, et al . "Voxel-based population analysis for correlating local dose and rectal toxicity in prostate cancer radiotherapy" 2013 *Physics in Medicine and Biology.* 58(8) 2581-2595 doi:10.1088/0031-9155/58/8/2581

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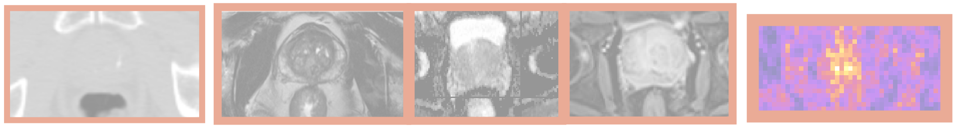

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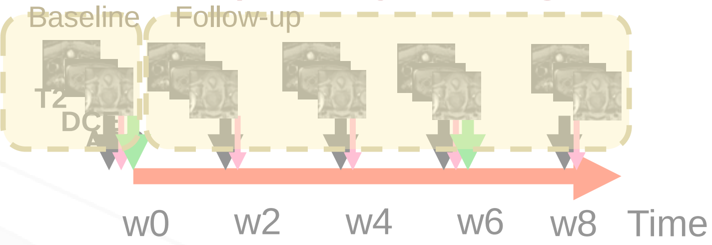

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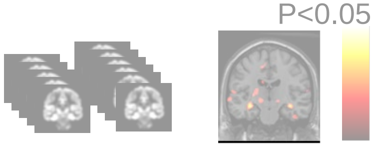

- Image-guided therapies (Multimodal, intra-individual)

Registration in medical applications

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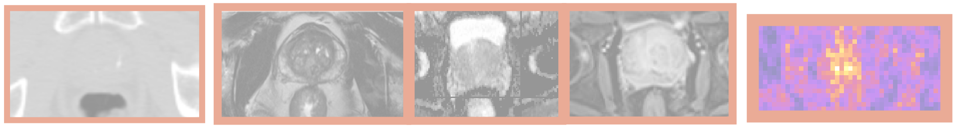

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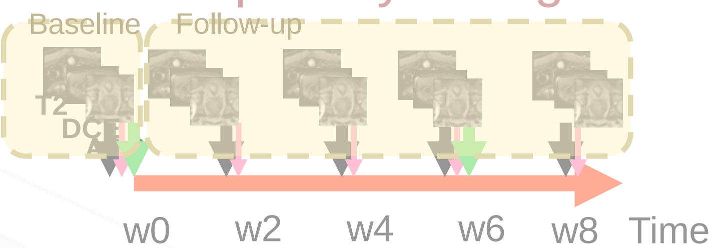

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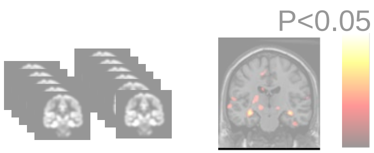

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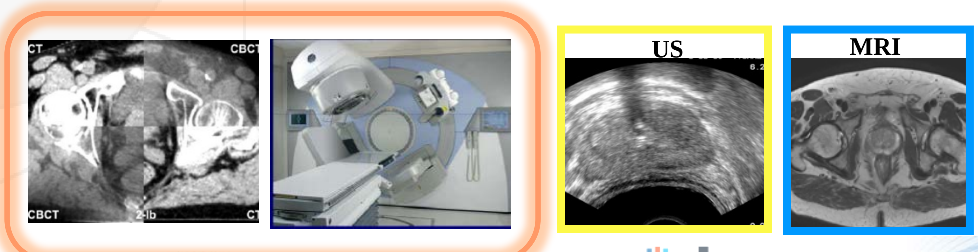
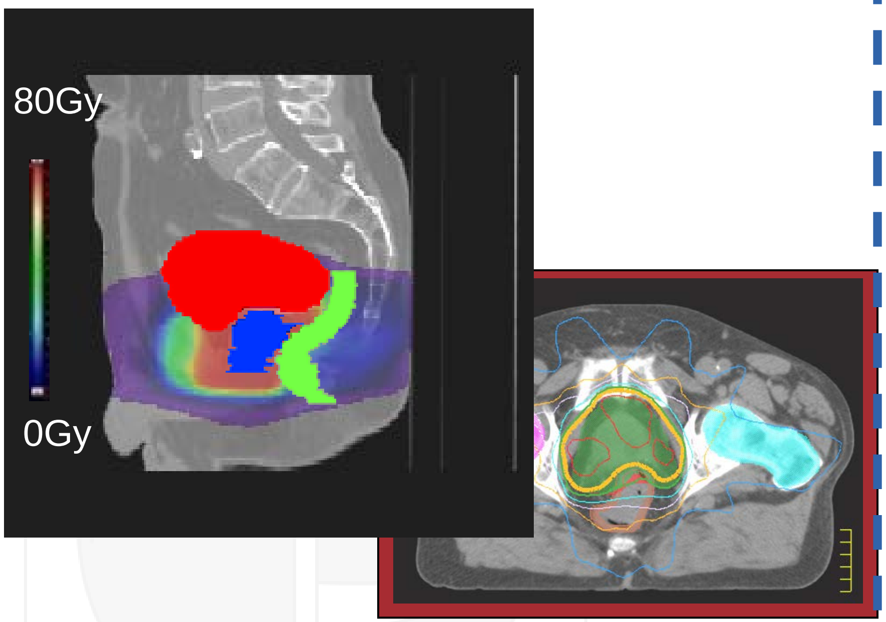
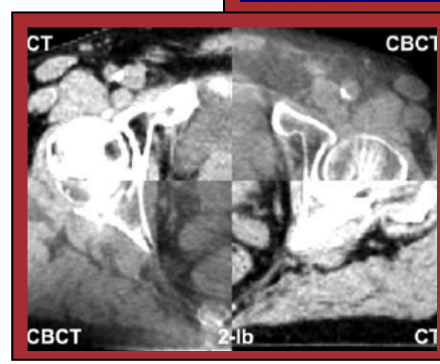


Medical applications

- Image guided procedures
  - Radiotherapy for prostate cancer





Planning

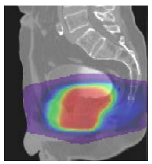
Intervention

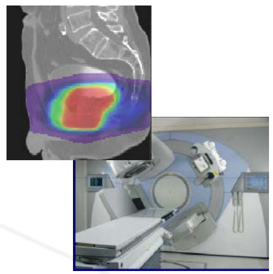
Image-Guided Radiotherapy

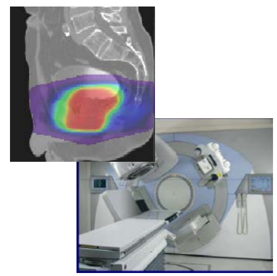
Fractionated

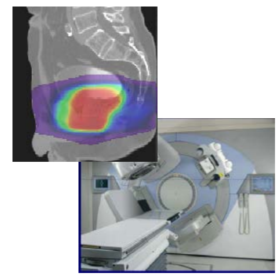
Planning **Treatment (several weeks)**

80Gy = 2 Gy + 2 Gy + 2 Gy + …







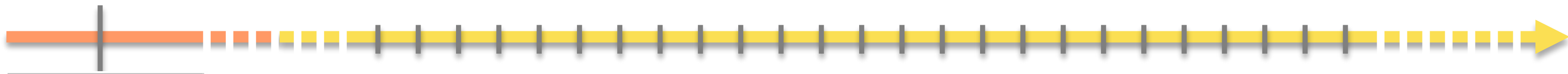


Patient setup at linear accelerator →

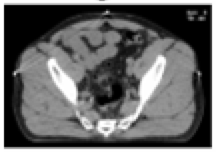
- Image Guided Radiotherapy (**IGRT**)

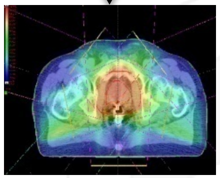
Image-Guided Radiotherapy

Planning **Treatment**

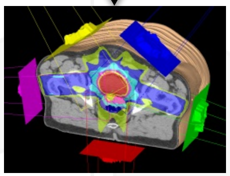


CT_p



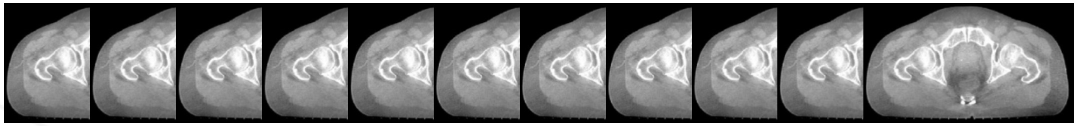


$dose_p$

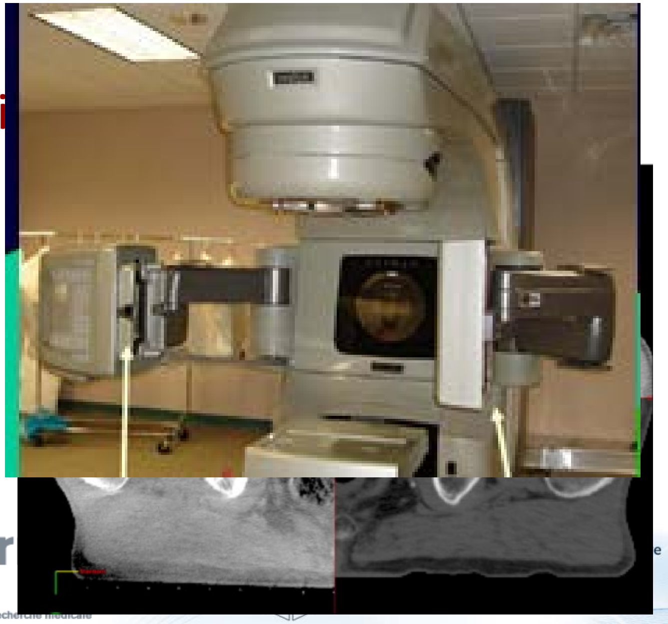


Treatment characteristics

Image guidance (CT, **CBCT**, …)



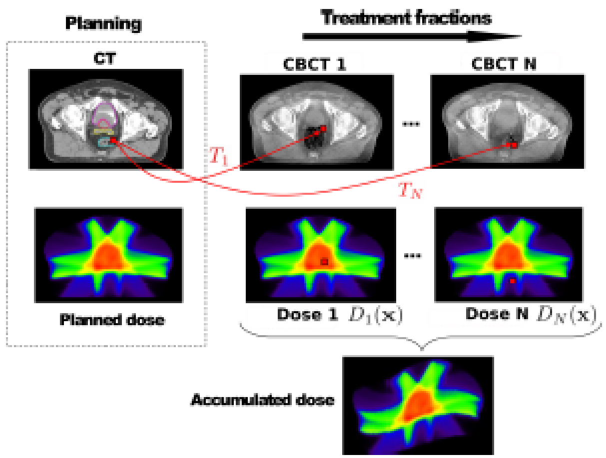
Target localization (rigid regi



- Local rigid registration (good initialization because of patient positioning according to skin marks)
- Metric: Mutual information

Image-Guided Radiotherapy

- Dose monitoring



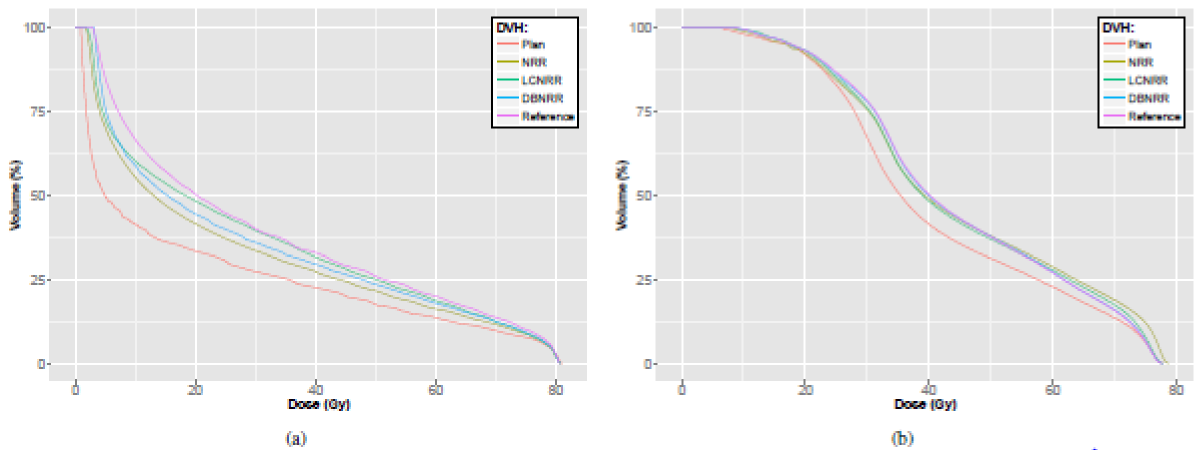
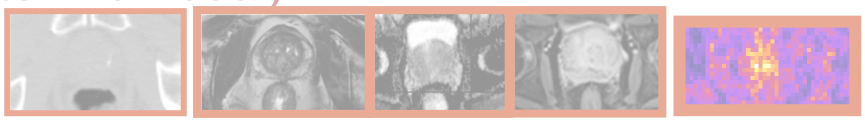


Fig. 9. Numerical phantom results: representation of the planned DVH, reference accumulated DVH and accumulated DVHs, as estimated with the three

Cazoulat, G.; Simon, A.; Dumenil, A.; Gnep, K.; de Crevoisier, R.; Acosta, O.; Haigron, P., "Surface-Constrained Nonrigid Registration for Dose Monitoring in Prostate Cancer Radiotherapy," *Medical Imaging, IEEE Transactions on* , vol.33, no.7, pp.1464,1474, July 2014. doi: 10.1109/TMI.2014.2314574

Registration in medical applications

- Multimodal fusion: to improve diagnosis, delineations or finding biomarkers (intra/inter-individual)



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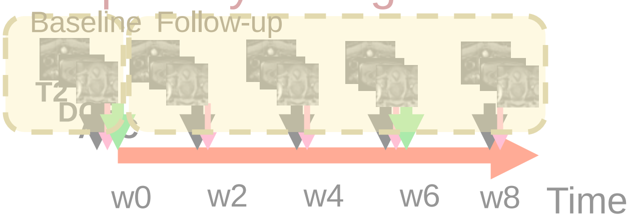

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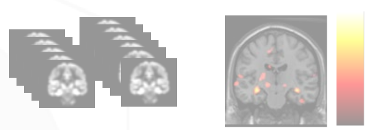
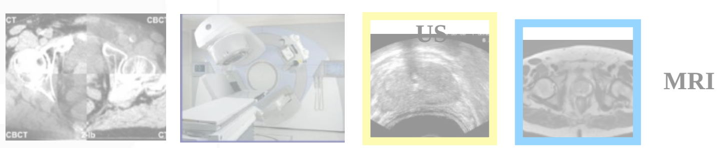


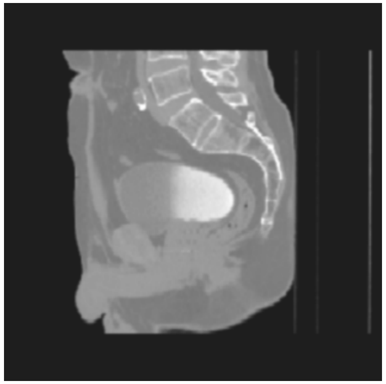

- Image-guided therapies (Multimodal, intra-individual)

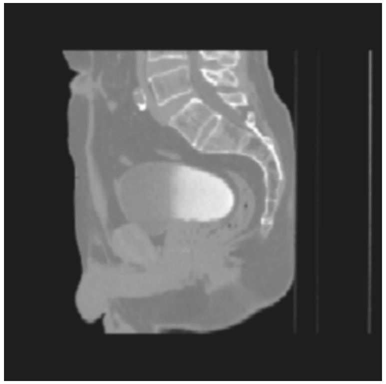


- **Atlas based Segmentation**

Registration for segmentation/fusion

- Atlas based segmentation
  - Using a priori knowledge (Atlas, models, etc.), registered to the individual data





https://hal.archives-ouvertes.fr/inserm-00910761/document

Acosta O, Dowling J, Drean G, SImon A, de Crevoisier R, Haigron P, "Multi-Atlas based segmentation of pelvic structures from CT scans for planning in prostate cancer radiotherapy", in Abdomen and Thoracic Imaging, an Engineering and Clinical Perspective, Springer, 2014. El-Baz, Saba and Suri. pp 623-656. ISBN: 978-1-4614-8497-4. doi: 10.1007/978-1-4614-8498-1_24

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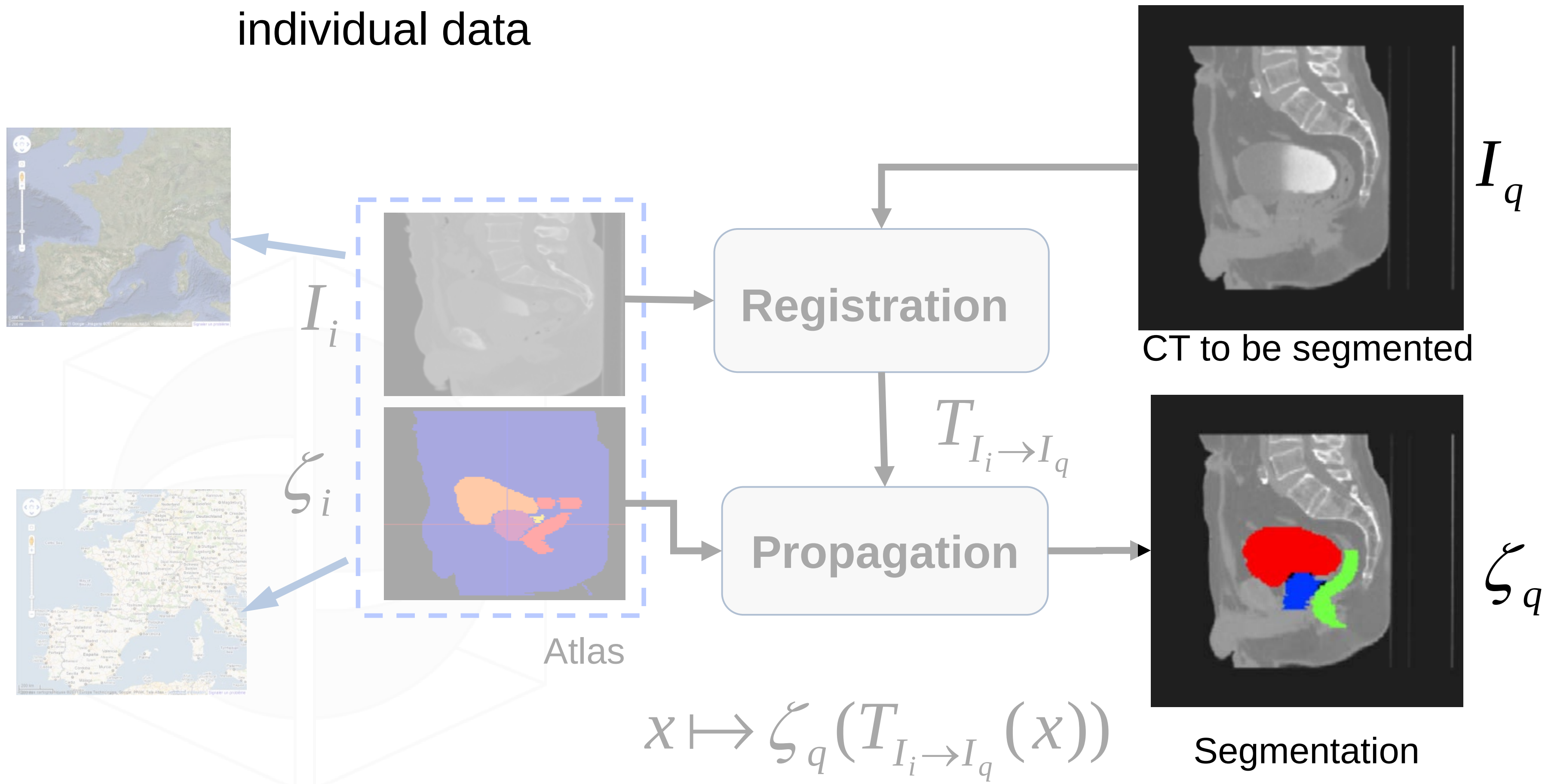

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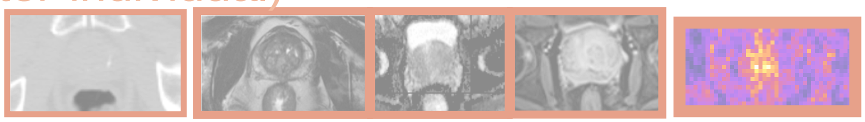
Take home message (1) : applications

- Multimodal **fusion**: to improve diagnosis, delineations or finding biomarkers (intra/inter-individual)



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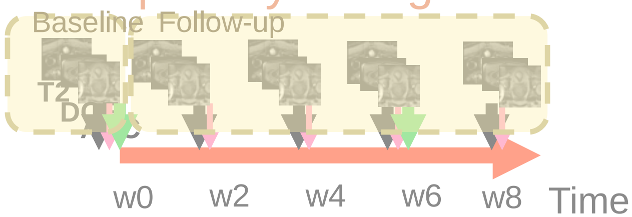

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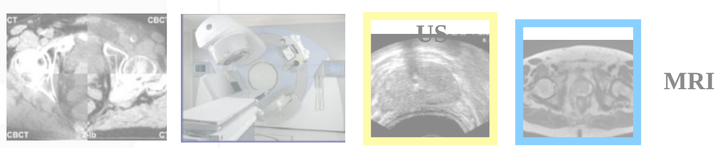
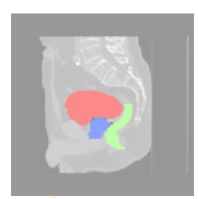


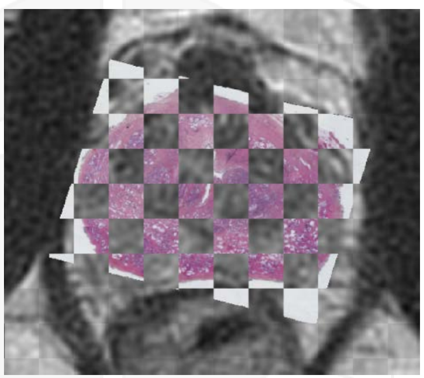
- Atlas-based **Segmentation**

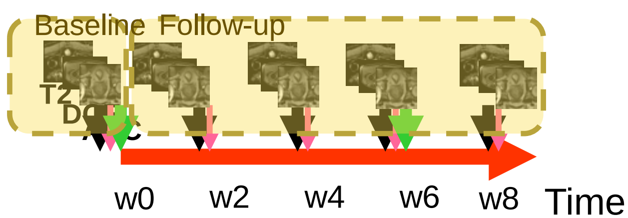


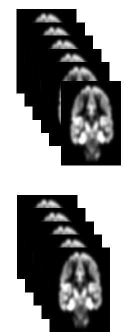
Take home message (1) : classification

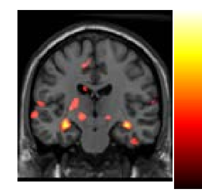
- According to the data

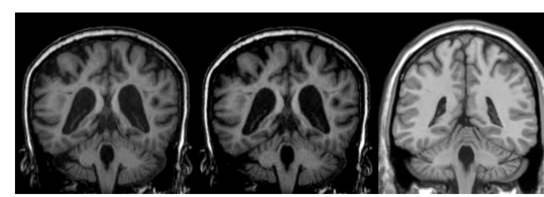
Modality	Origin	Number of inputs
• Monomodal • Multimodal	• Intra-individual • Inter-individual	• Pair-wise • Group-wise









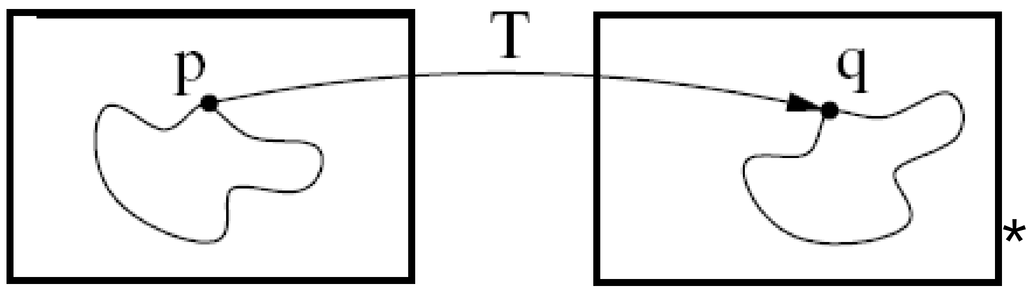


Outline

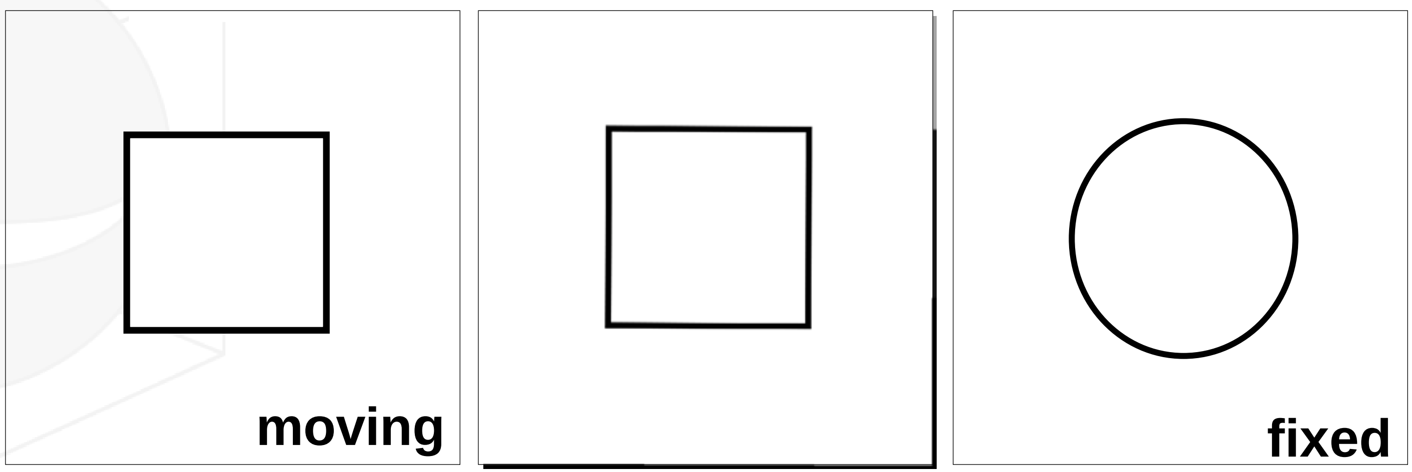
- Registration in medical applications
- Image registration in a nutshell
- Validation
- Conclusions

Key idea

- The registration problem
  - Registration is the task of aligning or defining meaningful correspondences between data. In other words, it is about computing a spatial transformation between two images.



Warping a **moving** object towards a **fixed** one



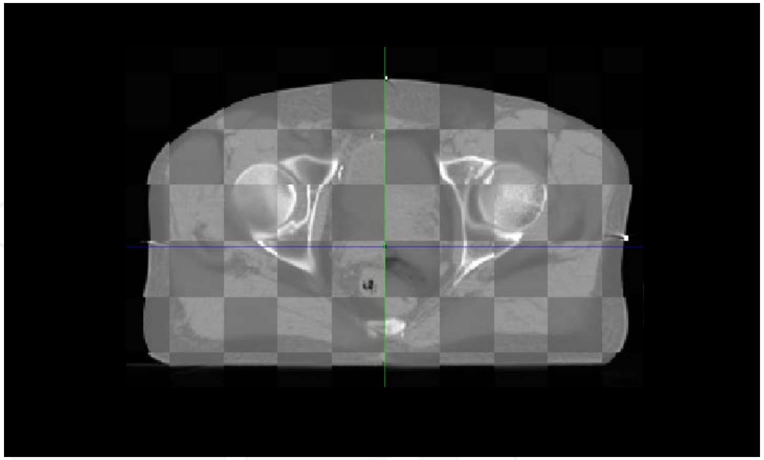
* L. Ibanez, W. Schroeder, L. Ng, and J. Cates. *The ITK Software Guide. Kitware, Inc*. ISBN 1-930934-15-7, second edition, 2005.

General registration framework

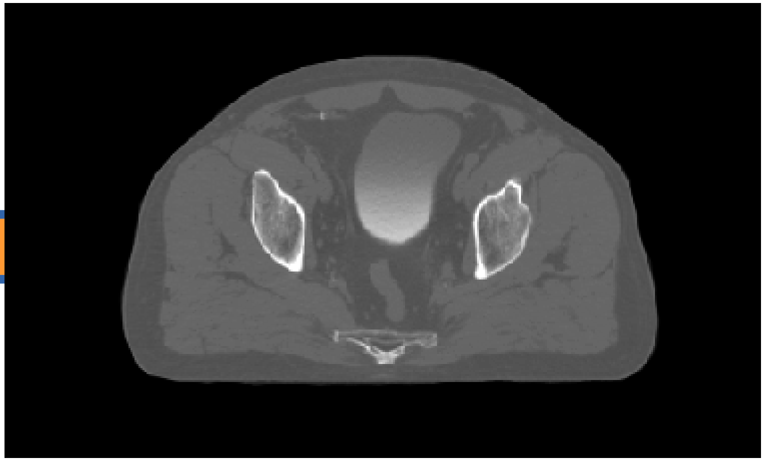
- How does it work?

General registration framework

– Image registration is the process of determining the spatial transform that maps points from one image to homologous points on an object in the second image…

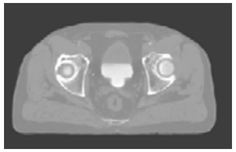


Fixed Image (F)

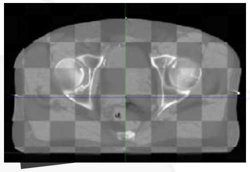


Moving Image (M)

Computerized registration framework

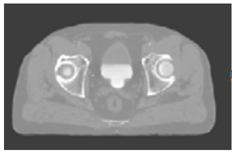


Fixed Image



Moving Image

Computerized registration framework



Fixed Image

$F(x)$

Feature Extraction

$$s(M(x), F(x))$$

IEEE TRANSACTIONS ON MEDICAL IMAGING 1

Surface-Constrained Nonrigid Registration for Dose Monitoring in Prostate Cancer Radiotherapy

Guillaume Cazoulat, Antoine Simon*, Aurelien Dumenil, Khemara Gnep, Renaud de Crevoisier, Oscar Acosta, and Pascal Haigron

IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 31, NO. 12, DECEMBER 2012 2343

Multi-Modal Image Registration Based on Gradient

Medical Image Analysis 16 (2012) 1–17

Contents lists available at ScienceDirect

Medical Image Analysis

journal homepage: www.elsevier.com/locate/media

Entropy and Laplacian images: Structural representations for multi-modal registration

Christian Wachinger *, Nassir Navab

Computer Aided Medical Procedures (CAMP), Technische Universität München, München, Germany

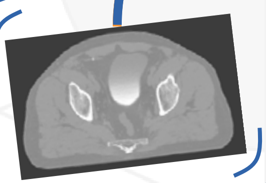
MIND: Modality independent neighbourhood descriptor for multi-m deformable registration

Mattias P. Heinrich a,b,*, Mark Jenkinson b, Manav Bhushan a,b, Tahreema Matin d, Fergu Sir Michael Brady c, Julia A. Schnabel a

Feature Extraction

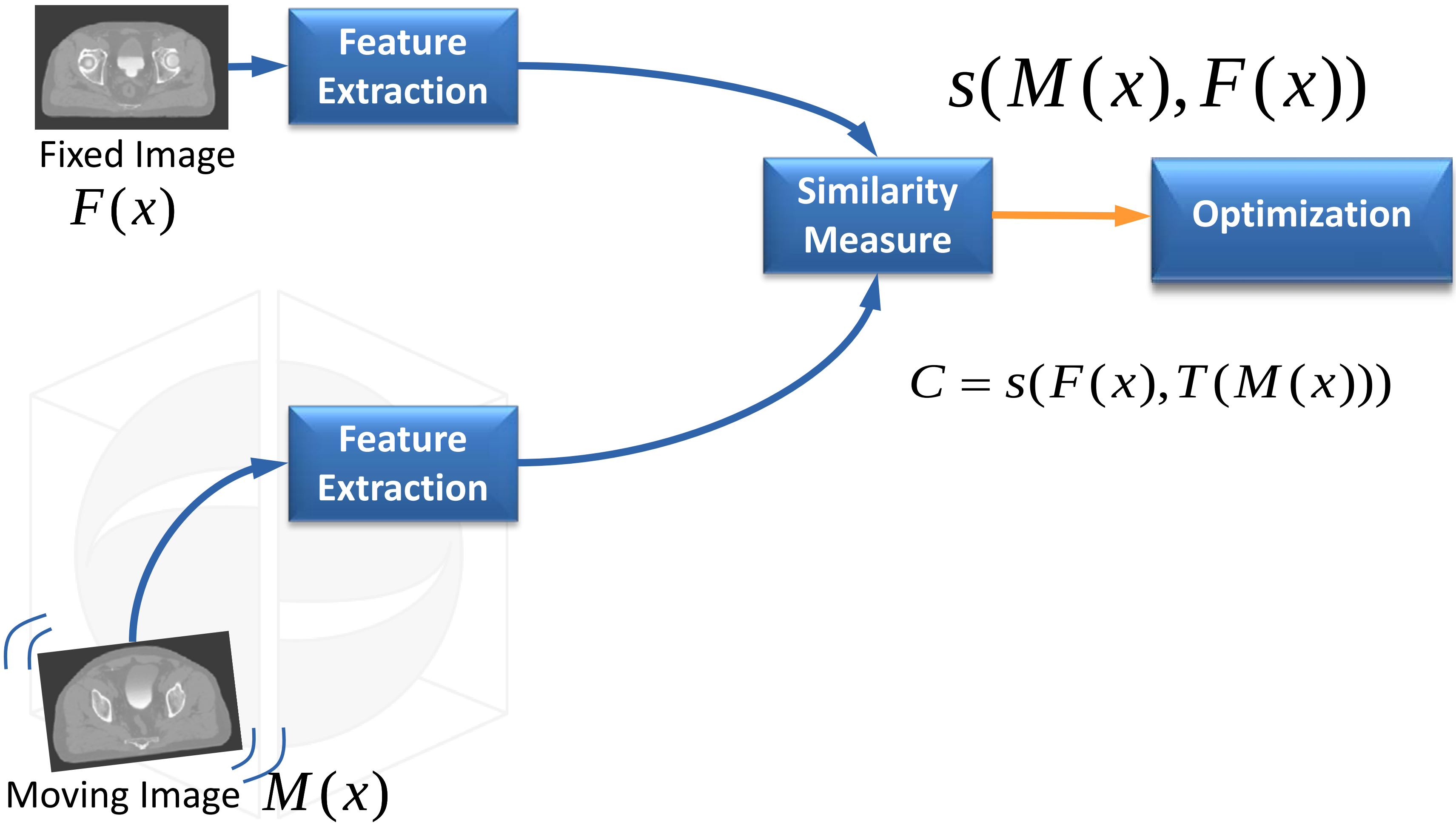
Charac

- Intens
- Visible
- Visible
- Gradients,
- Entropy
- Self similarity ...

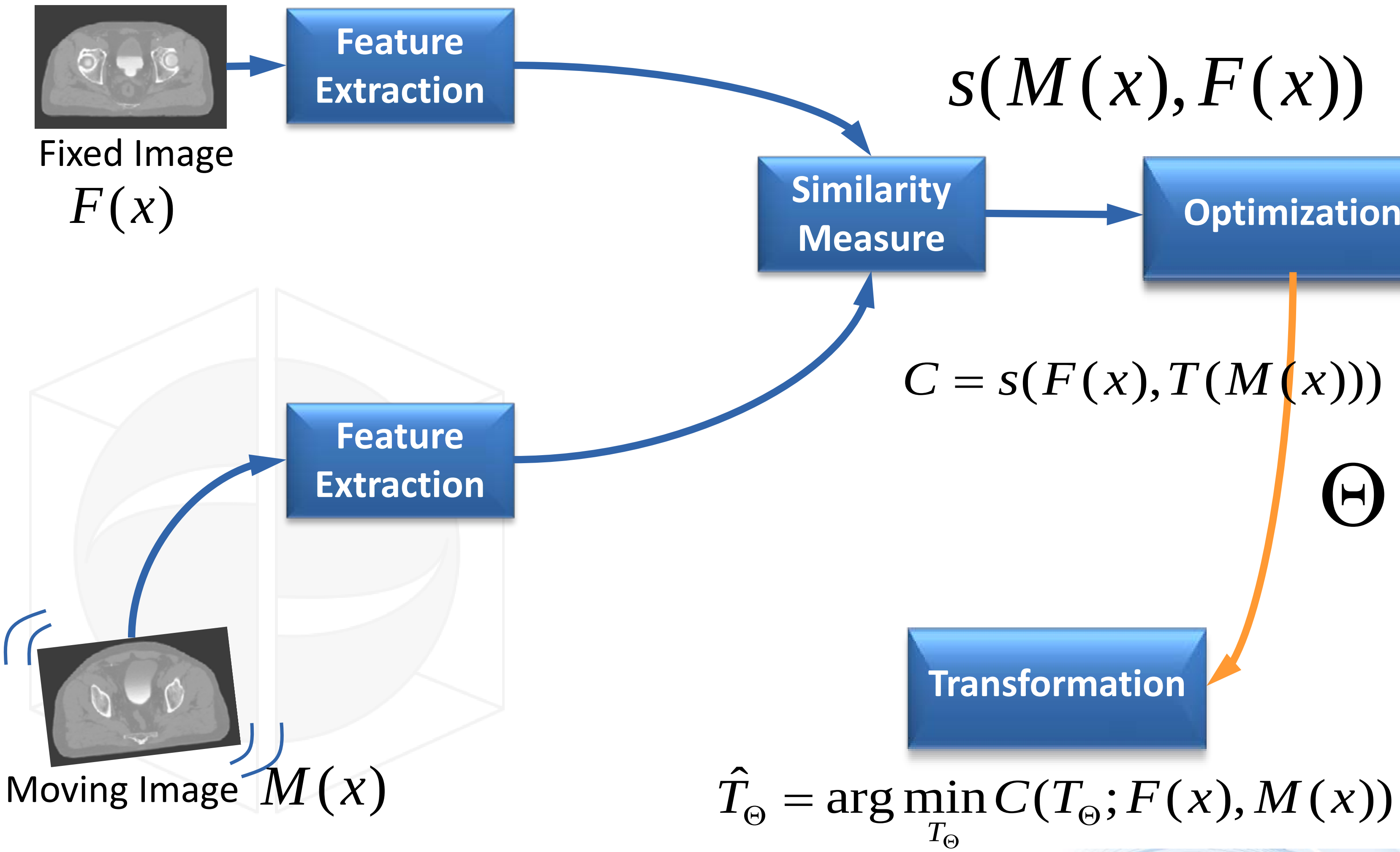


Moving Image $M(x)$

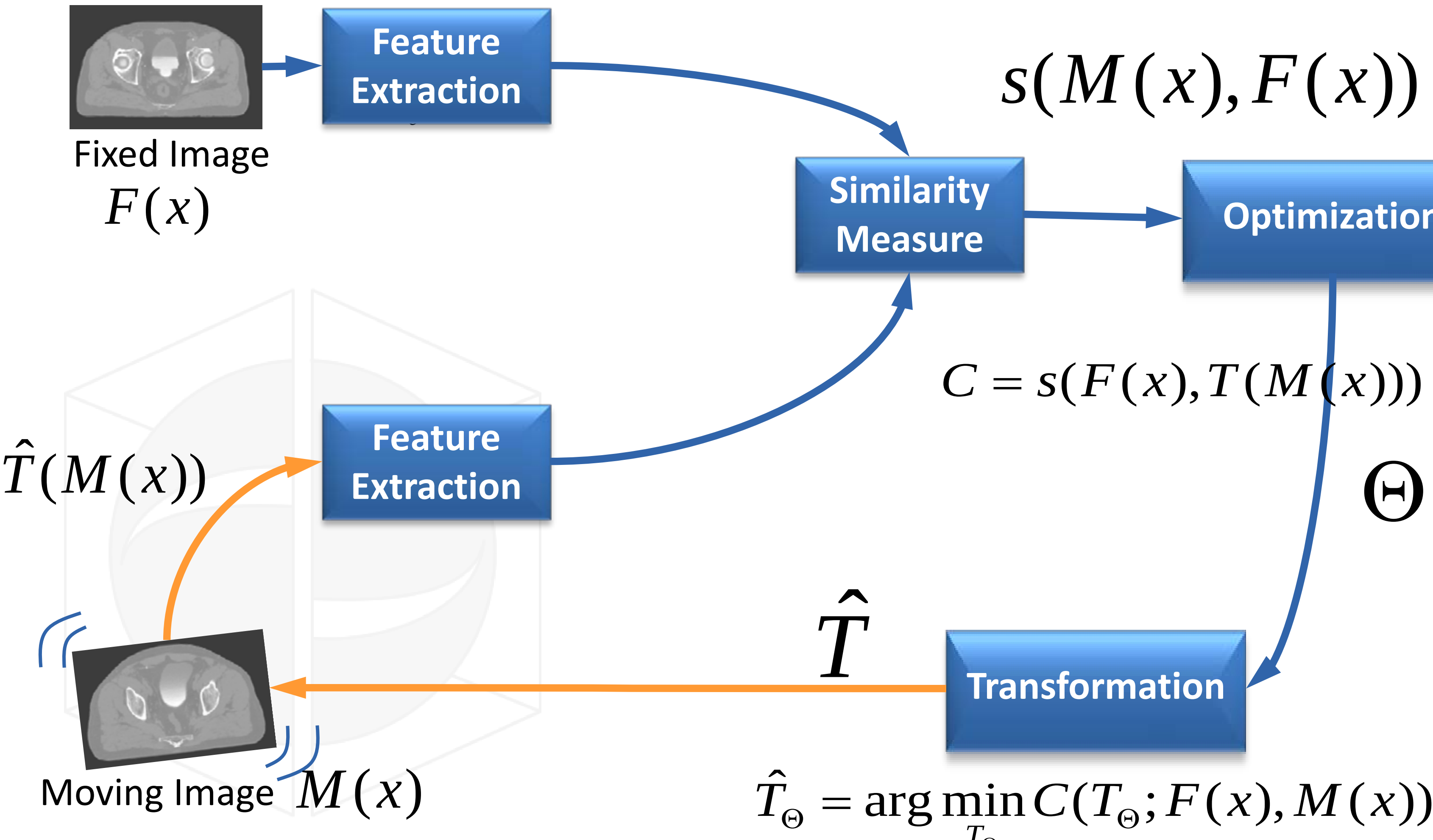
Computerized registration framework



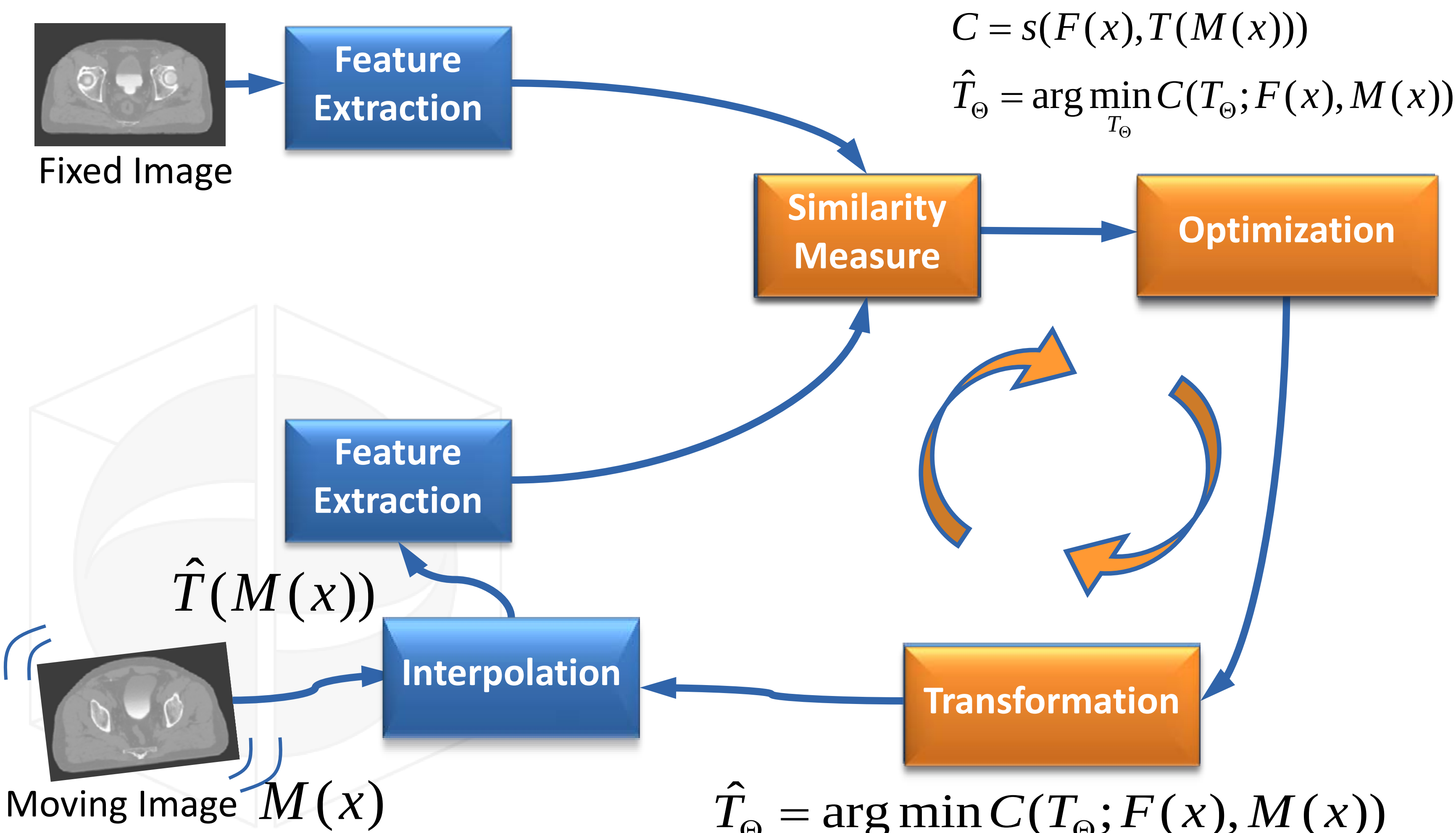
Computerized registration framework



Computerized registration framework

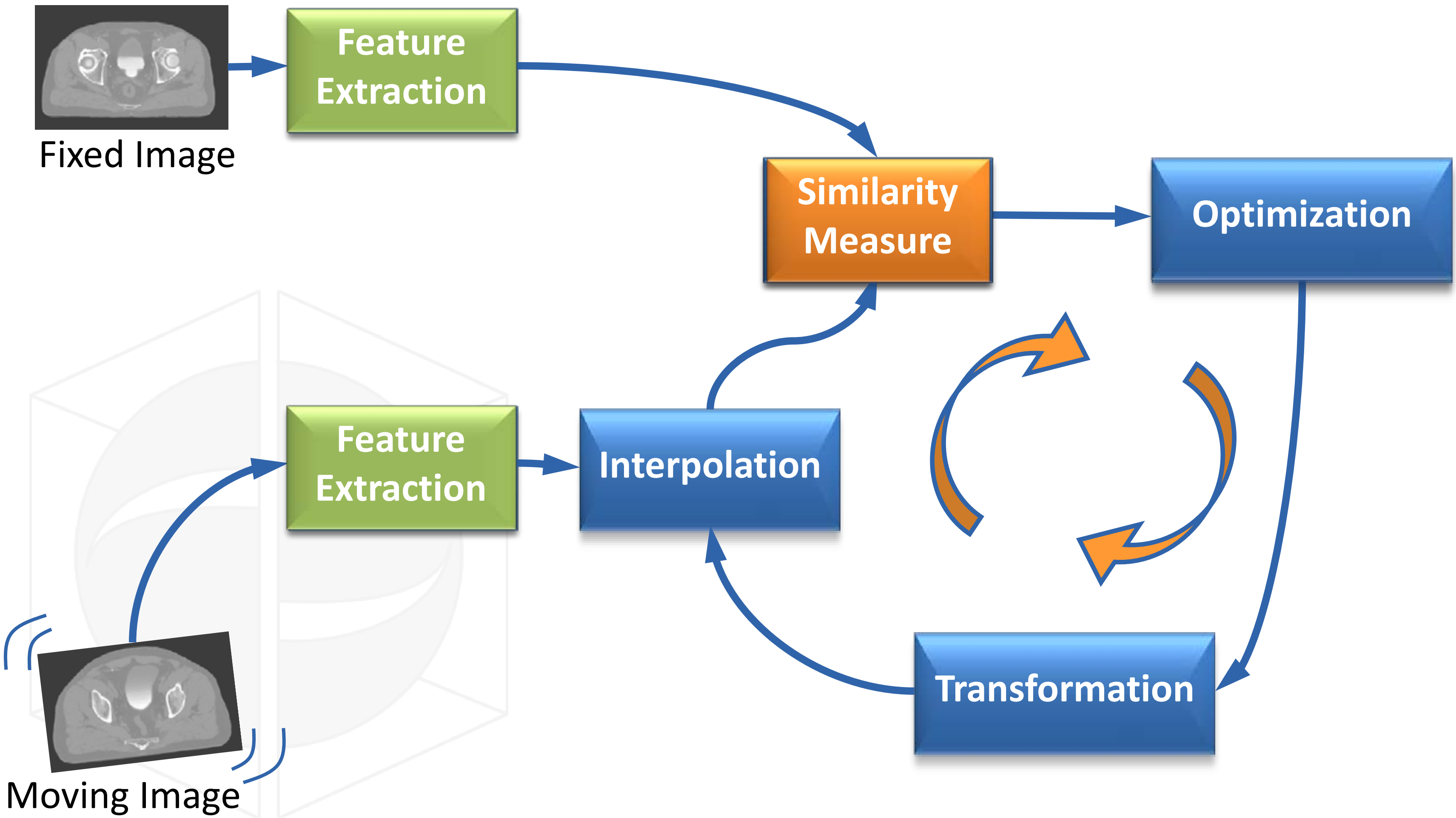


Computerized registration framework

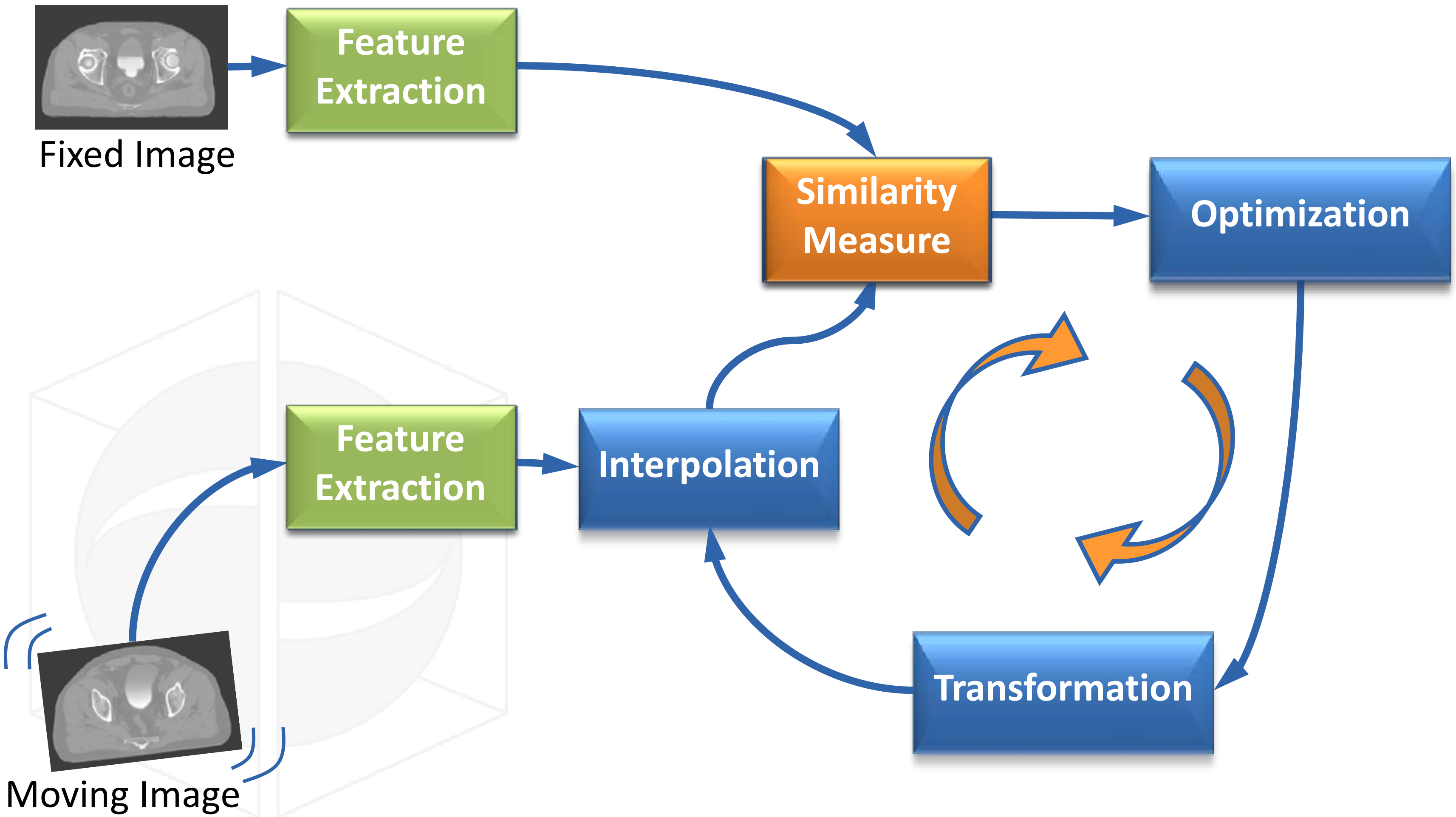


$$\hat{T}_\Theta = \arg\min_{T_\Theta} C(T_\Theta; F(x), M(x))$$

Computerized registration framework



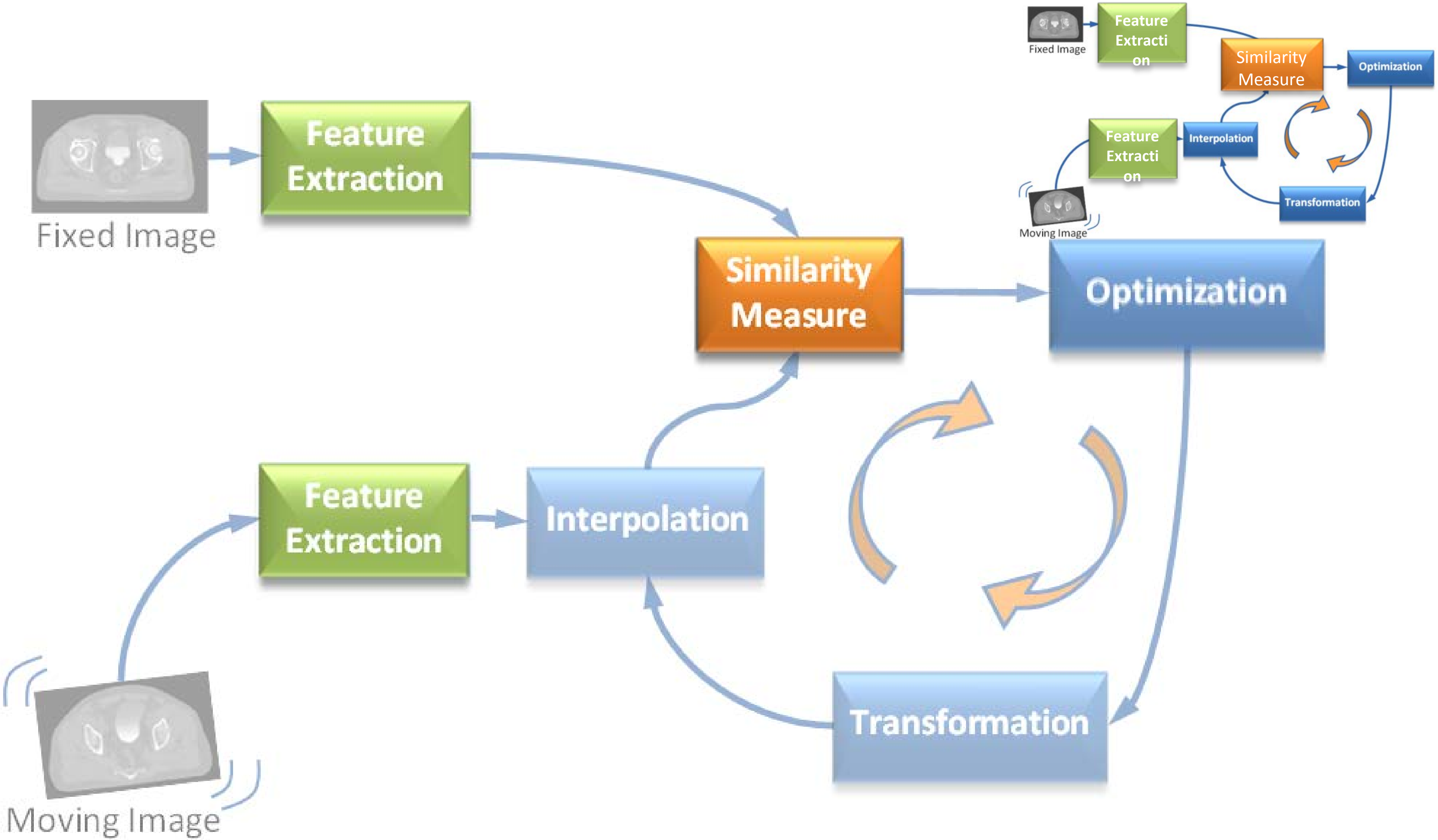
Computerized registration framework



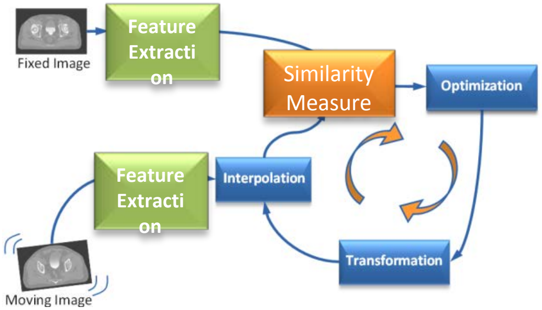
https://hal.archives-ouvertes.fr/inserm-00910761/document

Acosta O, Dowling J, Drean G, SImon A, de Crevoisier R, Haigron P, "Multi-Atlas based segmentation of pelvic structures from CT scans for planning in prostate cancer radiotherapy", in Abdomen and Thoracic Imaging, an Engineering and Clinical Perspective, Springer, 2014. El-Baz, Saba and Suri. pp 623-656. ISBN: 978-1-4614-8497-4. doi: 10.1007/978-1-4614-8498-1_24 or https://hal.archives-ouvertes.fr/inserm-00910761/document

Computerized registration framework



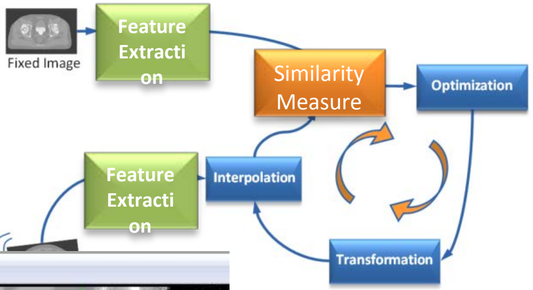
Similarity Measure

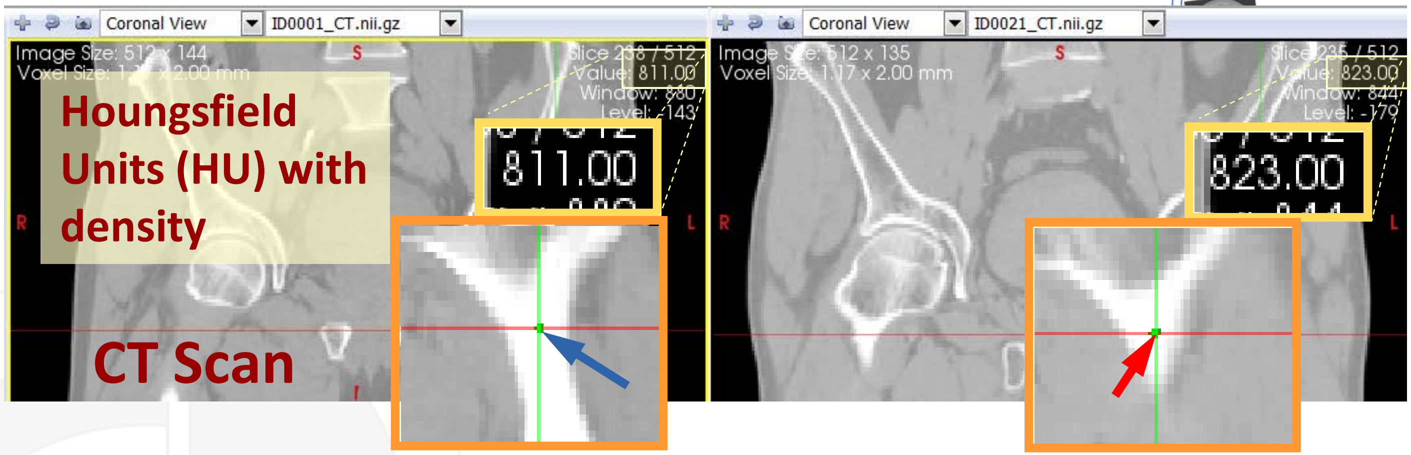


- Which features?
  - Intensity
    - Same modality
      - MR/MR, CT/CT, etc..
    - Different modality
      - MRI-PET-CT-CBCT, etc.
  - Landmarks
  - Distance maps
  - …

Similarity Measure

- Intensity-based
  - Same modality
    - The gray levels can be directly compared





- Sum of squared differences (SSD), point to point :

$$SSD = \frac{1}{n}\sqrt{\sum_i (\boxed{F(x_i)} - \boxed{T(M(x_i)})^2}$$

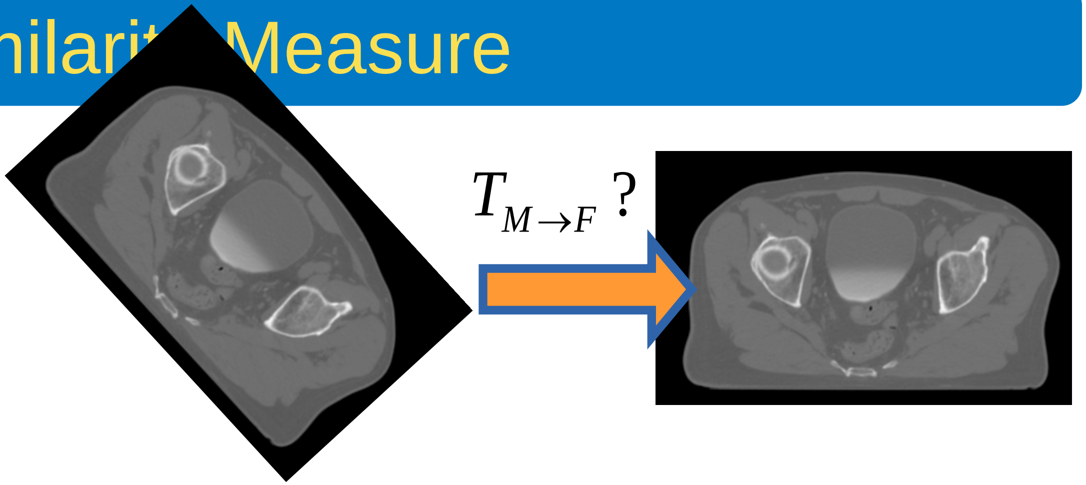
- Cross Correlation (CC)

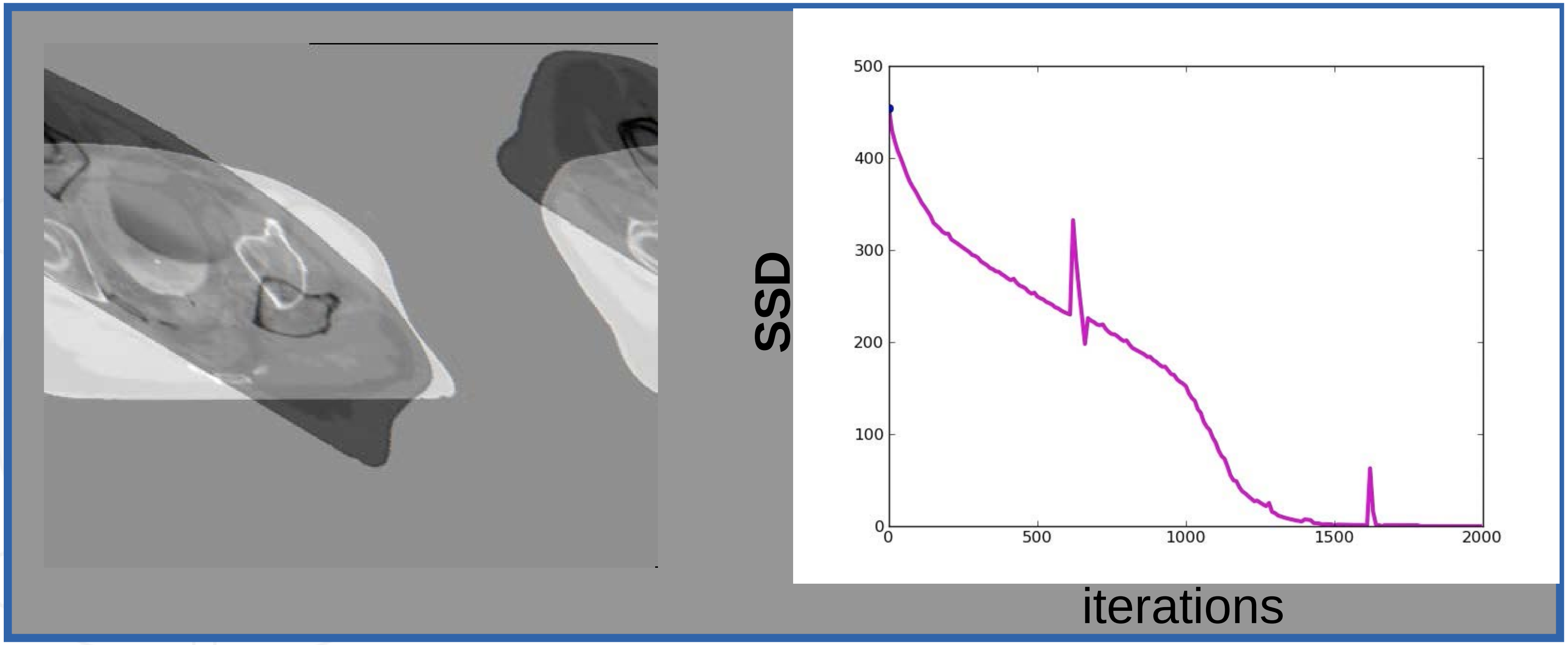
$$CC = \frac{\sum_i (F(x_i) - \bar{F}(x))(T(M(x_i)) - T(\bar{M}(x)))}{\sqrt{\sum_i (F(x_i) - \bar{F}(x))^2}\sqrt{\sum_i (T(M(x_i)) - T(\bar{M}(x)))^2}}$$

- ...

Similarity Measure

- Intensity-based



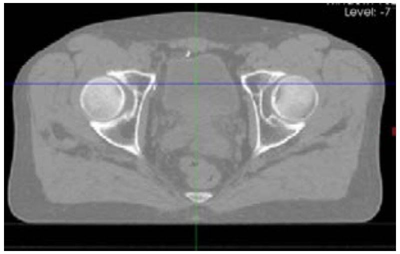


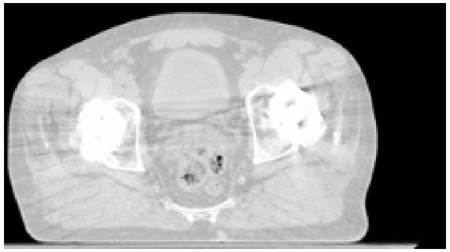
Difference

$$F(x_i) - T(M(x_i))$$

Similarity Measure

- Intensity based
  - Multimodal inputs!!!
    - Gray levels in different images can not be directly compared





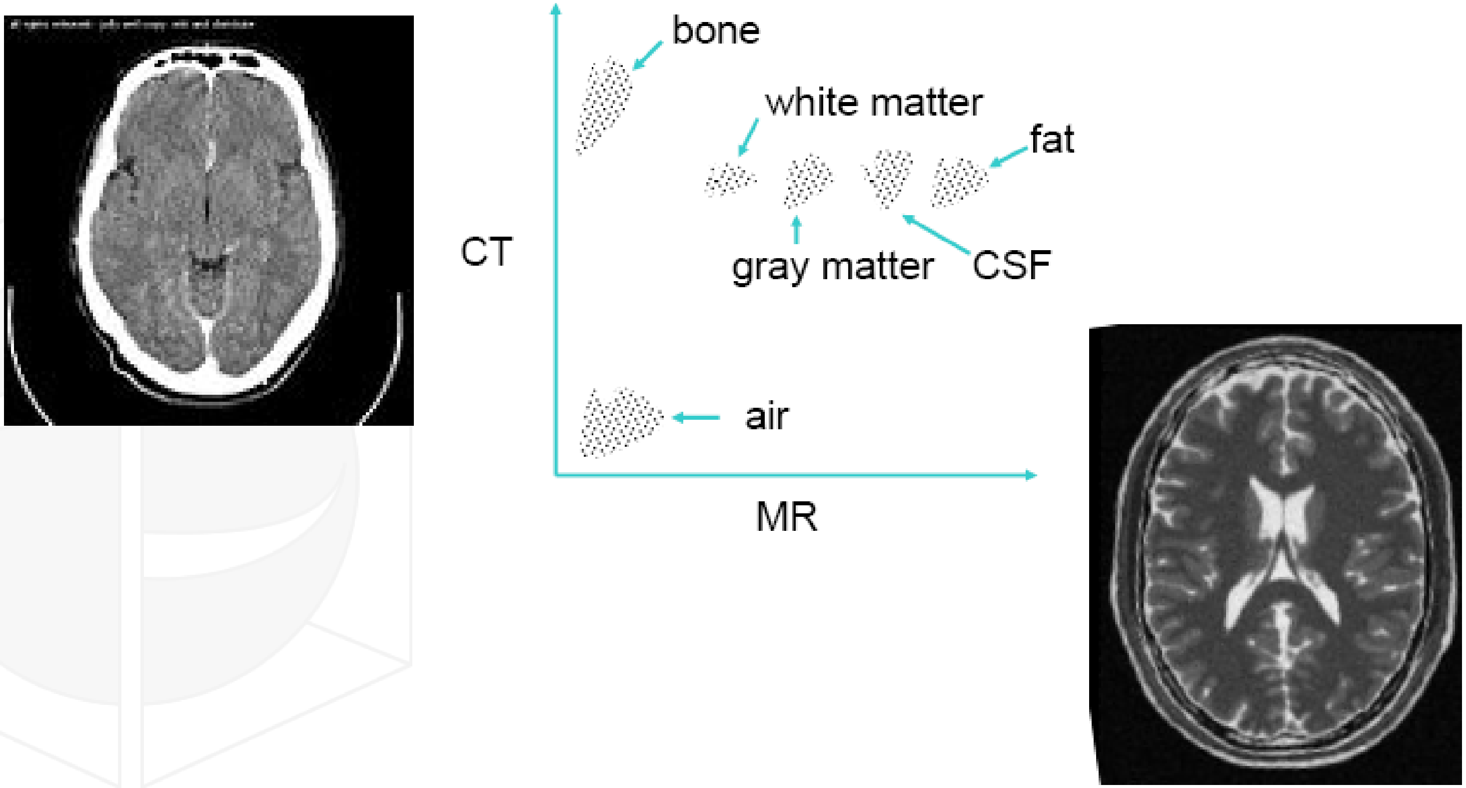
MRI CT/CBCT

  - Solutions
    - Apply a special intensity transform between modalities, then compute correlation [VanDenElsen *et al.* 1993]
    - More sophisticated similarity measures, *i.e.* Information theory (Mutual information) $MI(F,M) = H(F) + H(M) - H(F,M)$

$$= \sum \sum p_{fm}(i,j) \log \frac{p_{fm}(i,j)}{p_f(i)\, p_m(j)}$$

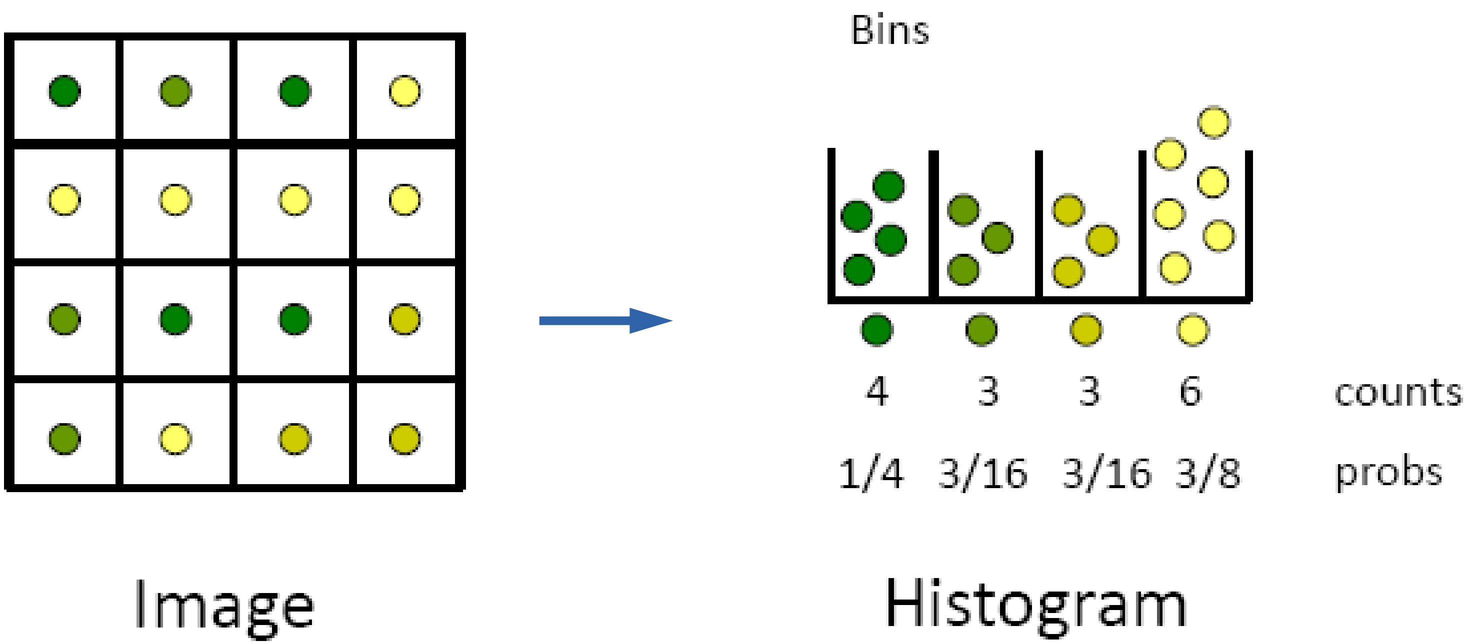
Mutual information

- It expresses the amount of information that one image A contains about a second image B
  - Information theoretical approach



Mutual information

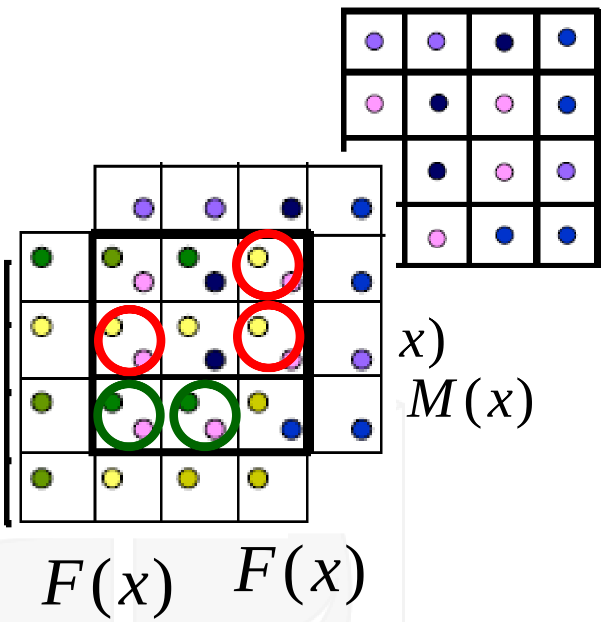
- Histogram calculation



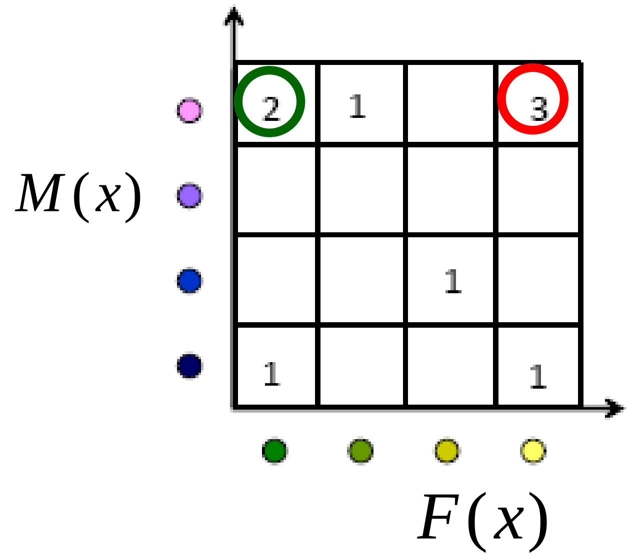
probability density function
which tells us the distribution of voxels

Mutual information

- Joint histogram calculation

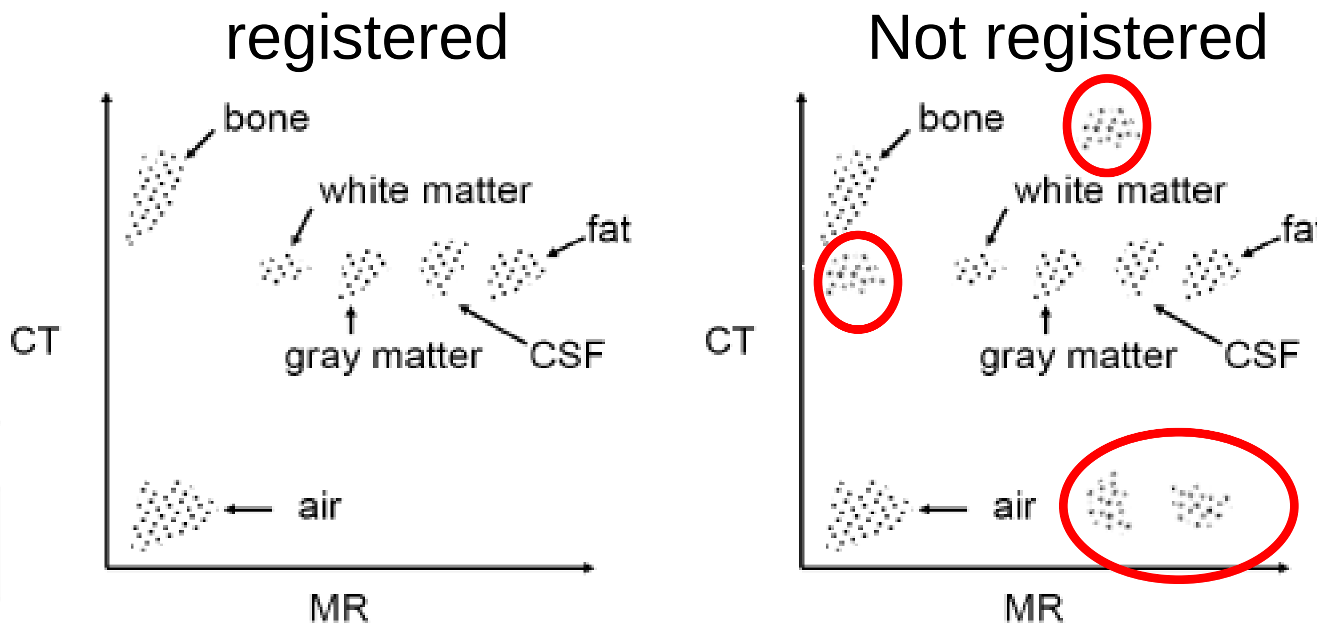


Given a transformation.. Tx= 1, ty =1..



The joint histogram represents the couples of information appearing..

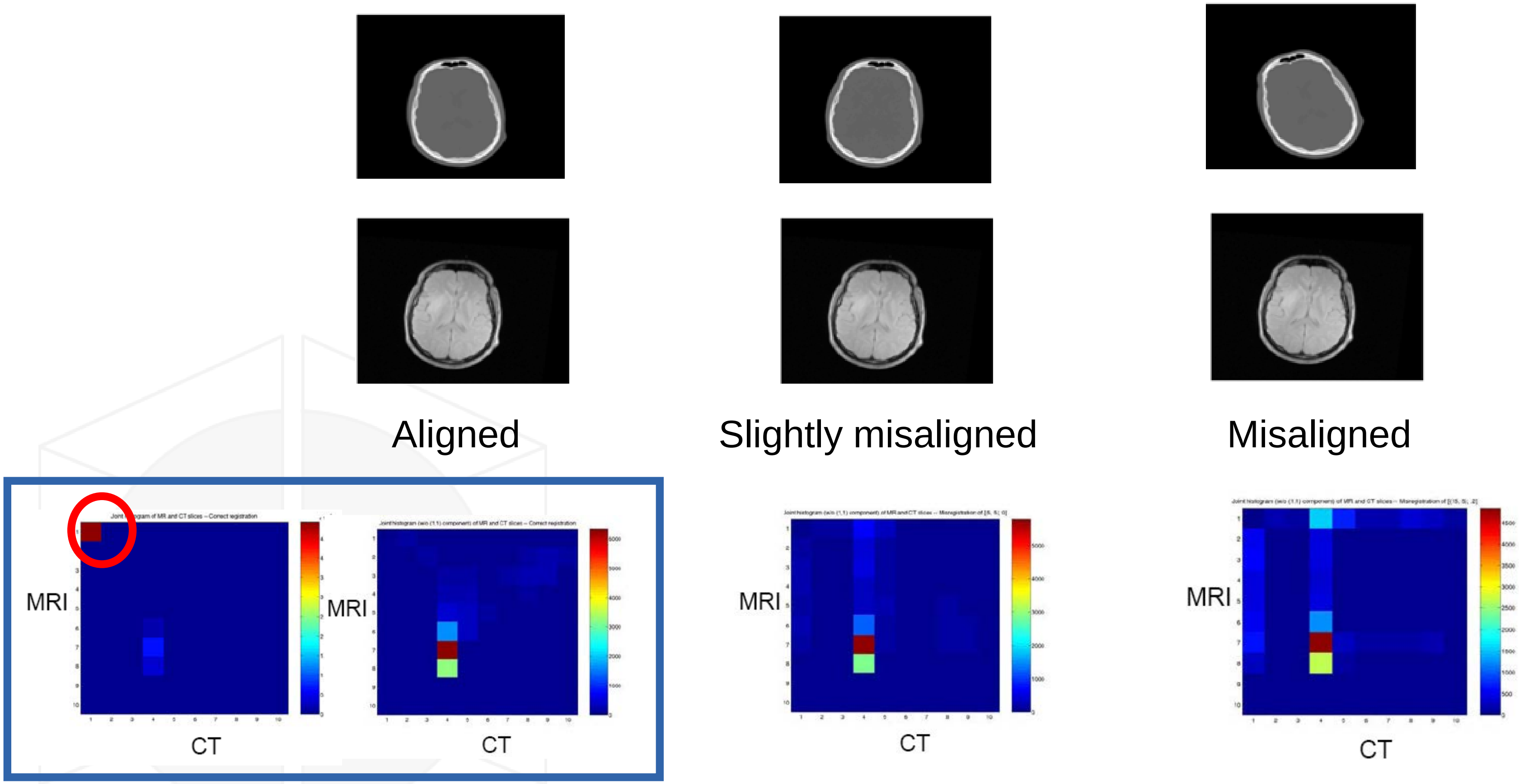
Mutual information



Source: W. Wells, MICCAI 2009

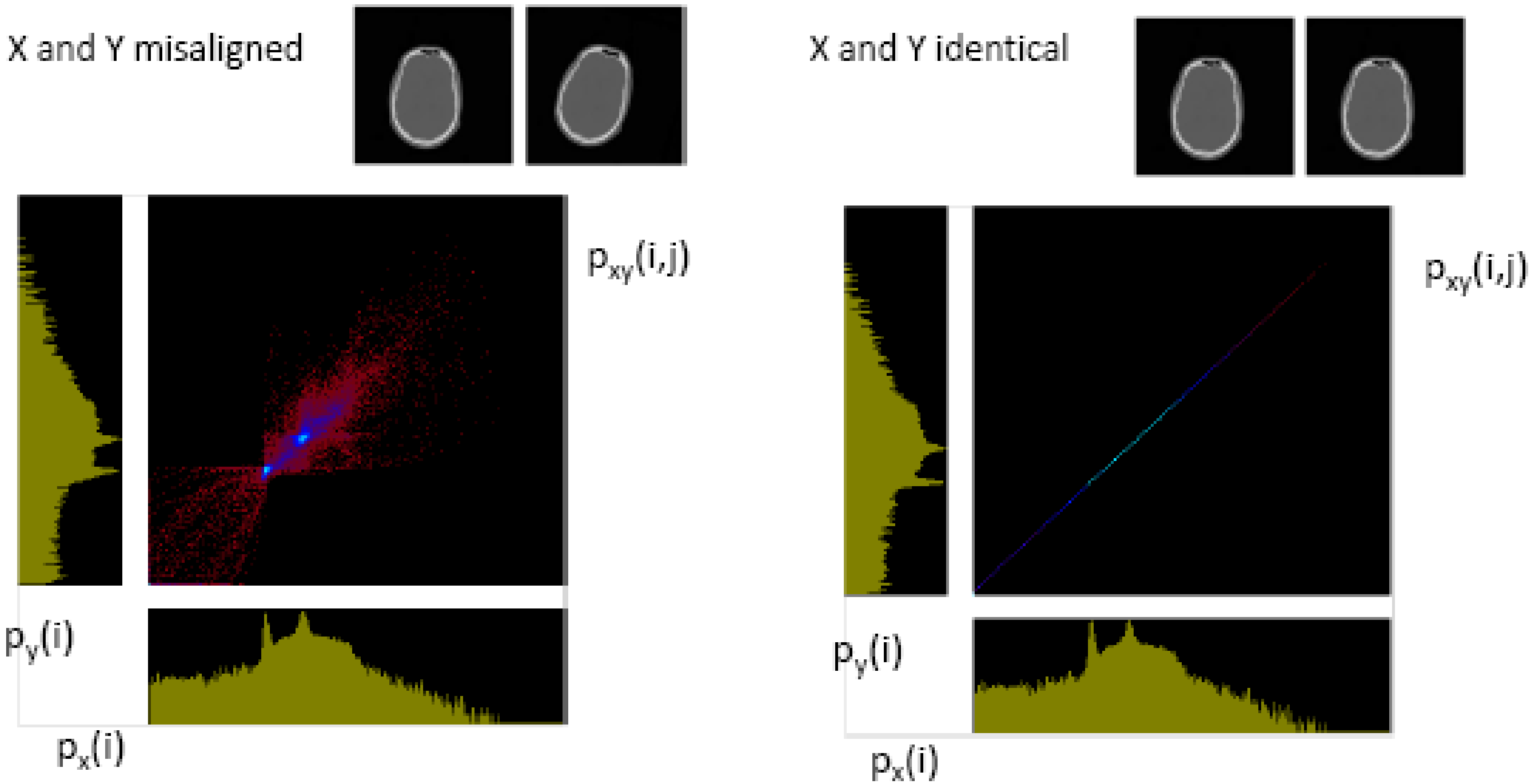
Mutual information

- Joint histogram



Lilla Zollei, IEEE EMBS Summer School Berder, Robust and accurate Alignment of structural images. 2010.

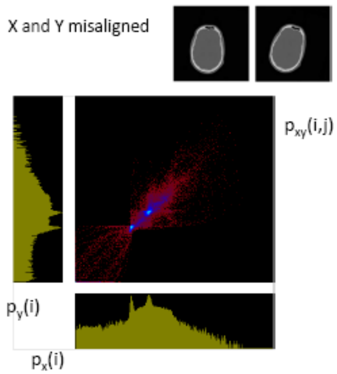
- Joint histogram similar modalities

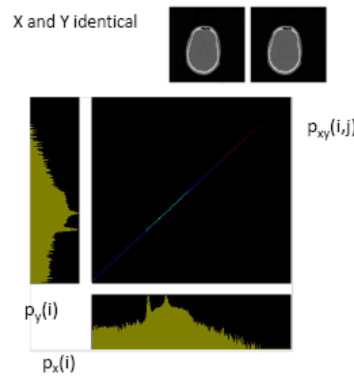


*Adapted from : Wachinger, MICCAI 2010, Tutorial Intensity Based Registration, Similarity Measures

Mutual information (MI)

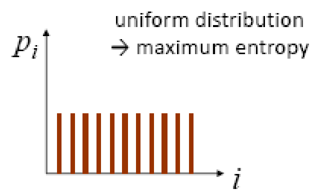
- Joint histogram similar modalities

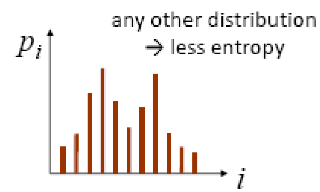




- Entropy

$$H(F) = -\sum_i p_f(i) \log$$





- MI

$$MI(F,M) = H(F) + H(M) - H(F,M)$$

$$= \sum \sum p_{fm}(i,j) \log \frac{p_{fm}(i,j)}{p_f(i)\, p_m(j)}$$

- NMI

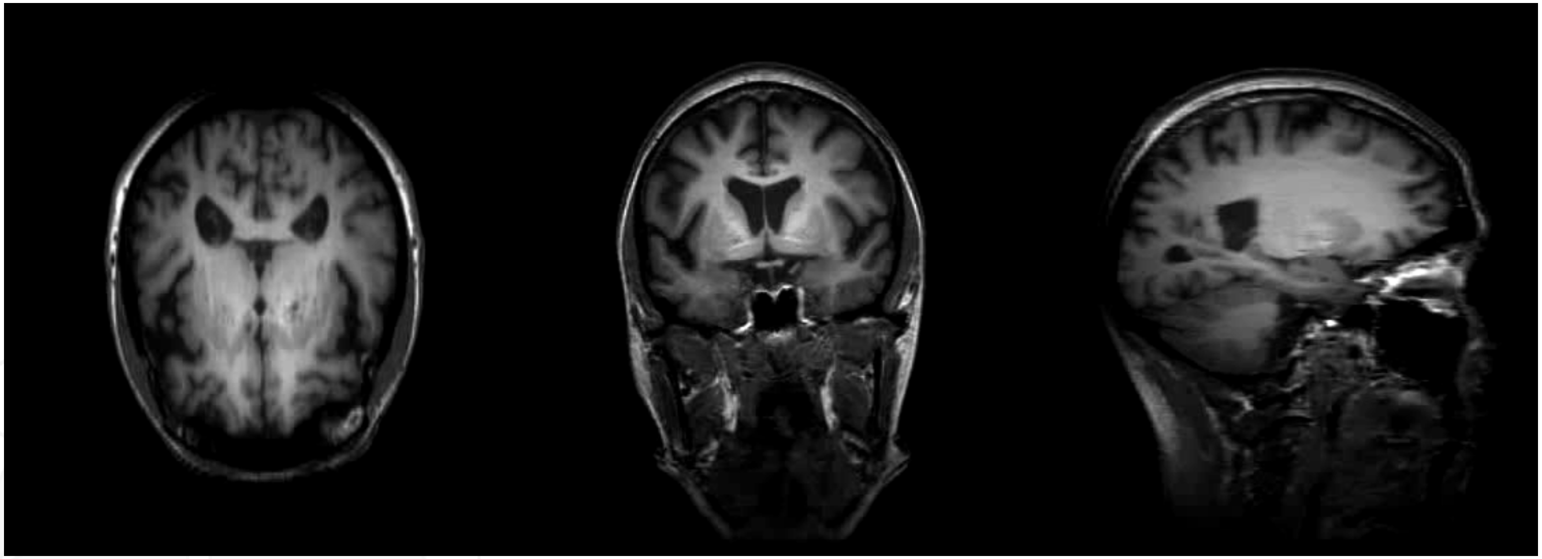
$$MI(F,M) = \frac{H(F)+H(M)}{H(F,M)}$$

- Maximized if F and M are perfectly aligned
- Maximization of mutual information leads to minimization of joint entropy

C. Studholme, D.L.G.Hill, D.J. Hawkes, An Overlap Invariant Entropy Measure of 3D Medical Image Alignment, Pattern Recognition, Vol. 32(1), Jan 1999, pp 71-86.

Mutual information

- Example (PET-MRI)

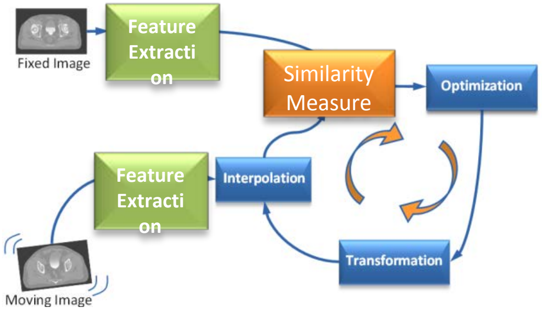


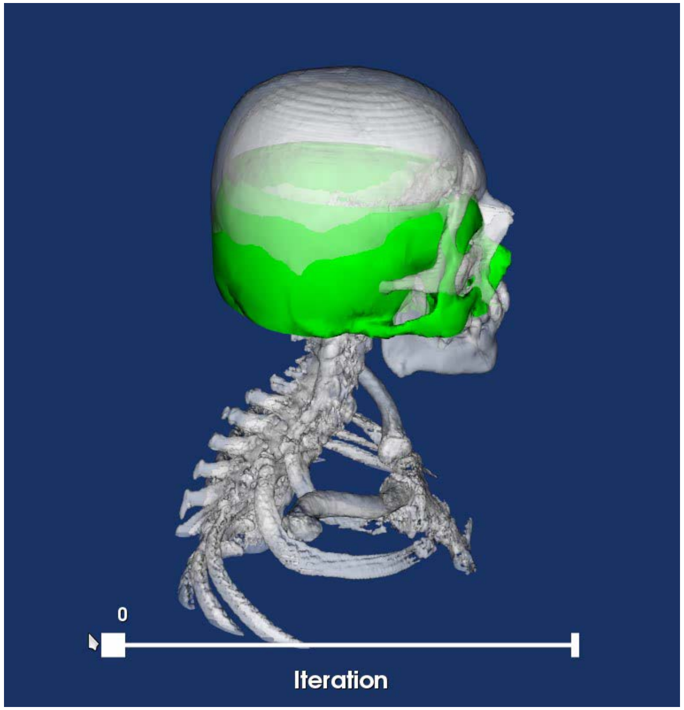
Courtesy CSIRO-Australia

β-Amyloid burden in the temporal neocortex is related to hippocampal atrophy in elderly subjects without dementiaP Bourgeat, G Chetelat, VL Villemagne, J Fripp, P Raniga, K Pike, ...
Neurology 74 (2), 121-127

Similarity Measure

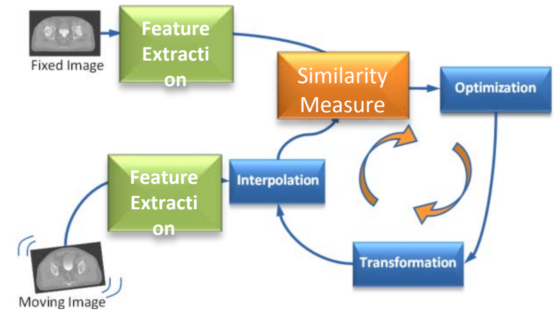
- Feature-based
  - Compute alignment quality based upon the agreement of 2 sets of landmarks features:
  - Assumption:
    - Landmarks are visible in both images
    - They can be reliably located
    - They can guide the alignment of the whole image





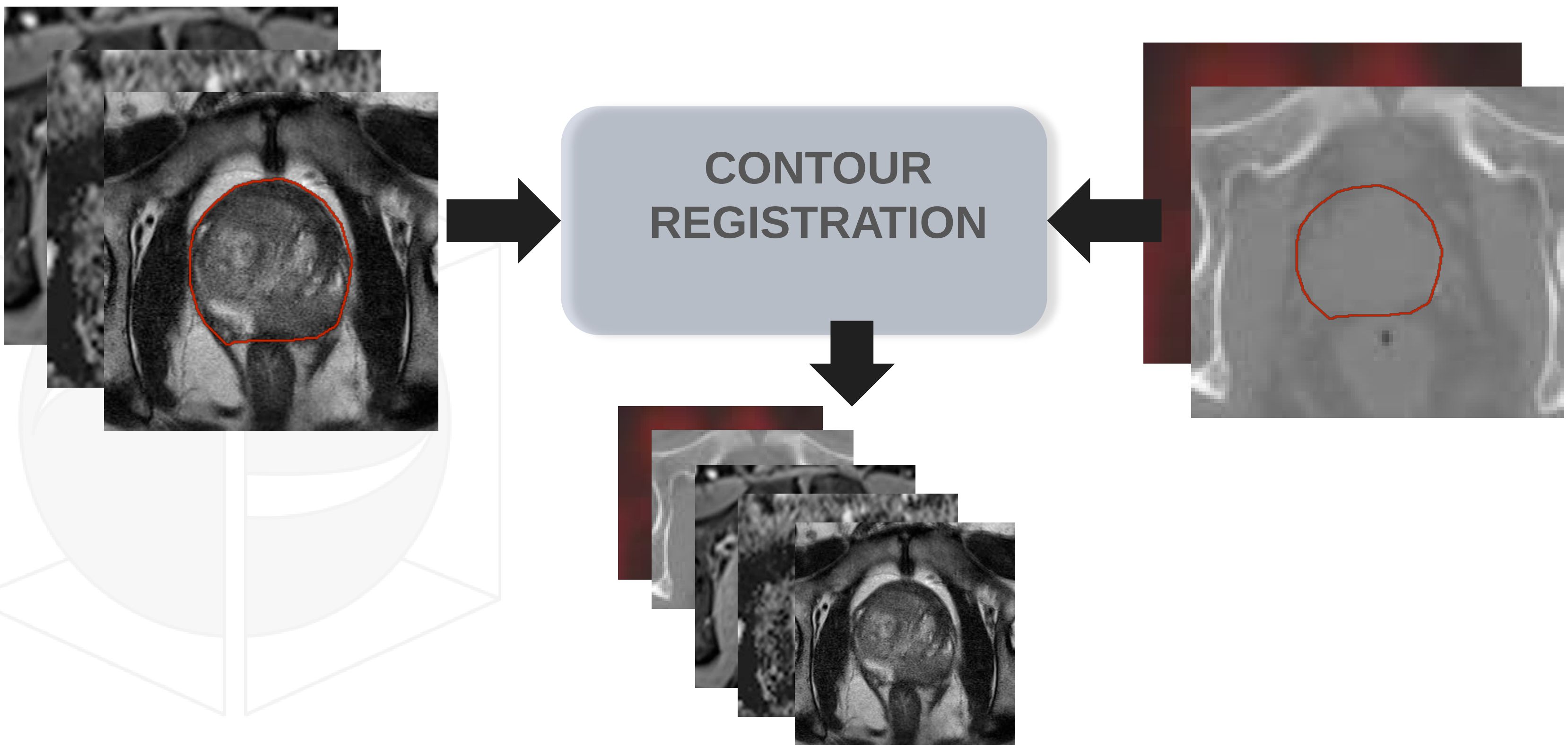
MR-CT Registration

- Feature-based

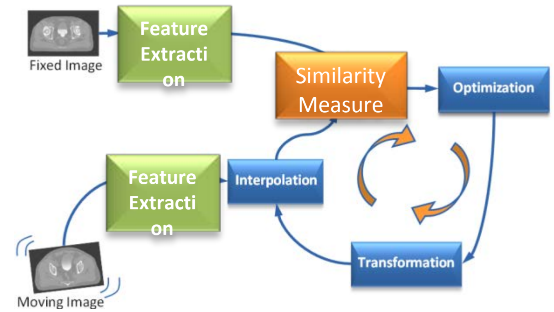


***in-vivo* T2MRI-CT Registration:**

- Small deformations.
- Displacent wrt neighboring structures

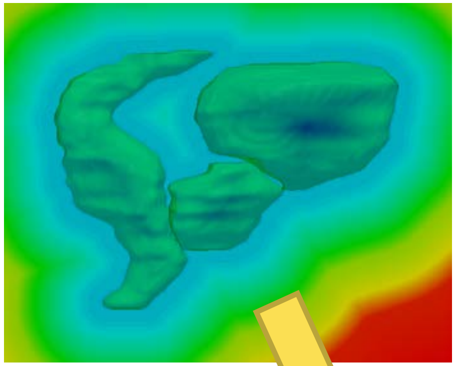


Similarity Measure

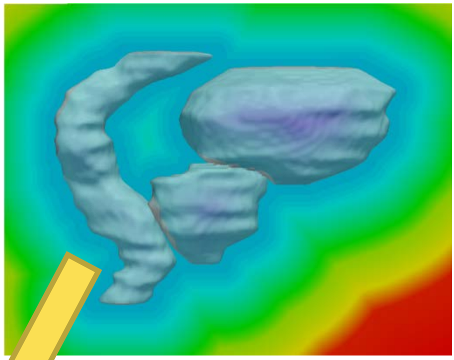


- Feature-based
  - Compute alignment quality based upon the agreement of 2 sets of landmarks features:
  - Assumption:
    - Landmarks are visible in both images
    - They can be reliably located
    - They can guide the alignment of the whole image

Distance Maps



CT Contours



CBCT Contours

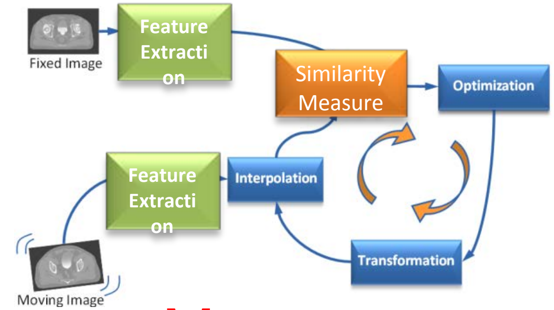
Constraints

“fast symmetric” Demons algorithm
[Wang, 2005]

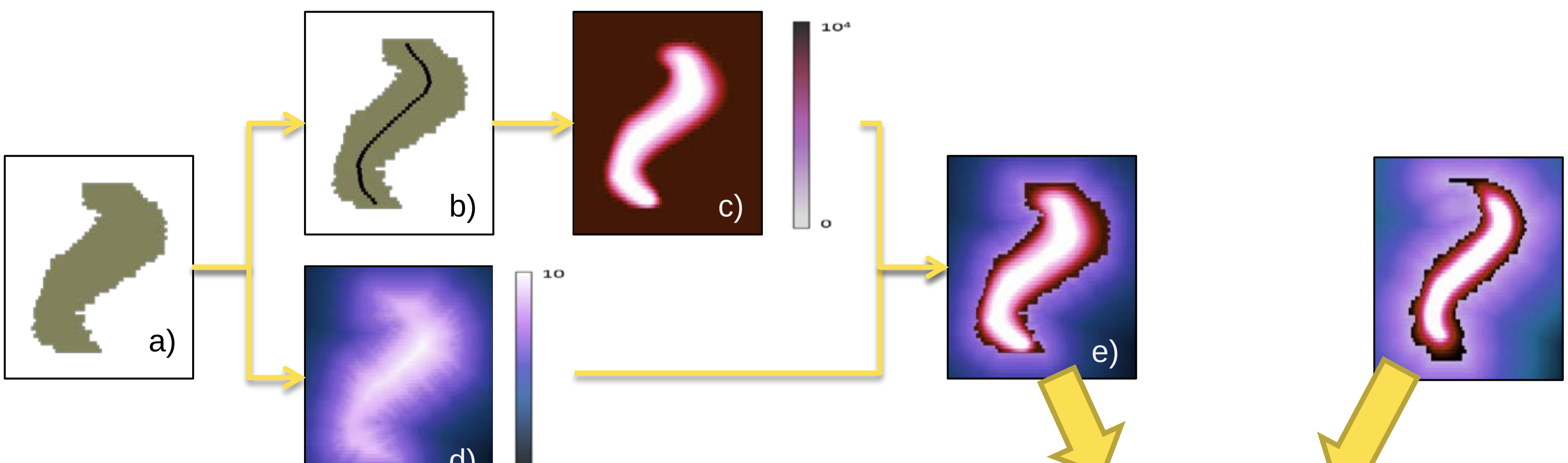
Cazoulat et al, 2014

Similarity Measure

- Feature-based
  - Compute alignment quality based upon the agreement of 2 sets of landmarks features:



Laplacian / Distance Maps

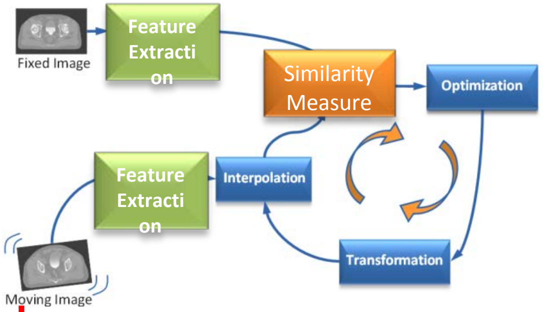


“fast symmetric” Demons algorithm
[Wang, 2005]

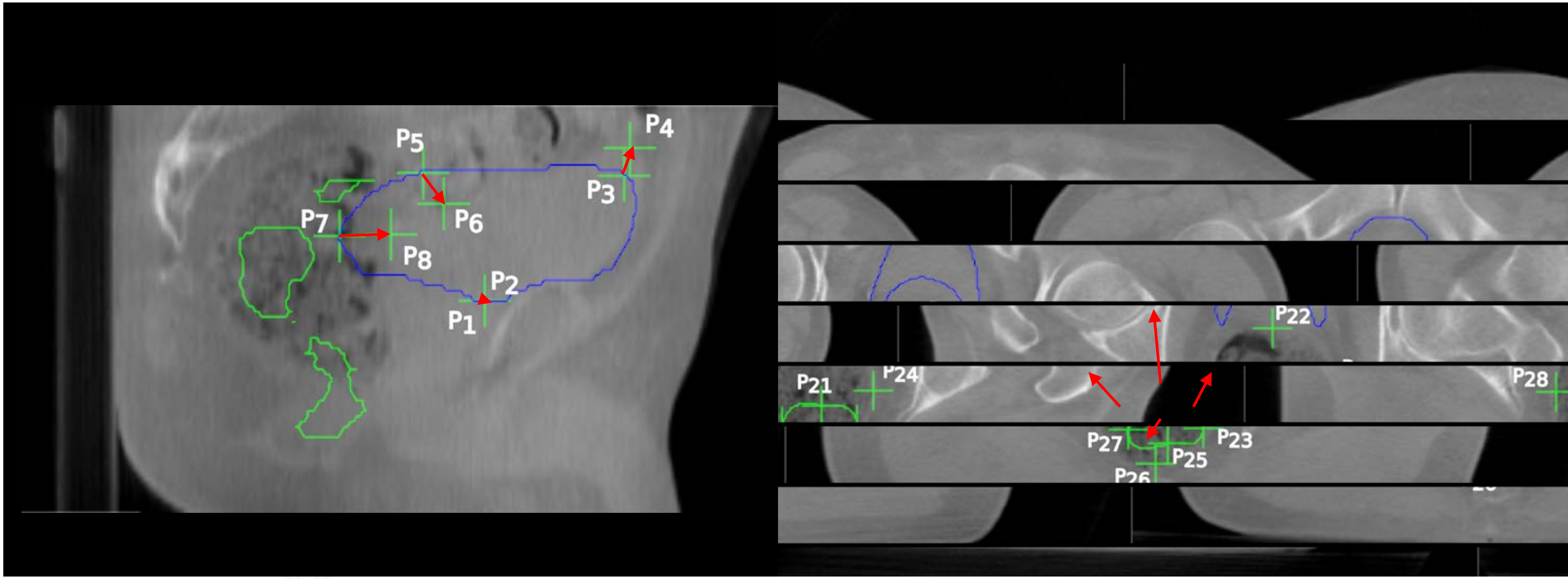
Drean et al, ESTRO 2015

Similarity Measure

- Feature-based
  - Compute alignment quality based upon the agreement of 2 sets of landmarks features:



Manual landmarks



Cazoulat et al, IEEE TMI 2014

Self similarity

Medical Image Analysis 16 (2012) 1423–1435

Contents lists available at SciVerse ScienceDirect

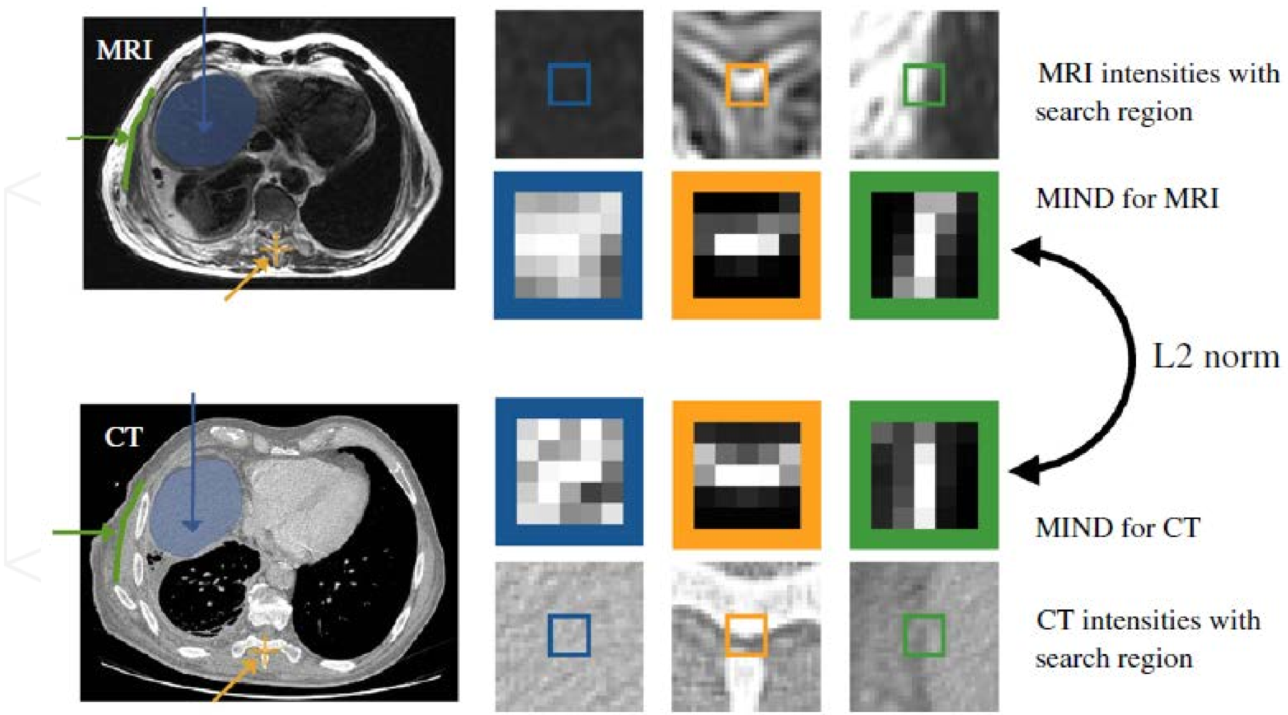
Medical Image Analysis

journal homepage: www.elsevier.com/locate/media

ELSEVIER

MIND: Modality independent neighbourhood descriptor for multi-modal deformable registration

Mattias P. Heinrich[a,b,*], Mark Jenkinson[b], Manav Bhushan[a,b], Tahreema Matin[d], Fergus V. Gleeson[d], Sir Michael Brady[c], Julia A. Schnabel[a]

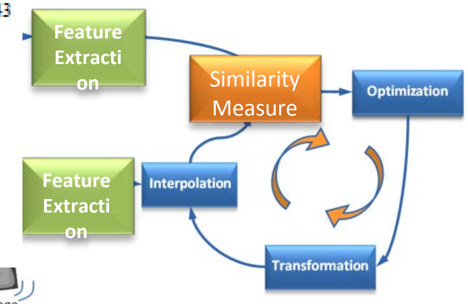


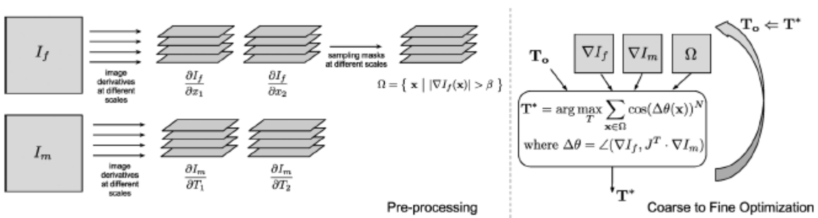
Gradient orientations

IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 31, NO. 12, DECEMBER 2012 2343

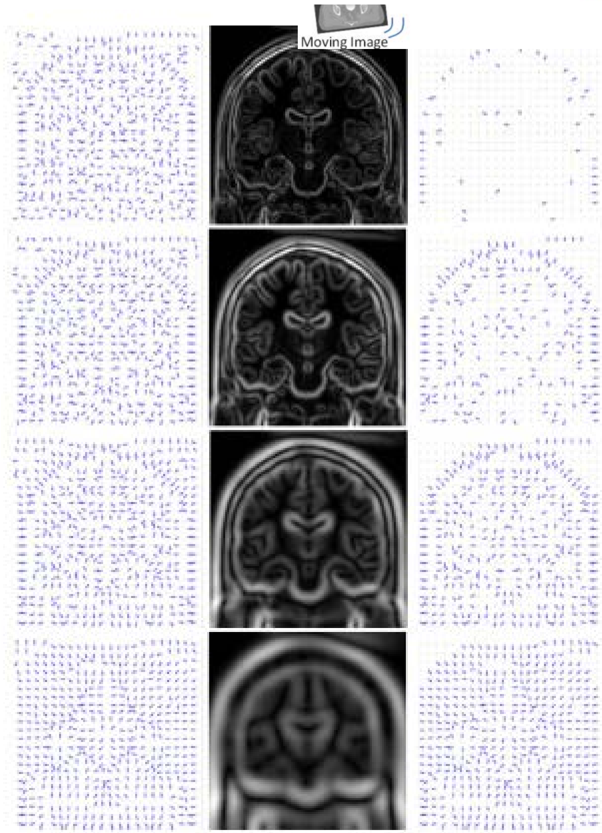
Multi-Modal Image Registration Based on Gradient Orientations of Minimal Uncertainty

Dante De Nigris*, D. Louis Collins, *Member, IEEE*, and Tal Arbel, *Member, IEEE*



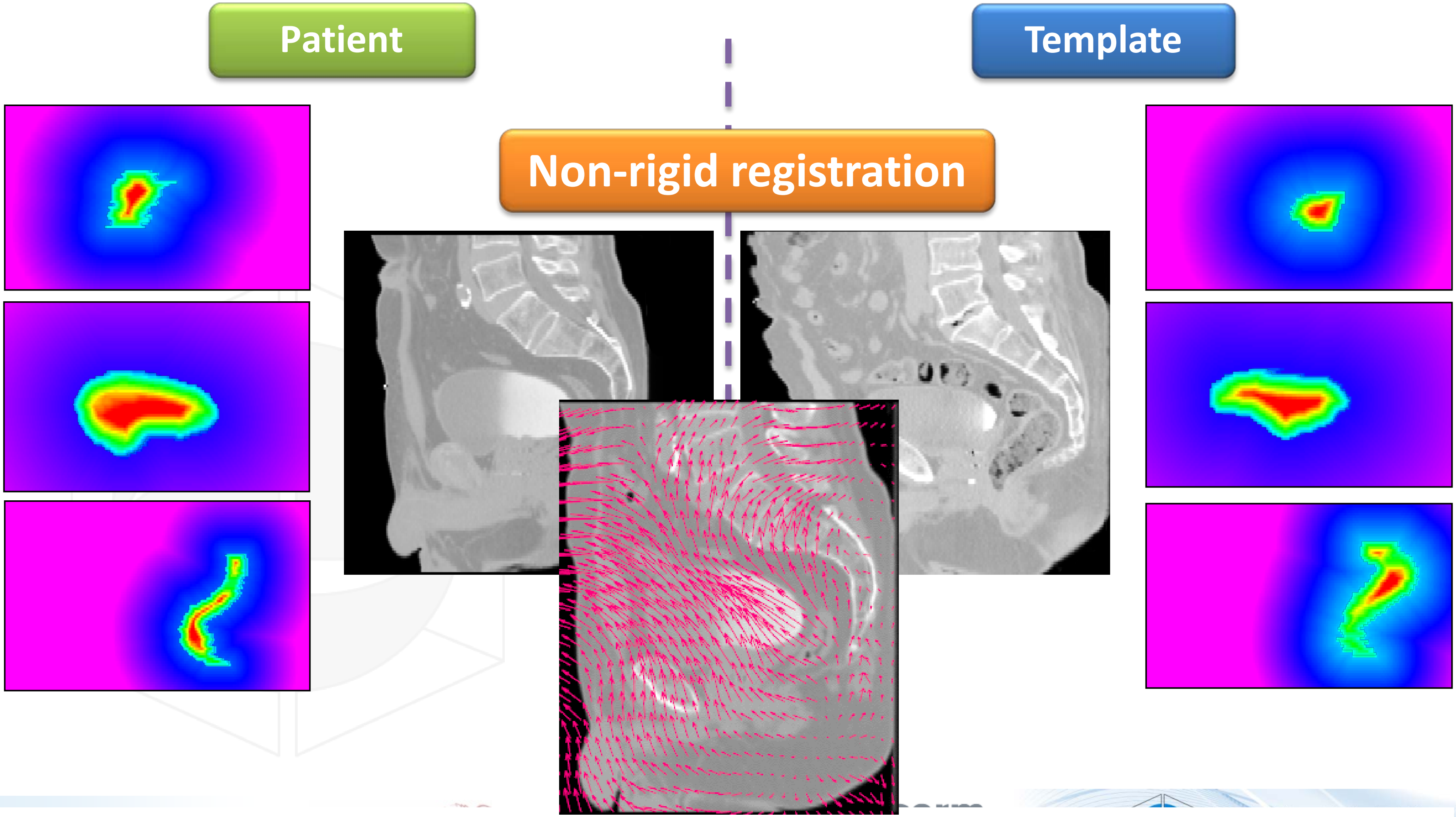


$$\left.\frac{\partial I_m}{\partial x_j}\right|_{T(x)} = \sum_i^D \left.\frac{\partial I_m}{\partial T_i}\right|_{T(x)} \cdot \left.\frac{\partial T_i}{\partial x_j}\right|_{x}$$



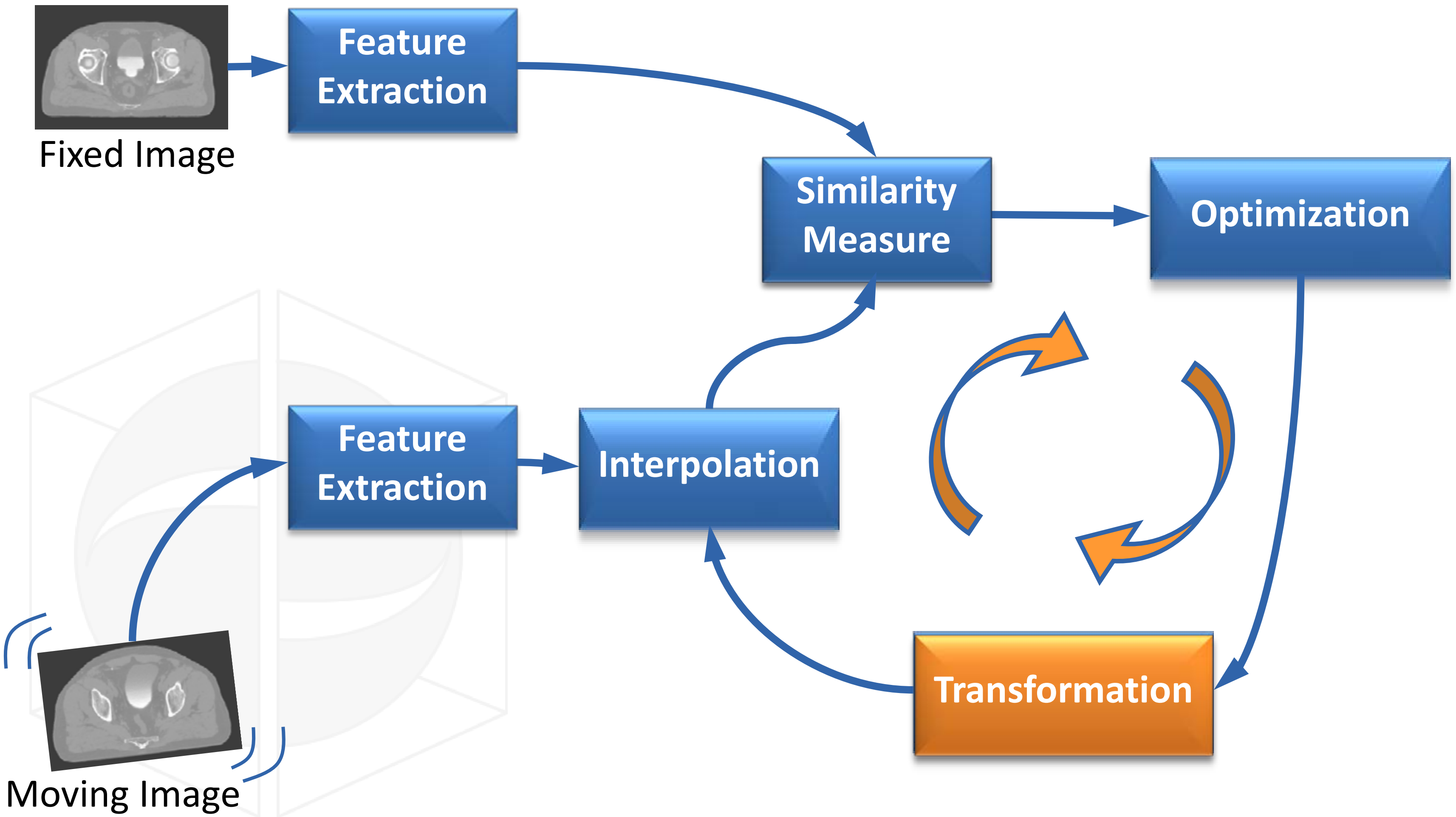
Combined intensity/features

- Taking advantage of organ segmentations



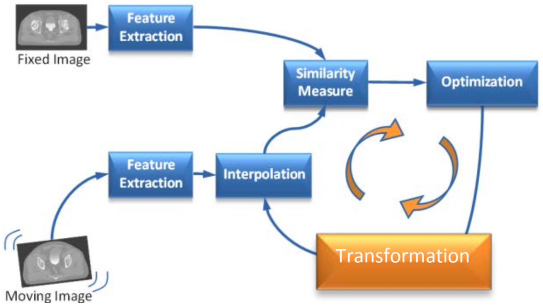
Dréan G, Acosta O., Simon A., de Crevoisier R. and Haigron P. , "Inter-individual organ-driven CT registration for dose mapping in prostate cancer radiotherapy", in The IEEE International Symposium on Biomedical Imaging (ISBI), Barcelona, SPAIN 2012. IEEE ISBI, p. 370-73

General registration framework



Transformation : Motions or distortions allowed?

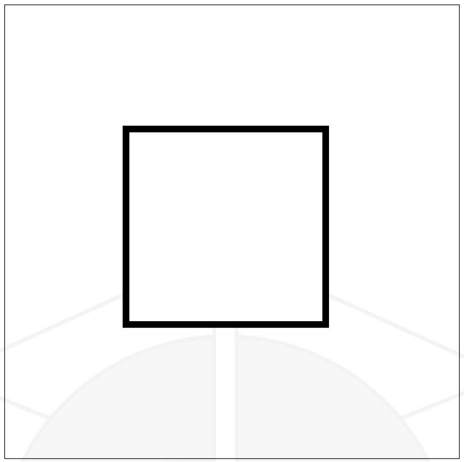
- Rigid
  - Displacement
  - Rotation & Displacement
- Affine / Piecewise-affine
  – Rotation & Displacement & shear
- Non-rigid
  – FFD → Geometric
  – FEM → Physical
  – FLUID → Physical, dynamic



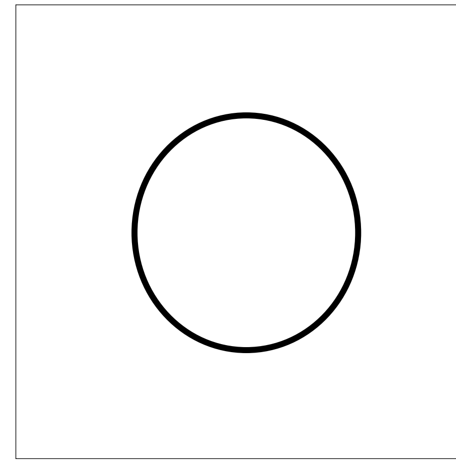
Transformation

- Rigid
  - Global deformation (Parametric)

$$T_{M \rightarrow F}\ ?$$



Moving image

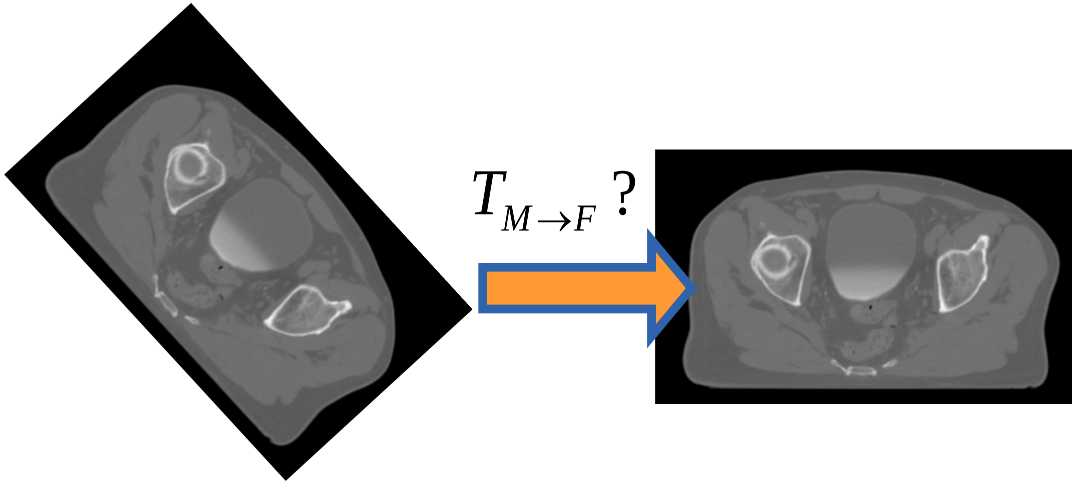


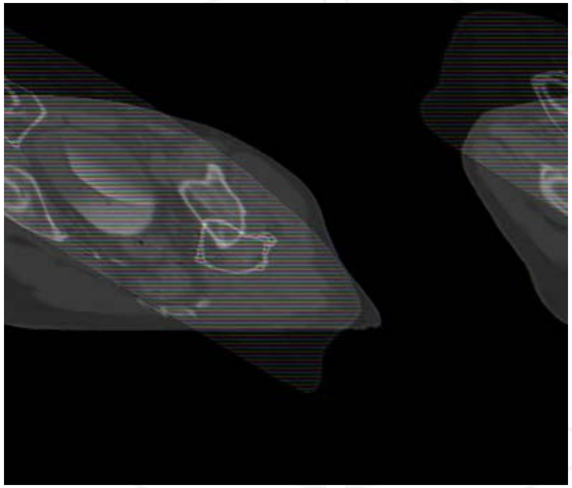
Fixed image

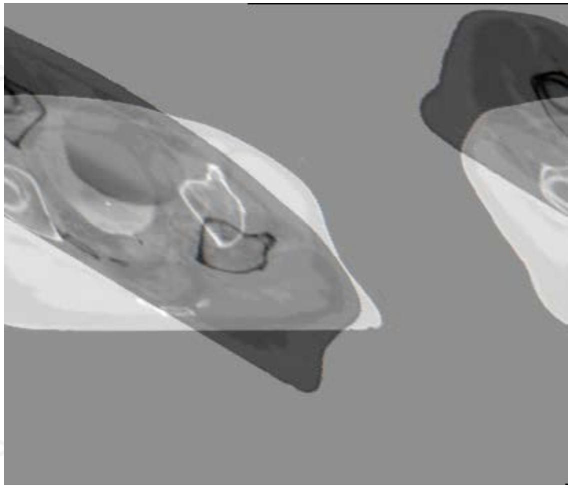
$$\begin{array}{c}
\\
\begin{vmatrix} x_{absolu(hom)} \\ y_{absolu(hom)} \\ z_{absolu(hom)} \\ w_{absolu(hom)} \end{vmatrix}
\end{array}
=
\begin{array}{c}
\text{rotation} \quad \text{scale} \qquad\qquad \text{translation} \\
\begin{vmatrix} M_{1,1} & M_{1,2} & M_{1,3} & M_{1,4} \\ M_{2,1} & M_{2,2} & M_{2,3} & M_{2,4} \\ M_{3,1} & M_{3,2} & M_{3,3} & M_{3,4} \\ M_{4,1} & M_{4,2} & M_{4,3} & M_{4,4} \end{vmatrix}
\end{array}
\times
\begin{array}{c}
\\
\begin{vmatrix} x_{local} \\ y_{local} \\ z_{local} \\ 1 \end{vmatrix}
\end{array}$$

Transformation

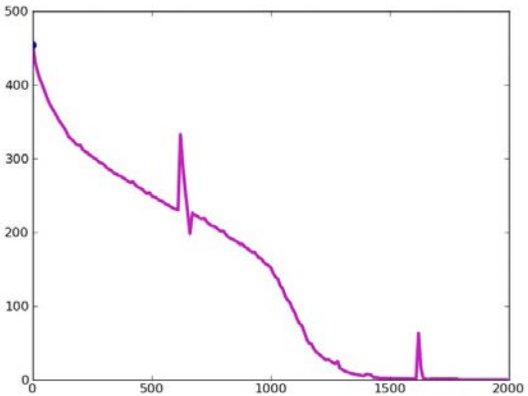
- Rigid
  - Global deformation





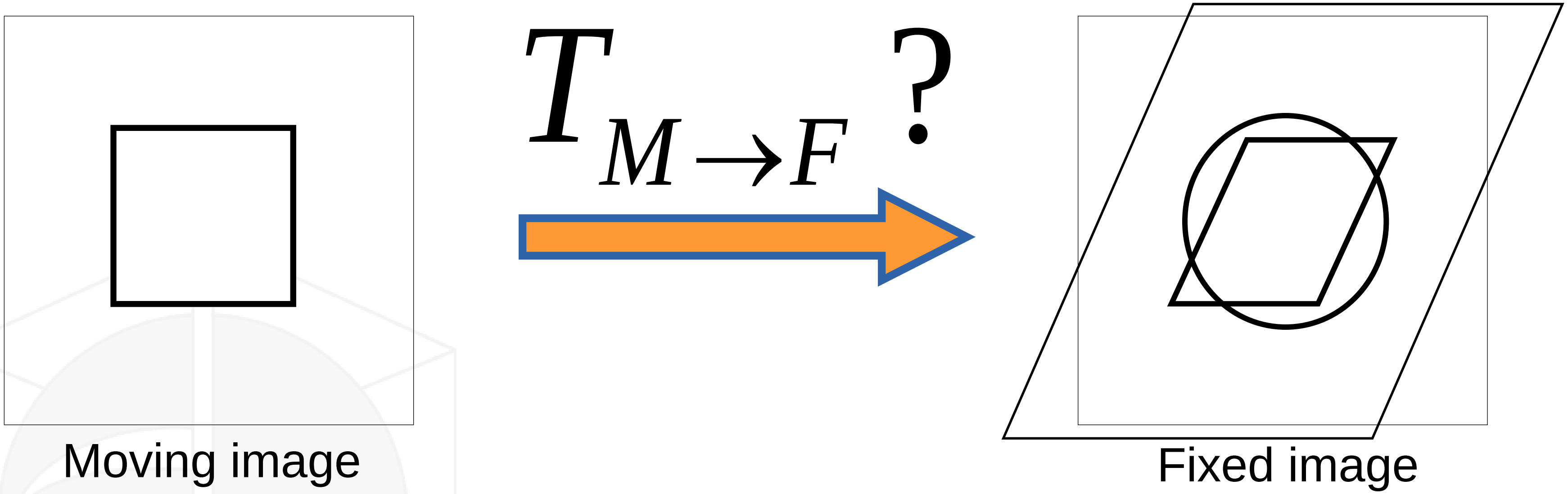


Pelvic CT



Transformation

- Affine
  - Global deformation (Parametric)



Rigide/Affine Transformations

- Rigide/Affine
  - General 2D form

$$[x\ y\ 1] = [v\ w\ 1]T = [v\ w\ 1]\begin{bmatrix} t_{11} & t_{12} & 0 \\ t_{21} & t_{22} & 0 \\ t_{31} & t_{32} & 1 \end{bmatrix}$$

Rigide/Affine Transformations

- Rigide/Affine
  - General 2D form

$$[x\ y\ 1] = [v\ w\ 1]T = [v\ w\ 1]\begin{bmatrix} t_{11} & t_{12} & 0 \\ t_{21} & t_{22} & 0 \\ t_{31} & t_{32} & 1 \end{bmatrix}$$

    - Identity

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

    - Scaling

$$\begin{bmatrix} c_x & 0 & 0 \\ 0 & c_y & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

    - Rotation

$$\begin{bmatrix} \cos\theta & \sin\theta & 0 \\ -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

    - Translation

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ t_x & t_y & 1 \end{bmatrix}$$

- Shear (vertical)

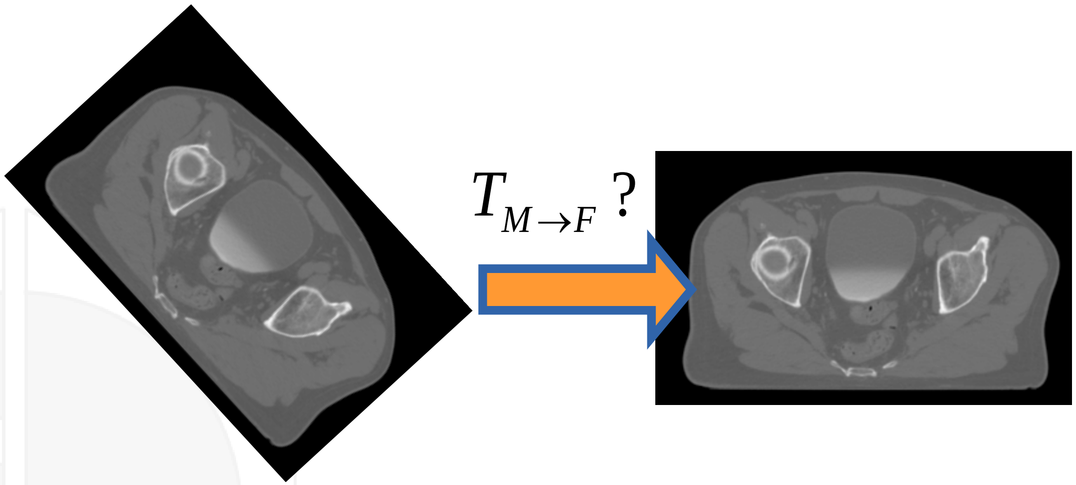
$$\begin{bmatrix} 1 & 0 & 0 \\ s_v & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

- Shear (horizontal)

$$\begin{bmatrix} 1 & s_h & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Rigide/Affine Transformations

– Rigide
– Affine

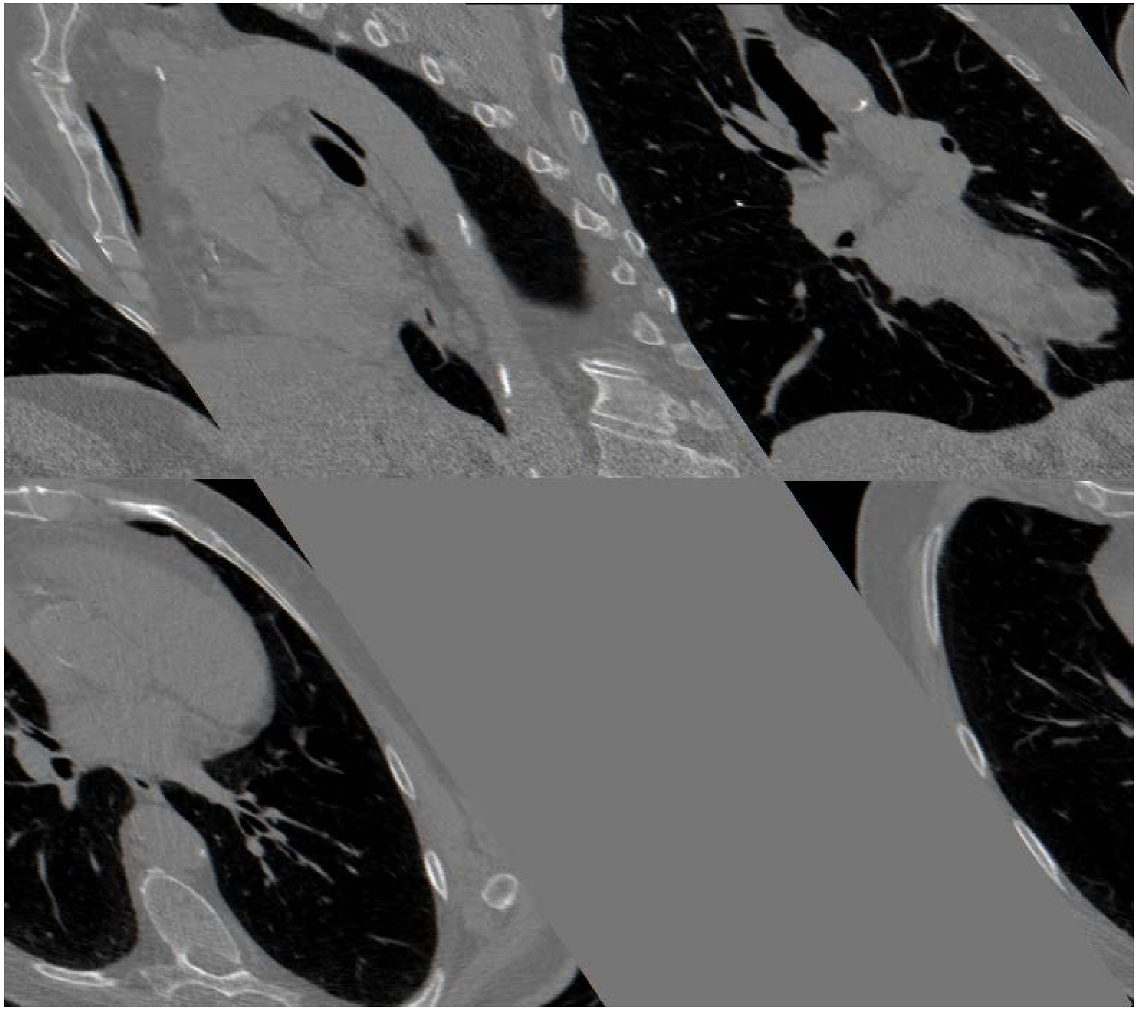


Exemple 2D

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Transformation

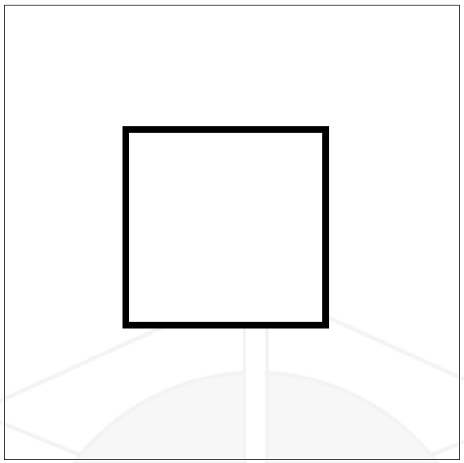
- Affine



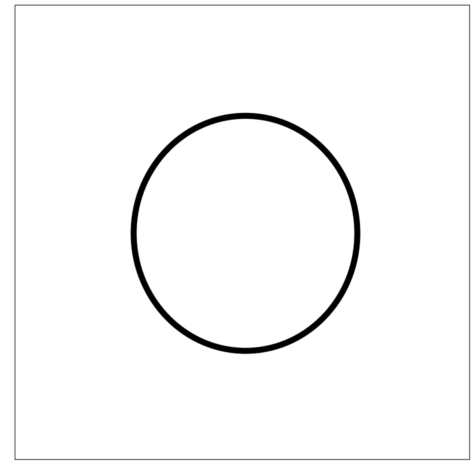
Lung CT

Transformation

- Non-rigid
  - Parametric/non parametric deformation

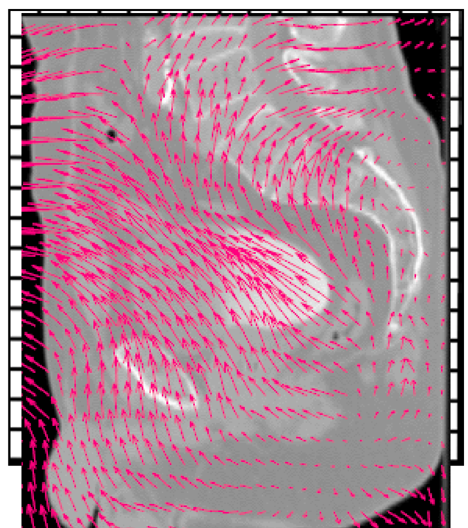


$$T_{M \to F}\ ?$$



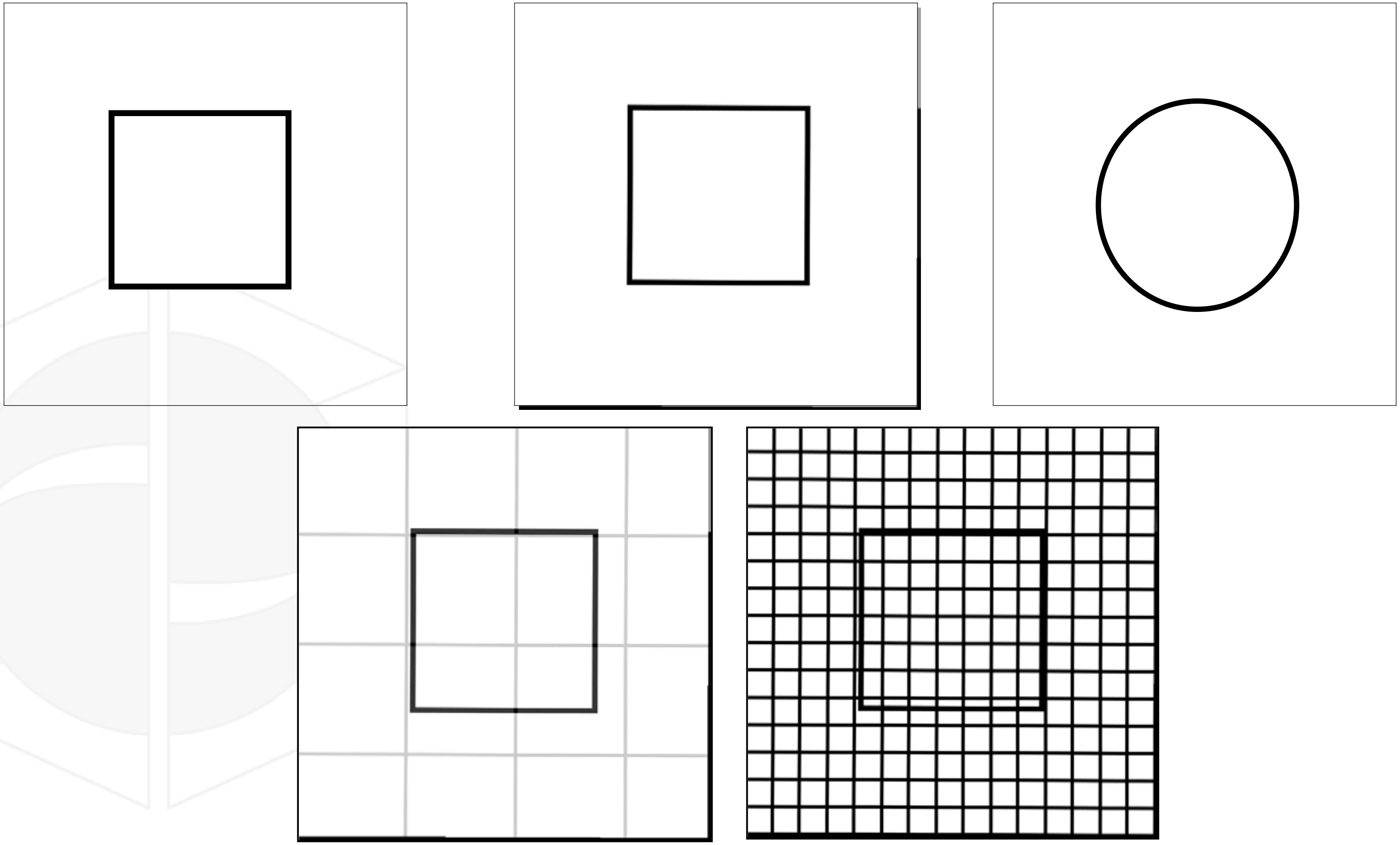
Moving image

Fixed image



Transformation

- Non-rigide
  - Parametric: Geometric and defined for instance by a bspline



Rueckert et al,"Non rigid registration using free form deformations: Application to breast MR Images" , IEEE TMI, 99

Transformation

- Non-rigide: Geometric (FFD),
  - Bspline deformation

$$\mathbf{T}_{\mathrm{local}}(x, y, z) = \sum_{l=0}^{3} \sum_{m=0}^{3} \sum_{n=0}^{3} B_l(u) B_m(v) B_n(w) \phi_{i+l,\, j+m,\, k+n}$$

$$B_0(u) = (1-u)^3/6$$
$$B_1(u) = (3u^3 - 6u^2 + 4)/6$$
$$B_2(u) = (-3u^3 + 3u^2 + 3u + 1)/6$$
$$B_3(u) = u^3/6.$$

712 IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 18, NO. 8, AUGUST 1999

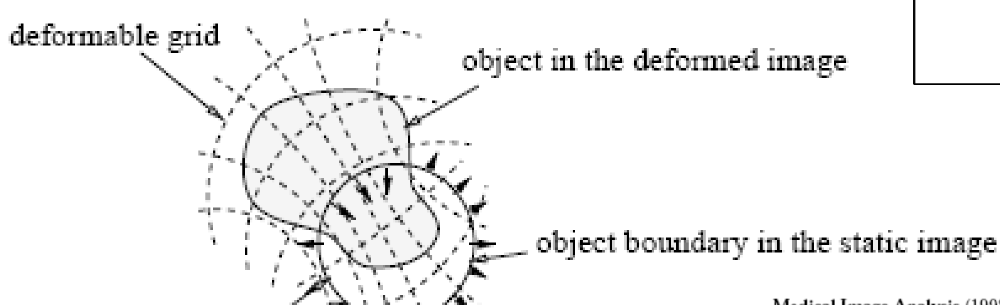
Nonrigid Registration Using Free-Form Deformations: Application to Breast MR Images

D. Rueckert,* L. I. Sonoda, C. Hayes, D. L. G. Hill, M. O. Leach, and D. J. Hawkes

- Non-rigide
  - Demons

Flux optique :

$$\vec{T} = \frac{2(m-s).\left(\vec{\nabla}(+) + \vec{\nabla}(s)\right)}{\left\|\vec{\nabla}(m) + \vec{\nabla}(s)\right\|^2}$$



243–260

650 IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 29, NO. 3, MARCH 2010

Spherical Demons: Fast Diffeomorphic Landmark-Free Surface Registration

B. T. Thomas Yeo*, Mert R. Sabuncu, Tom Vercauteren, Nicholas Ayache, Bruce Fischl, and Polina Golland

process: an analogy with Maxwell's

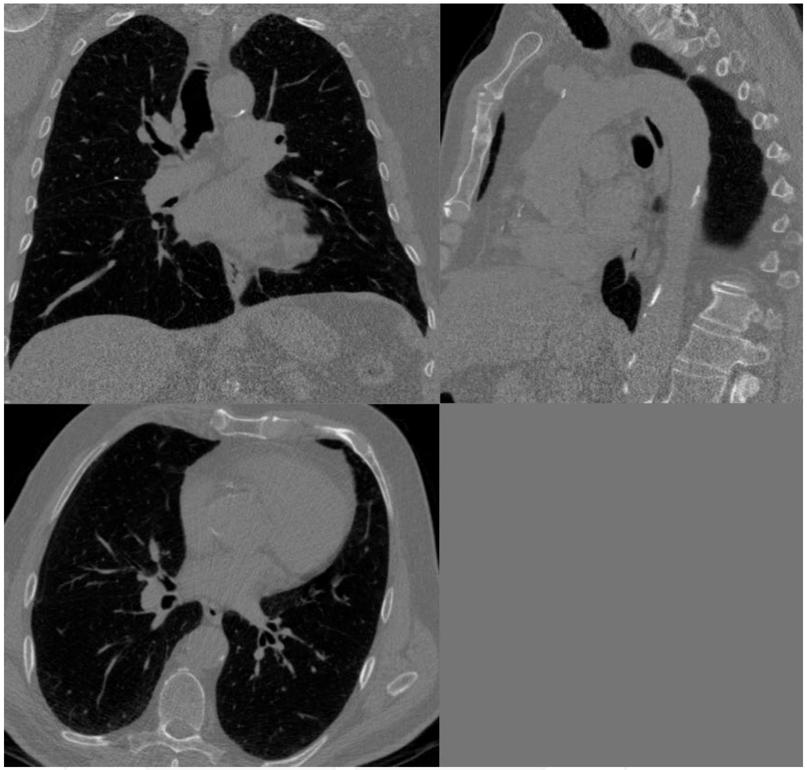
J.-P. Thirion*

Thyrion et al, 1999

Vercauteren, et al, *Non-parametric diffeomorphic image registration with demons algorithm*, in Medical Image Computing and Computer-Assisted Intervention, October 2007, vol. 4792 of LNCS, pp. 319-326.

Transformation

- Lung intra-individual CT to CT

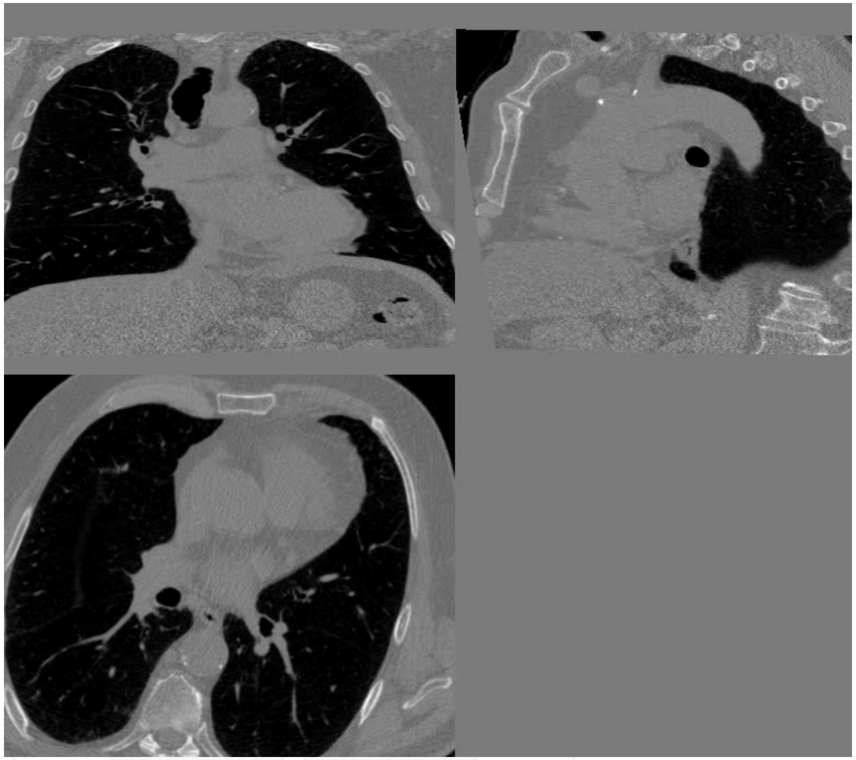


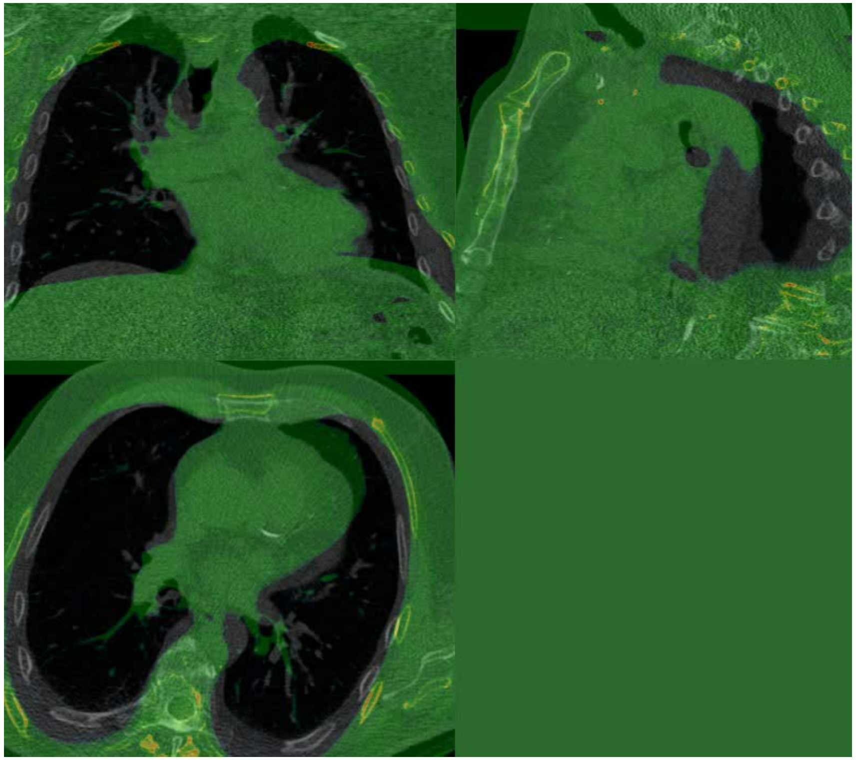
Moving

Fixed

Transformation

- Lung intra-individual CT to CT





• **Similarity**: Rubeaux et al. Edgeworth-based approximation of Mutual Information for medical image registration, International Conference on Image Processing Theory, Tools and Applications (IPTA), Evry, 2010.
• **Optimization**: S. Klein, J.P.W. Pluim, M. Staring and M.A. Viergever, "Adaptive Stochastic Gradient Descent Optimisation for Image Registration," International Journal of Computer Vision, in press.

Transformation

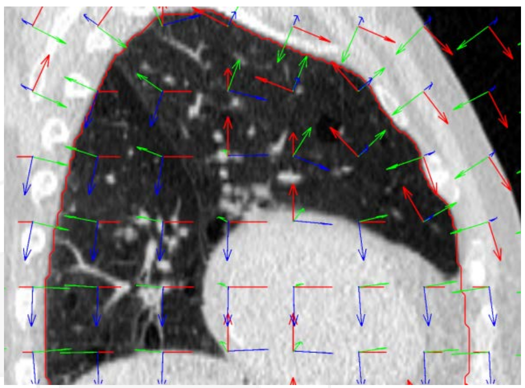
- Prostate inter-individual
  - Global deformation (regular non-rigid)

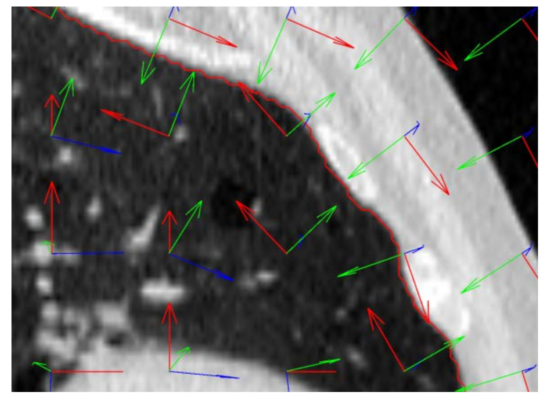
Large deformations
Poor tissue contrast

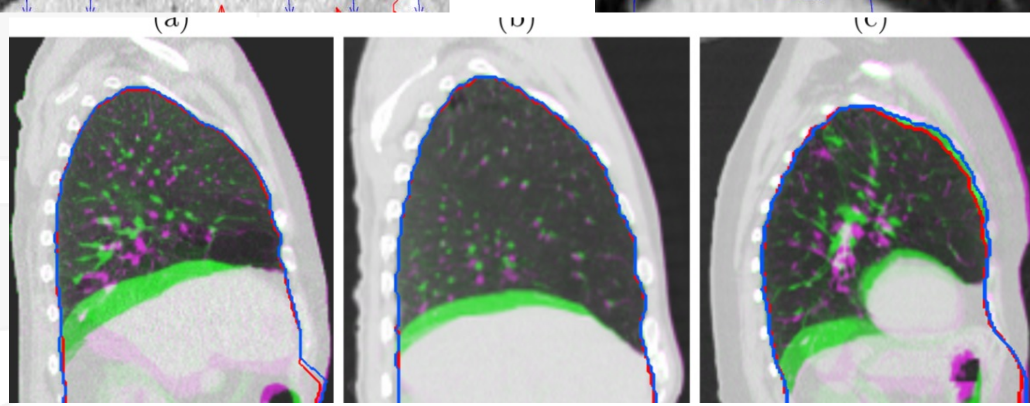
Dréan G, et al. "Evaluation of inter-individual pelvic CT-scans registration", Imagerie et Recherche Biomédicale IRBM, 32 (5), Nov 2011, 288-292

Transformation

- Lung interface
  - Constrained transformation (free at the interface)
  - Region-wise regular (non-rigid)







Vivien Delmon, et al. PMB / PhD CREATIS Lyon
Vandemeulebroucke et al.:, Medical Physics, Vol. 39, No. 2, February 2012

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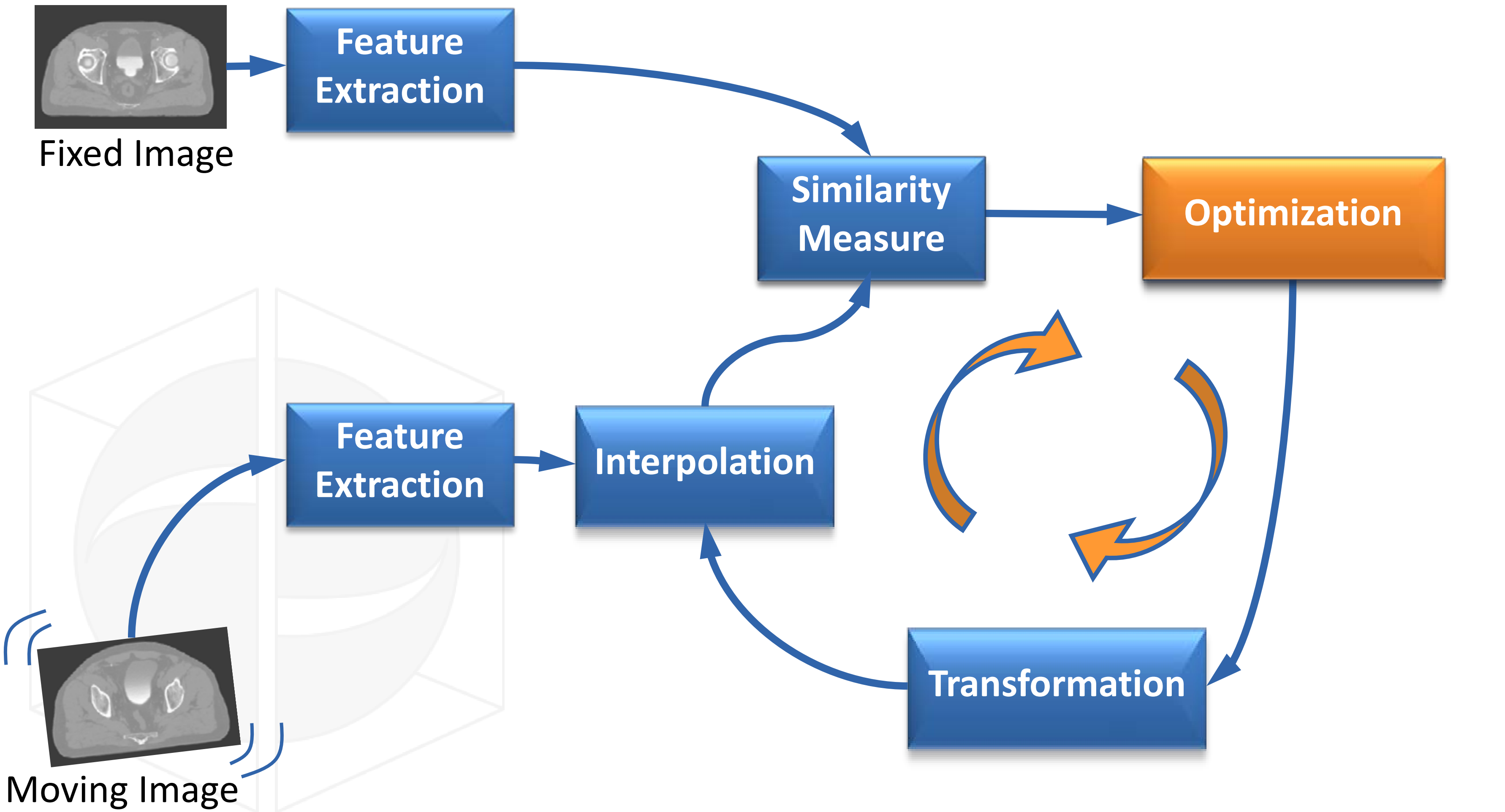
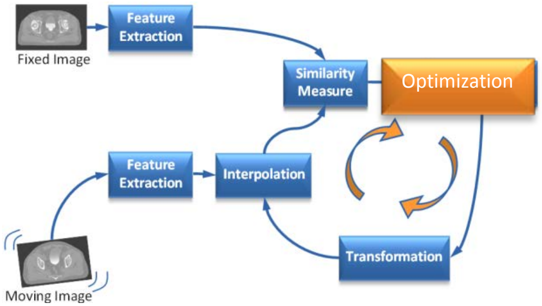
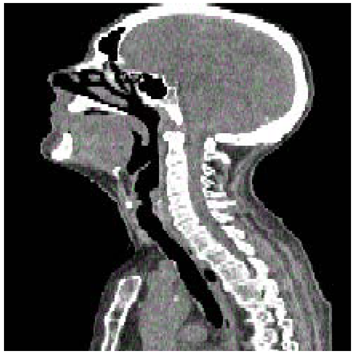
General registration framework

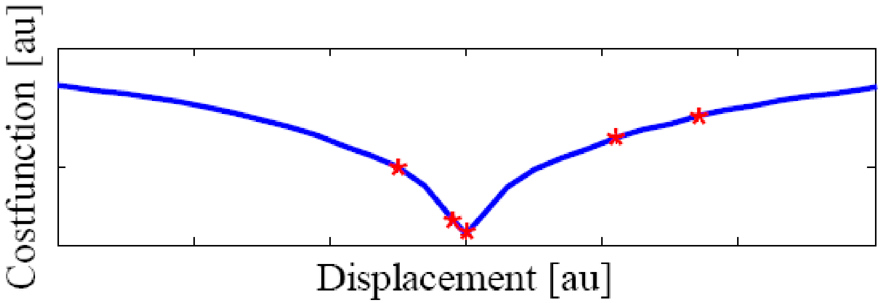


Optimization



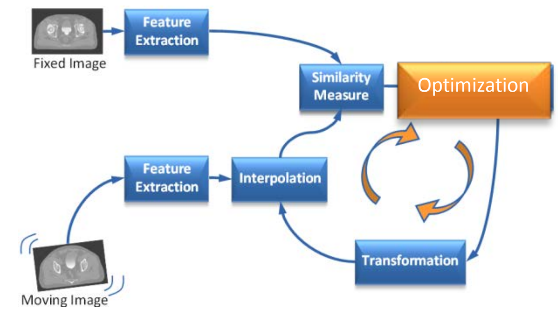
- Objective functions
  - Measure how well things are lined up
  - Asssumption:
    - The images (Features), are related to each other by some transformation T



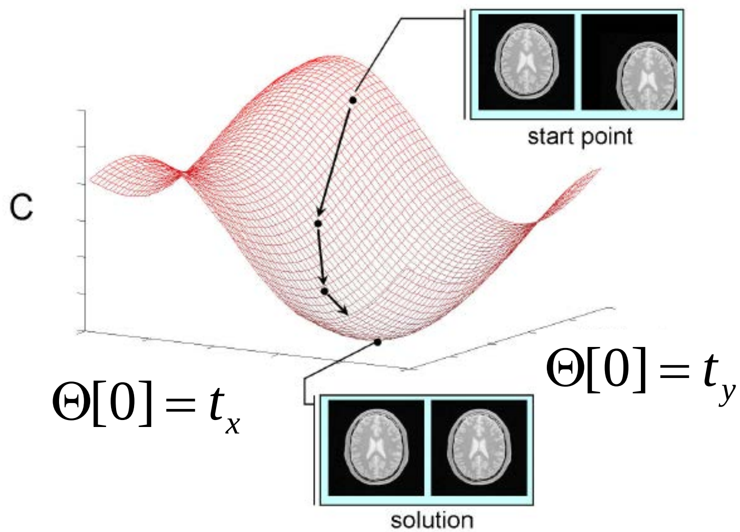


Adapted from JJ Sonke, NKI

Optimization



- Objective functions
  - Measure how well things are lined up
  - Asssumption:
    - The images (Features), are related to each other by some transformation T
  - Define an energy (cost) function to be optimized



$$C = s(F(x), T(M(x)))$$

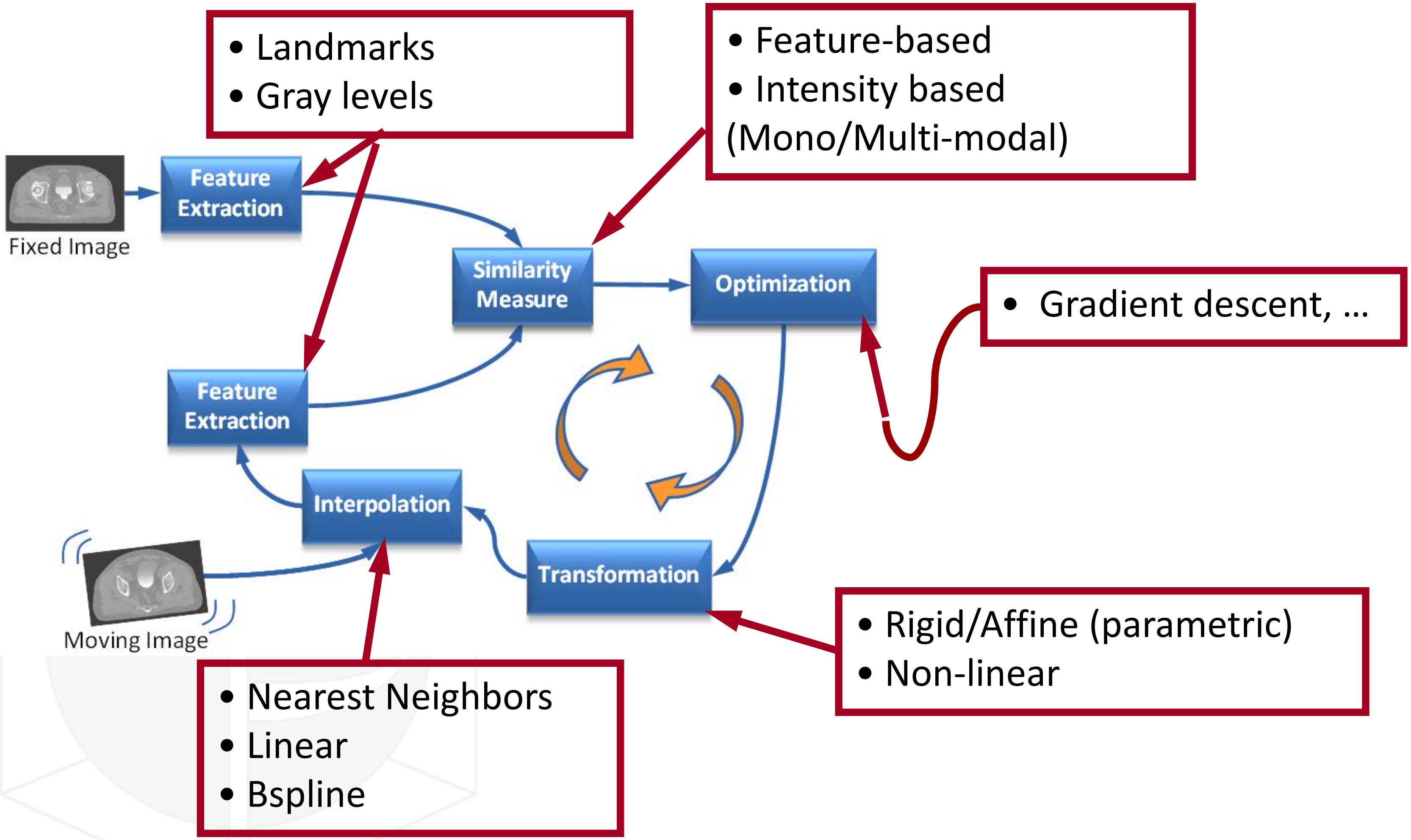
$$\hat{T}_\Theta = \arg\min_{T_\Theta} C(T_\Theta; F(x), M(x))$$

Goal: find T, that optimizes C

Courtesy Elastix

S. Klein, M. Staring, and J. P. W. Pluim. Evaluation of optimisation methods for nonrigid medical image registration using mutual information and B-splines. *IEEE Trans. Image Process.*, 16(12):2879 – 2890, December 2007.

Putting everything together

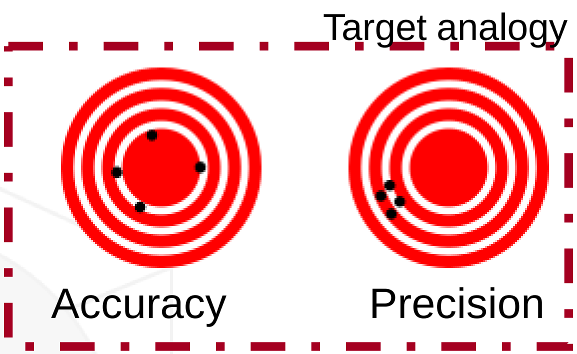


Validation

- How do you verify that your registration was successful?
  - Qualitatively - Visually

Validation

- How do you verify that your registration was successful?
  – Qualitatively - Visually

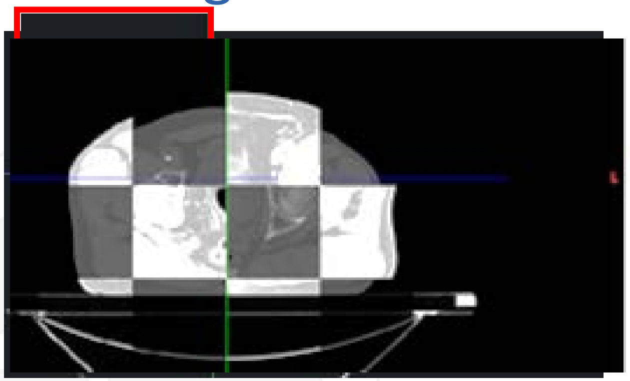


People are happy with a simple validation?

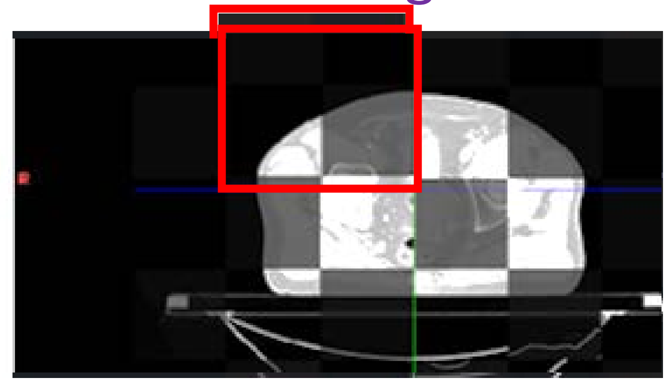
Validation

- How do you verify that your registration was successful?
  - Visually

Before registration



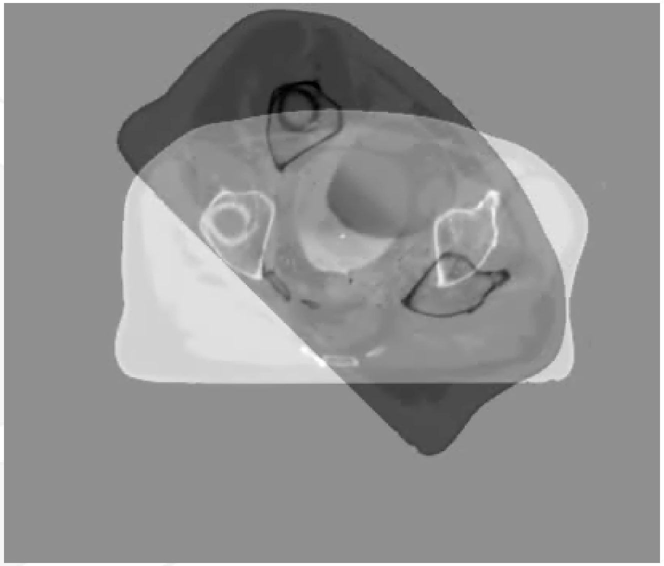
After registration



Initial Affine FFD

Validation

- How do you verify that your registration was successful?
  - Visually
  - Difference image



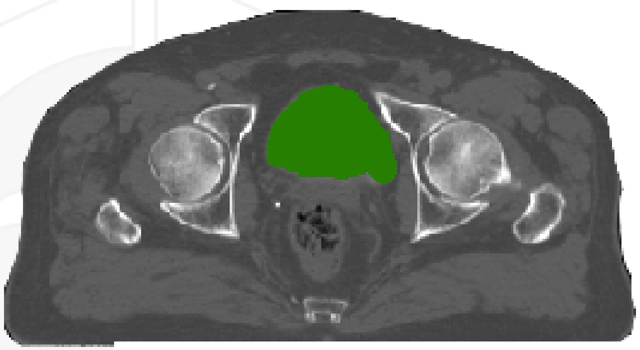
Quantitively?

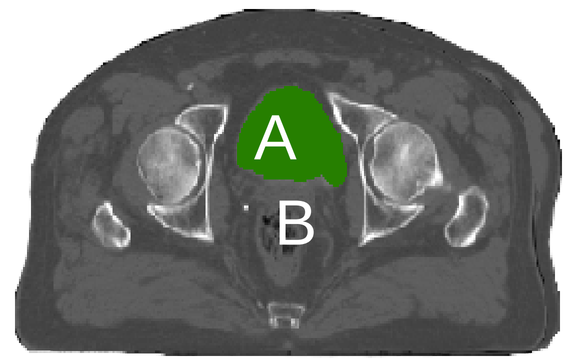
- **It may be.. but it is not fair if it was the used similarity measure**

Validation

- How do you verify that your registration was successful?
  - Visually
  - Difference image
  - Overlap of segmented structures (Dice Score,Hausdorff)

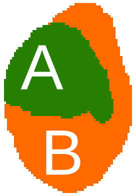
If manual segmentations are available?





$$Dice(A,B) = \frac{2|A \cap B|}{|A| + |B|}$$

$$0 \leq Dice \leq 1$$



Organ **A,B**

Validation

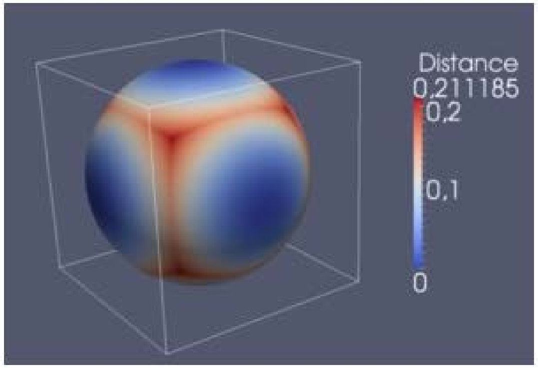
- Hausdorff Distance

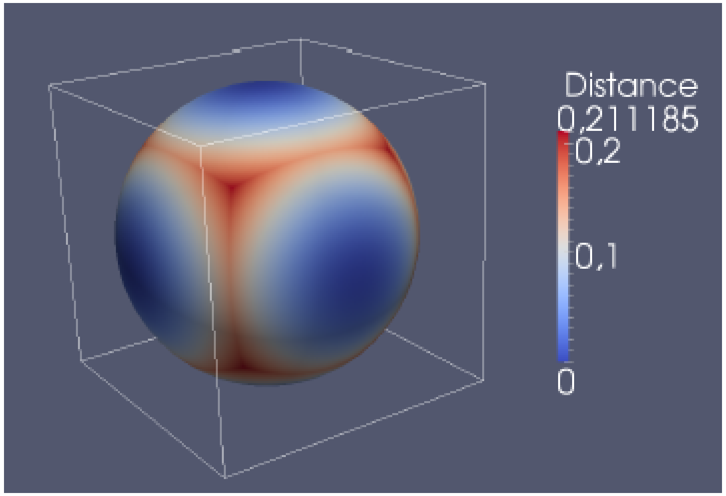
$$DH(V_F, V_M) = \max\{h(V_F, V_M), h(V_M, V_F)\},$$

$$h(V_F, V_M) = \max_{f \in V_F} \min_{m \in V_M} \|V_F - V_M\|$$

A VTK Algorithm for the Computation of the Hausdorff Distance

Commandeur F., Velut J., Acosta O.
INSERM, U 642, Rennes, F-35000, France, Université de Rennes 1, LTSI

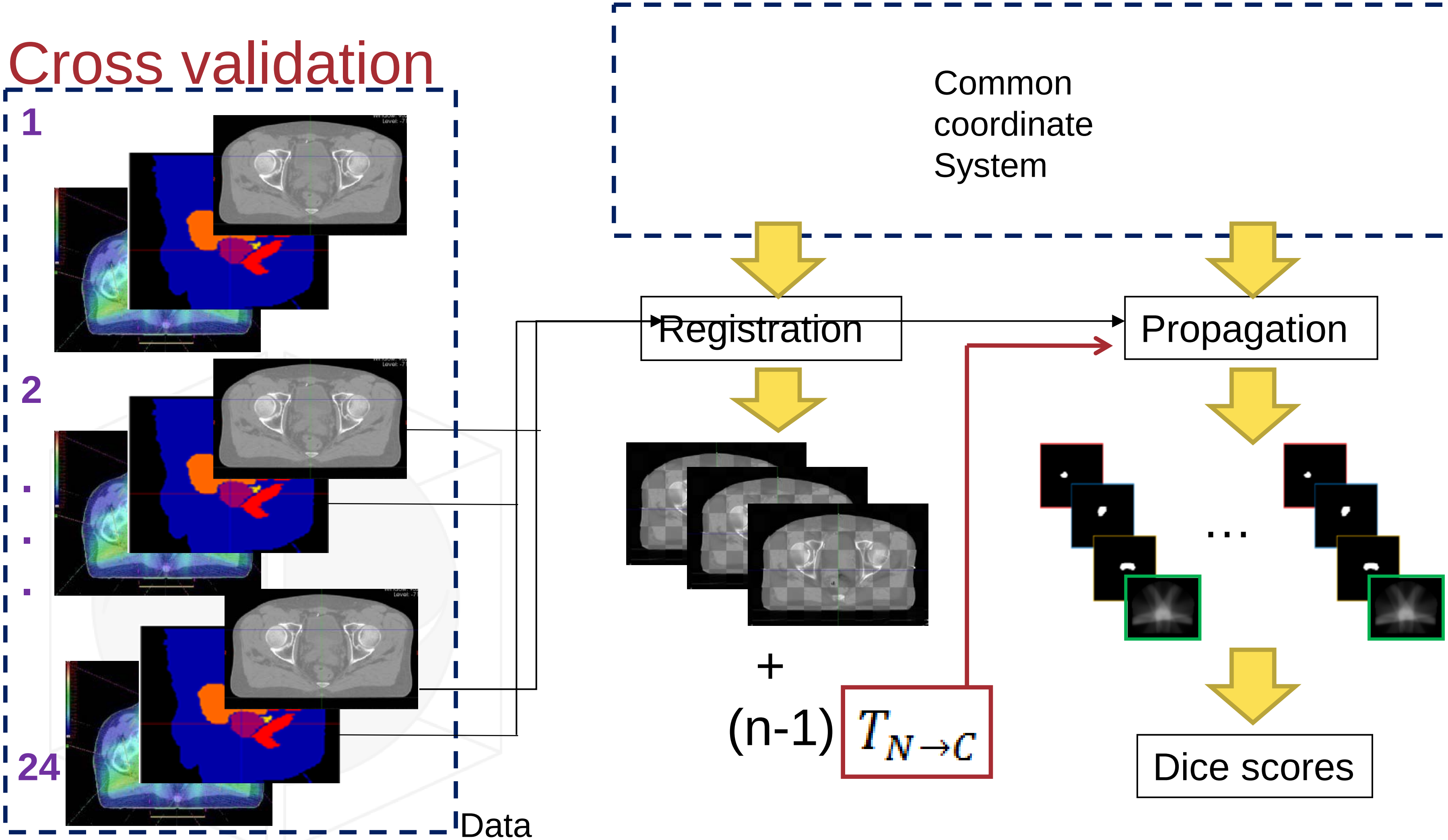




(b) point-to-cell computation method
$\Delta(\mathcal{S}, \mathcal{C}) = 0.211$
$\Delta(\mathcal{C}, \mathcal{S}) = 0.366$
$d(\mathcal{C}, \mathcal{S}) = 0.366$

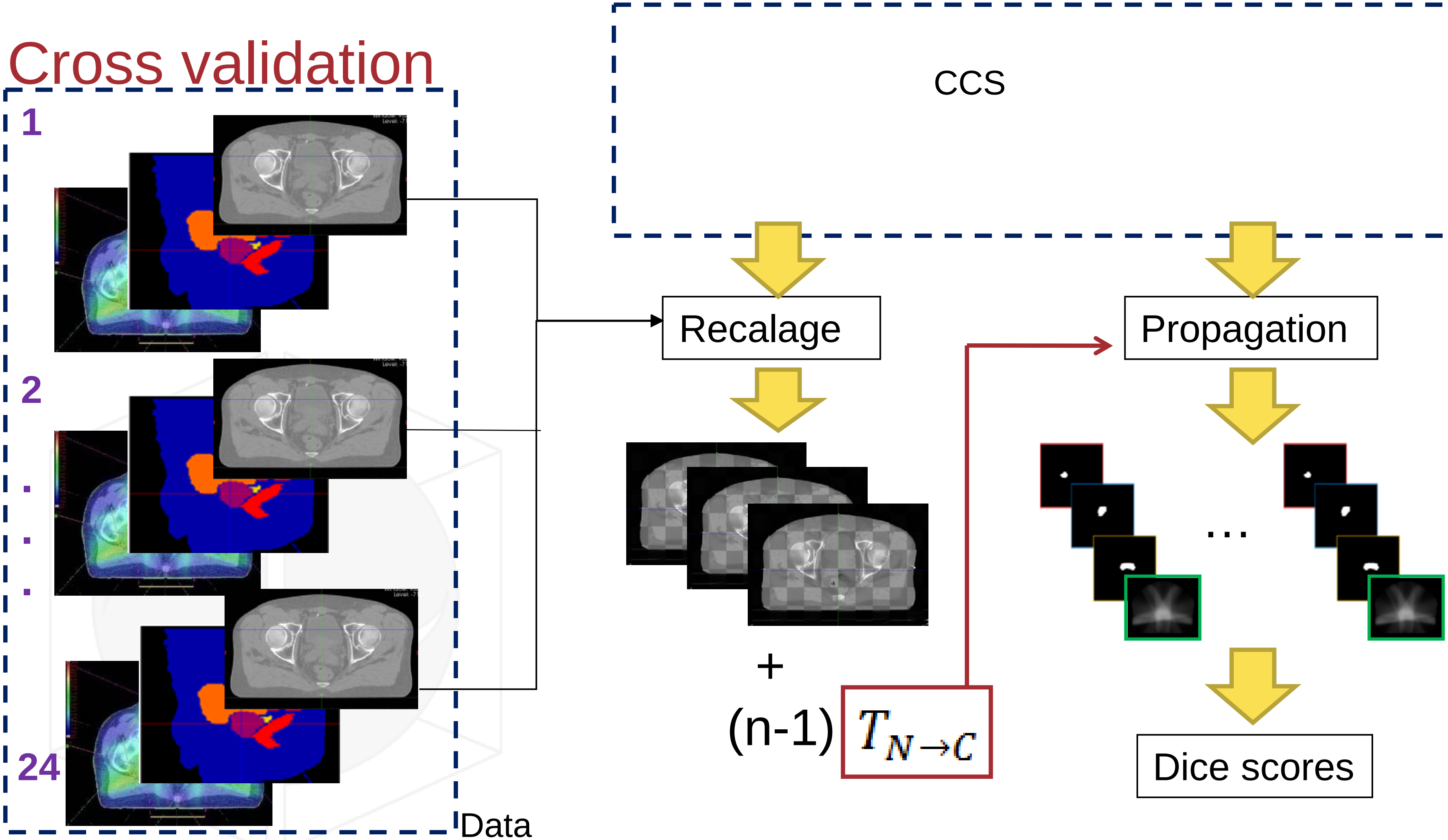
http://www.vtkjournal.org/browse/publication/839
(Hausdorff, 1918)

Cross validation



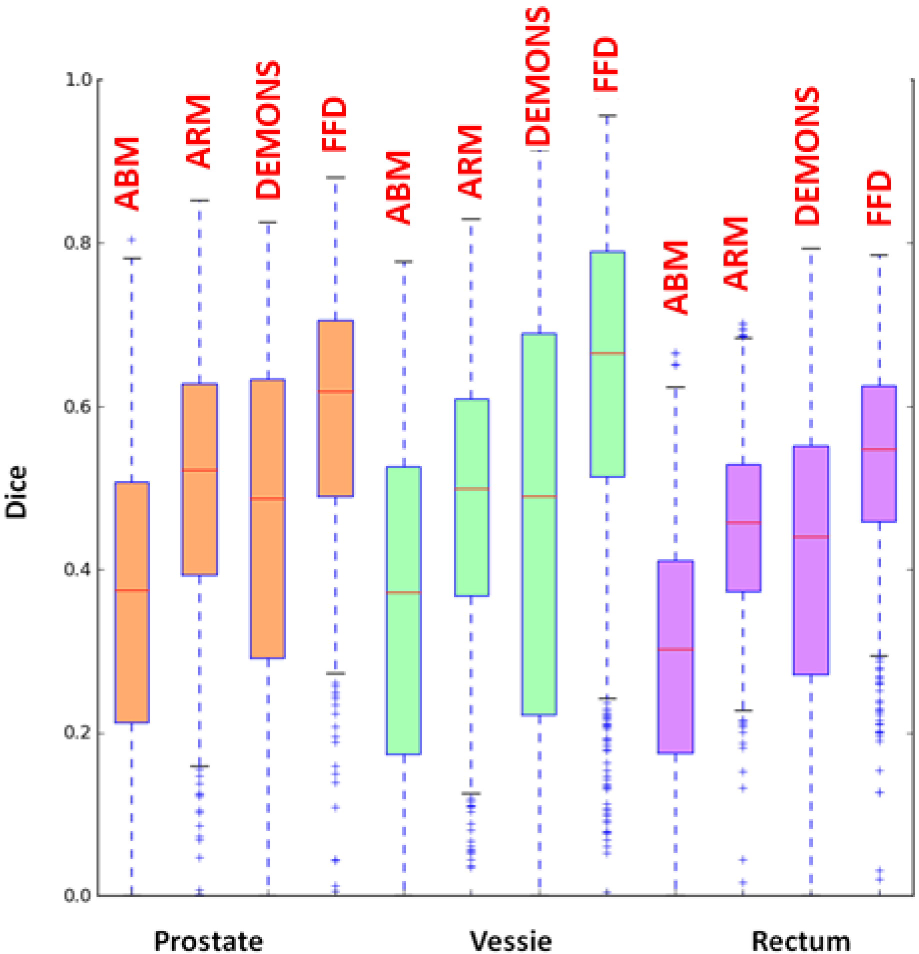
Dréan G, Acosta **O.**, Simon A., de Crevoisier R. and Haigron P. "Evaluation of inter-individual pelvic CT-scans registration", Imagerie et Recherche Biomédicale IRBM, 32 (5), Nov 2011, 288-292 , doi:10.1016/j.irbm.2011.08.002

Validation



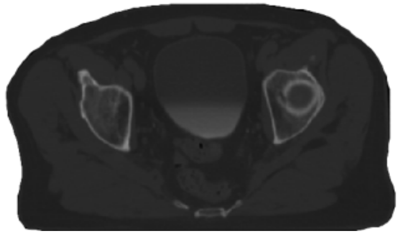
Dréan G., Acosta **O.**, Simon A., de Crevoisier R. and Haigron P. "Evaluation of inter-individual pelvic CT-scans registration", Imagerie et Recherche Biomédicale IRBM, 32 (5), Nov 2011, 288-292 , doi:10.1016/j.irbm.2011.08.002

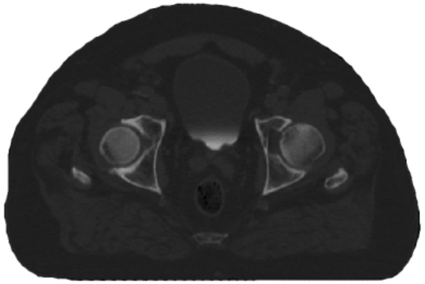
Results



ABM : Affine « Block Matching »
ARM : ABM$_{\backslash masque}$
DEMONS : RBM + DEMONS
FFD : RRM + FFD

- Challenges
  - Poor contrast
  - Large deformations

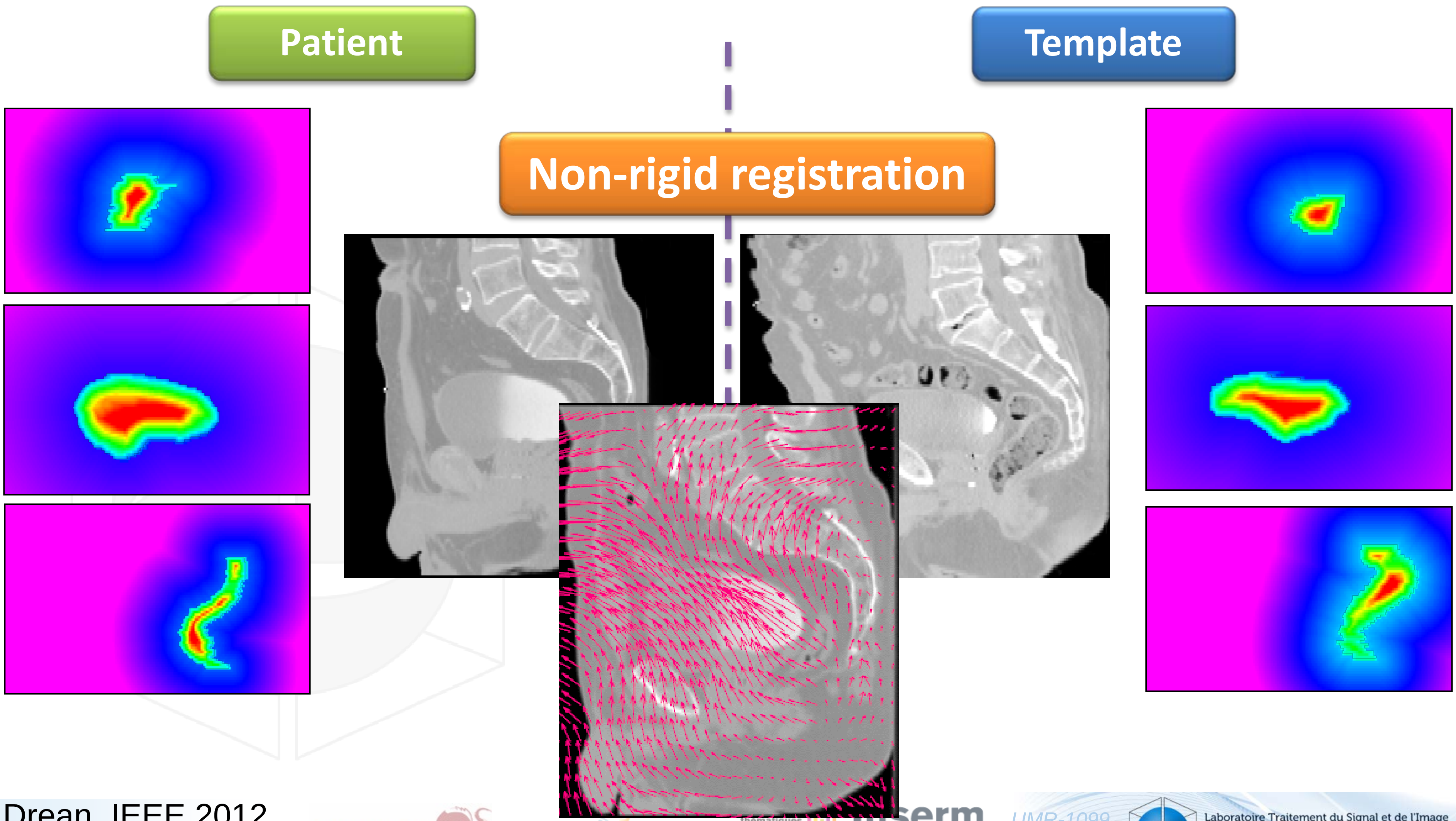




Dréan G, Acosta **O.**, Simon A., de Crevoisier R. and Haigron P. "Evaluation of inter-individual pelvic CT-scans registration", Imagerie et Recherche Biomédicale IRBM, 32 (5), Nov 2011, 288-292 , doi:10.1016/j.irbm.2011.08.002

Non-rigid registration proposed strategy

- Taking advantage of organ segmentations



Drean, IEEE 2012

NRR Validation


ARTICLE IN PRESS

IRBM

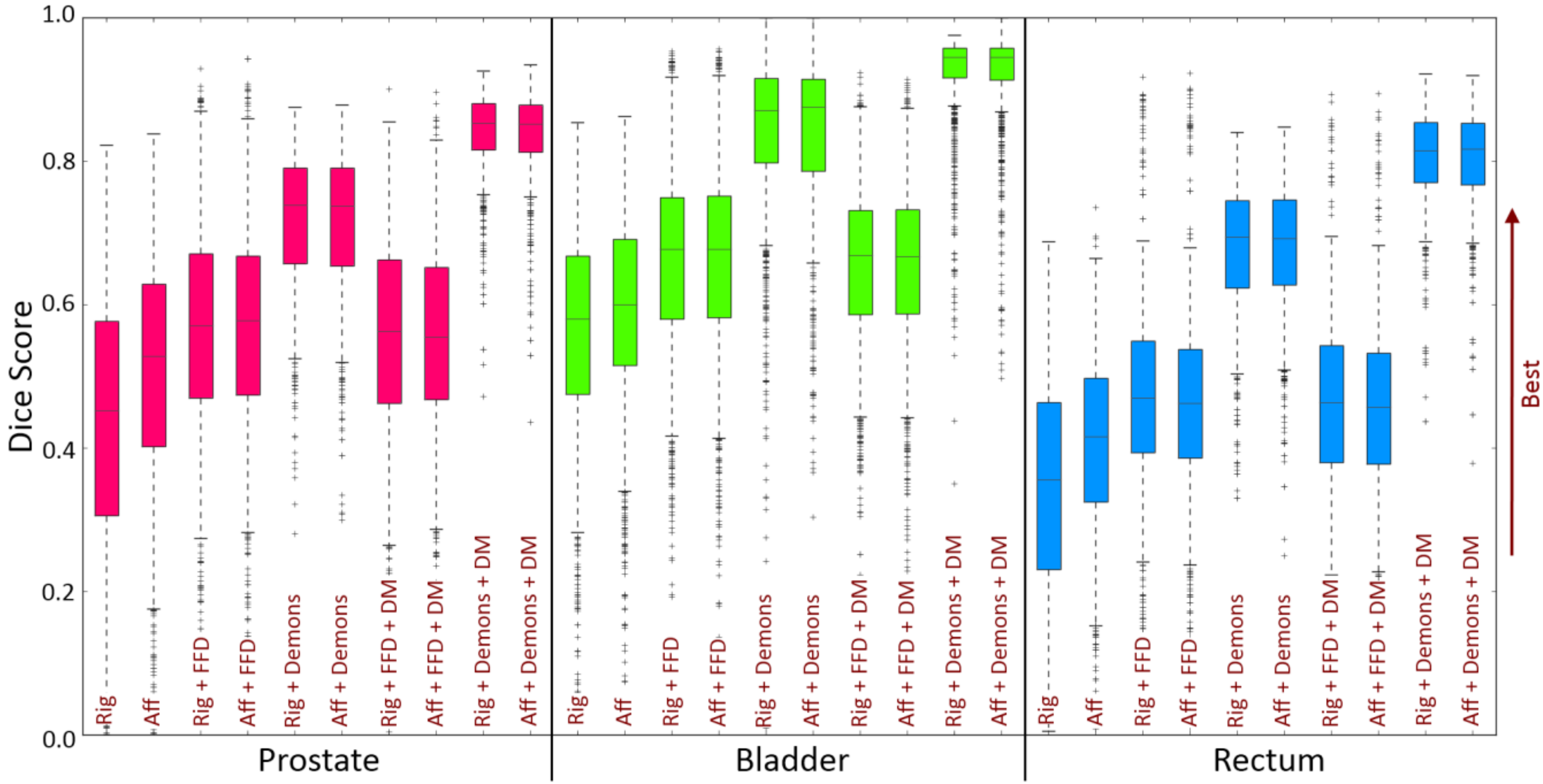
Original article

Evaluation of inter-individual pelvic CT-scans registration

Évaluation de recalage inter-individus de tomodensitométries pelviennes

G. Dréan, O. Acosta, A. Simon, R. de Crevoisier, P. Haigron

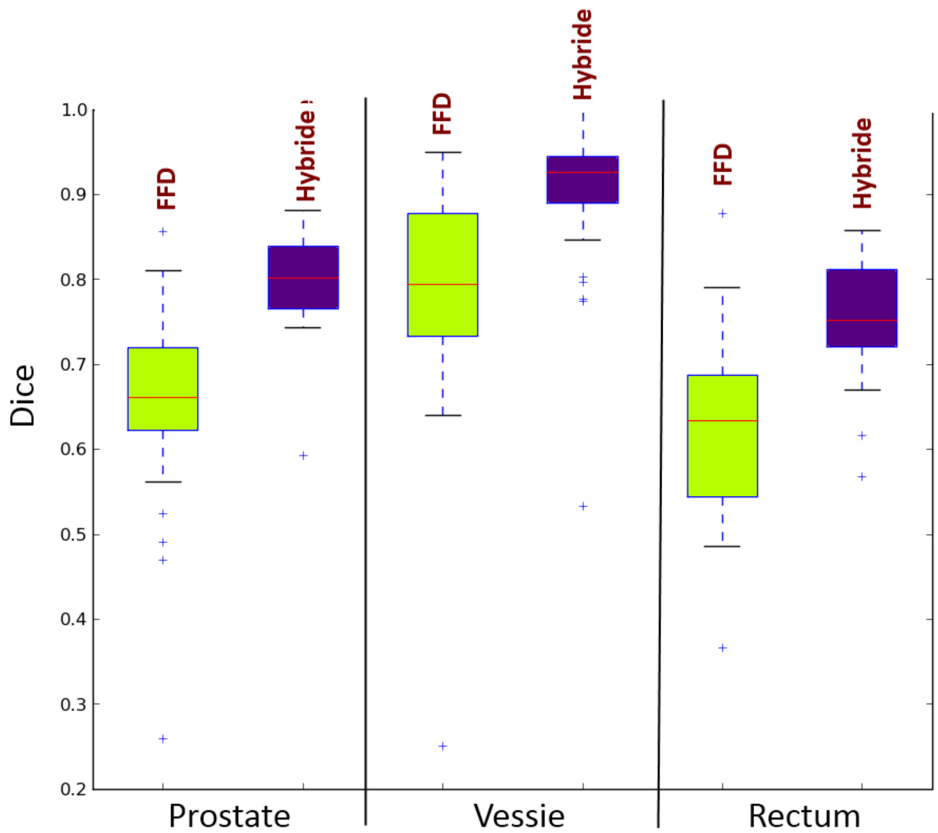
- <u>Results : Dice Score</u>



Leave one out cross validation (30 patients)

*Dréan G, **Acosta O.**, Simon A., de Crevoisier R. and Haigron P. "Evaluation of inter-individual pelvic CT-scans registration", Imagerie et Recherche Biomédicale IRBM, 32 (5), Nov 2011, 288-292 , doi:10.1016/j.irbm.2011.08.002*

Combined strategy



Dréan G, **Acosta O.**, Simon A., de Crevoisier R. and Haigron P. "Evaluation of inter-individual pelvic CT-scans registration", Imagerie et Recherche Biomédicale IRBM, 32 (5), Nov 2011, 288-292 , doi:10.1016/j.irbm.2011.08.002

Multiple validation approaches

NeuroImage 51 (2010) 214–220

Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/ynimg

ELSEVIER

Evaluation of volume-based and surface-based brain image registration methods

Arno Klein [a,*], Satrajit S. Ghosh [b], Brian Avants [c], B.T.T. Yeo [d], Bruce Fischl [e,f], Babak Ardekani [h,i], James C. Gee [c], J.J. Mann [a], Ramin V. Parsey [a]

[a] New York State Psychiatric Institute, Columbia University, NY, NY 10032, USA
[b] Research Laboratory of Electronics, Massachusetts Institute of Technology, Cambridge, MA, USA
[c] Penn Image Computing and Science Laboratory, Department of Radiology, University of Pennsylvania, Philadelphia, PA 19104–2644, USA
[d] Cognitive Neuroscience Lab, Harvard University, USA
[e] Athinoula A Martinos Center, Massachusetts General Hospital, USA
[f] Department of Radiology, Harvard Medical School, USA
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16,000 registrations between 80 manually labeled brain images

Radiotherapy and Oncology 89 (2008) 1–12
www.thegreenjournal.com

Adaptive RN in HN cancer

Comparison of 12 deformable registration strategies in adaptive radiation therapy for the treatment of head and neck tumors ☆,☆☆

Pierre Castadot [a,1], John Aldo Lee [a,1], Adriane Parraga [b,c], Xavier Geets [a], Benoît Macq [c], Vincent Grégoire [a,*]

[a] *Department of Radiation Oncology, Université catholique de Louvain, St-Luc University Hospital, Brussels, Belgium,*

Int. J. Radiation Oncology Biol. Phys., Vol. 76, No. 2, pp. 583–596, 2010
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0360-3016/10/$–see front matter

EVIER

doi:10.1016/j.ijrobp.2009.06.031

YSICS CONTRIBUTION

RESULTS OF A MULTI-INSTITUTION DEFORMABLE REGISTRATION ACCURACY STUDY (MIDRAS)

Kristy K. Brock, Ph.D., on behalf of the Deformable Registration Accuracy Co

rincess Margaret Hospital, University Health Network, Departments of Radiation Oncology and Medical Biophysic
Toronto, Toronto, Ontario, Canada

Purpose: To assess the accuracy, reproducibility, and computational performance of deformable image
tion algorithms under development at multiple institutions on common datasets.

IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 30, NO. 11, NOVEMBER 2011

Evaluation of Registration Methods on Thoracic CT
The EMPIRE10 Challenge

Keelin Murphy, Bram van Ginneken*, *Member, IEEE*, Joseph M. Reinhardt, *Senior Member, IEEE*, Sven Kabus, Kai Ding, Xiang Deng, Kunlin Cao, Kaifang Du, Gary E. Christensen, Vincent Garcia, Tom Vercauteren, Nicholas Ayache, Olivier Commowick, Grégoire Malandain, Ben Glocker, *Member, IEEE*, Nikos Paragios, *Fellow, IEEE*, Nassir Navab, *Member, IEEE*, Vladlena Gorbunova, Jon Sporring, Marleen de Bruijne, Xiao Han, *Senior Member, IEEE*, Mattias P. Heinrich, Julia A. Schnabel, *Member, IEEE*, Mark Jenkinson, *Member, IEEE*, Cristian Lorenz, Marc Modat, Jamie R. McClelland, Sébastien Ourselin, Sascha E. A. Muenzing, Max A. Viergever, *Fellow, IEEE*, Dante De Nigris, D. Louis Collins, Tal Arbel, Marta Peroni, Rui Li, Gregory C. Sharp, Alexander Schmidt-Richberg, Jan Ehrhardt, René Werner, Dirk Smeet, Dirk Loeckx, Gang Song, Nicholas Tustison, Brian Avants, James C. Gee, Marius Staring, Stefan Klein, Berend C. Stoel, Martin Urschler, Manuel Werlberger, Jef Vandemeulebroucke, Simon Rit, David Sarrut, and Josien P. W. Pluim, *Senior Member, IEEE*

+Model
IRBM-151; No. of Pages 5

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IRBM

IRBM xxx (2011) xxx–xxx

Original article

Evaluation of inter-individual pelvic CT-scans registration

Évaluation de recalage inter-individus de tomodensitométries pelviennes

G. Dréan [a,*,b], O. Acosta [a,b], A. Simon [a,b], R. de Crevoisier [a,b,c], P. Haigron [a,b]

[a] *LTSI, université de Rennes 1, campus de Beaulieu, bâtiment 22, 35000 Rennes, France*
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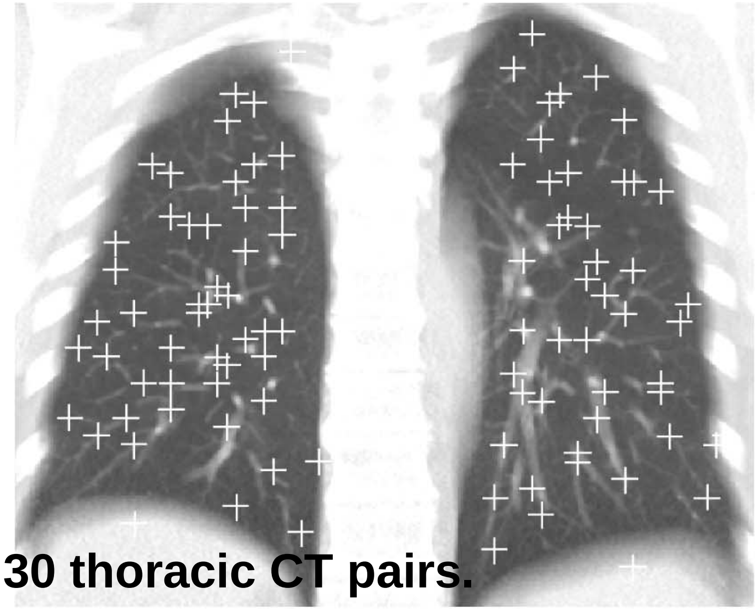
[c] *Département de radiothérapie, centre Eugène-Marquis, Rennes, France*

Received 19 July 2011; received in revised form 29 August 2011; accepted 29 August 2011

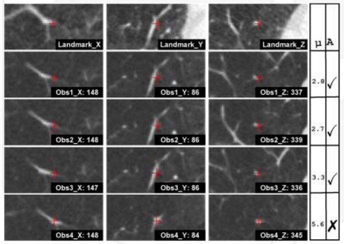
Multiple validation approaches

- Empire Challenge



30 thoracic CT pairs.

Breathhold Inspiration and Expiration Scan Pairs



Marked by either three or four observers independently

http://empire10.isi.uu.nl

Label	Automatic?	Open Source?	Non-rigid Transformation Model	Similarity Measure	Lung Masks?	Placement Phase 1 (/34)	Placement Phase 2 (/20)
A	Fully	✗	Displacement field	SSD	✓	9	10
B	Fully	✗	Displacement field	CC	✓	17	14
C	Fully	✗	Dense displacement field	Hybrid MI/SSD	✓▷	6	1
D	Fully	✗	B-Spline	MPSSD	✓	20	17
E	Fully	✗∗†	B-Spline	SAD	✗	19	16
F	Fully	✓∗	B-spline	NCC	✓	7	3
G	Fully	✗	Optical Flow	SAD	✓	28	19
H	Fully	✗∗○	Diffeomorphic with static velocity fields	NSSD	✓	4	4
I	Fully	✗	B-Spline	SSTVD/ SSVMD	✓	3	7
J	Fully	✗	Diffeomorphic Diffusion	NSSD	✓	16	8
K	Fully	✓	B-Spline	MI	✓	14	13
L	Semi-(3)	✓∗	B-Spline	SSD	✓	12	15
M	Fully	✓∗	B-Spline	NCC/ NMI	✓	2	5
N	Fully	✗	Optical Flow	SAD	✗	26	17

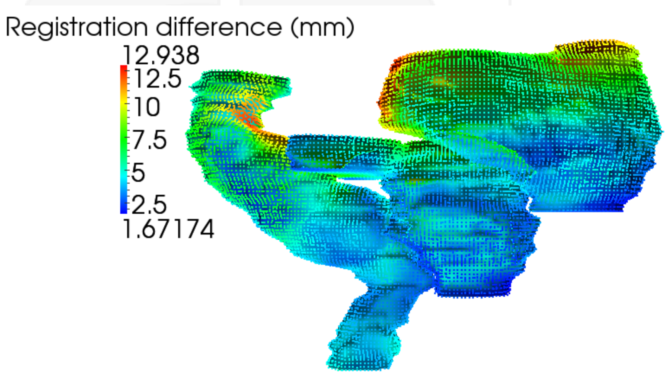
20 individual algorithms from leading academic and industrial research groups

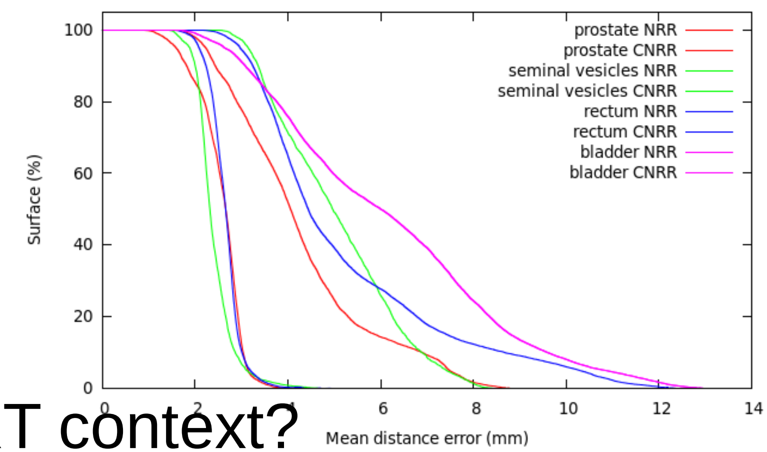
	Lung Boundaries		Fissures		Landmarks		Singularities		Overall	
Label	Avg Score	Avg Rank	Avg Score	Avg Rank	Avg Score	Avg Rank	Avg Score	Avg Rank	Avg Rank	Placed (/20)
C	0.00	6.05	0.11	6.25	0.59	2.34	0.00	8.39	5.76	1
Q	0.00	5.70	0.16	5.90	0.65	4.05	0.00	8.39	6.01	2
F	0.00	9.10	0.46	7.65	0.77	3.20	0.00	11.05	7.75	3
H	0.00	8.05	0.61	7.85	1.06	5.70	0.00	9.89	7.87	4
M	0.00	7.05	0.26	8.00	0.88	8.39	0.00	8.39	7.96	5
O	0.00	7.25	0.58	10.35	1.03	9.00	0.00	8.39	8.75	6
I	0.21	7.35	0.52	11.70	5.04	8.10	0.00	8.39	8.88	7
J	0.03	15.75	0.32	7.75	0.72	3.90	0.00	8.39	8.95	8
P	0.00	7.10	0.25	8.45	1.03	9.70	0.00	12.75	9.50	9
A	0.00	8.60	0.95	12.15	2.02	12.30	0.00	8.39	10.36	10
T	0.00	11.85	0.87	9.89	1.44	13.50	0.00	8.39	10.91	11
S	0.00	11.95	0.61	10.20	1.32	13.30	0.00	8.39	10.96	12
K	0.00	11.80	0.89	12.20	1.84	11.00	0.12	10.35	11.33	13
B	0.02	11.80	0.46	11.70	1.30	14.10	0.00	8.39	11.50	14
L	0.06	12.10	1.68	11.15	4.51	13.40	1.62	9.70	11.58	15
E	0.00	7.70	2.23	15.40	2.34	17.00	0.00	8.39	12.12	16
N	0.00	11.80	0.85	10.00	1.08	10.30	0.00	16.65	12.18	17
D	0.05	14.75	1.26	12.50	2.14	15.80	0.00	8.39	12.86	18
G	0.04	14.65	4.94	16.50	6.52	17.79	2.16	19.40	17.08	19
R	1.93	19.60	0.63	14.40	2.61	17.10	1.45	19.40	17.62	20

Laboratoire Traitement du Signal et de l'Image
LTSI

Take home message (validation)

- How do you verify that your registration was successful?
  - Visually
  - Difference image
  - Overlap of segmented structures (Dice Score, etc)
  - Distance between surfaces
  - Landmarks (annotated databases)





Within an IGRT context?

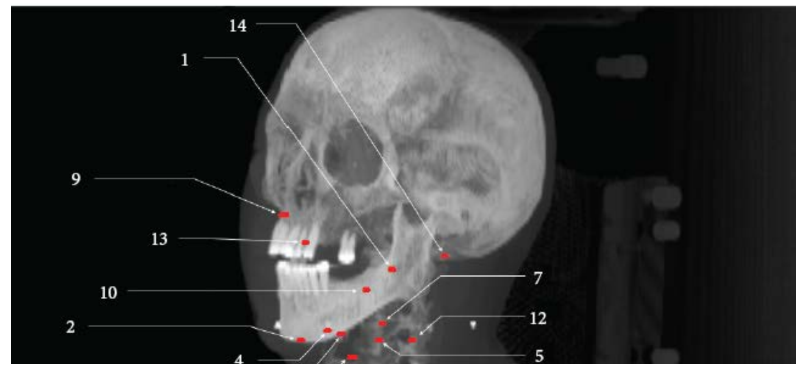
Dose accumulation

Evaluation

DIR: tissue/voxels tracking
→ « local » evaluation of the tracking = point-based evaluation

- 14 patients, 102 per-treatment CTS
- 14 landmarks (7 bones, 7 soft tissues)

Landmark index	Tissue landmark	Description
1		The odontoid
2		The lower part of the mandible
3		The superior thyroid notch (part of the thyroid cartilage
4-5	Bone	The righ lesser co bone
6		The sup of the st left sterr
7		The post interver
8		The vall
9		The phil
10		The low palatine
11-12	Soft	The righ carotid l
13-14		The righ parotid



BioMed Research International
Volume 2015 (2015), Article ID 726268, 16 pages
http://dx.doi.org/10.1155/2015/726268

Research Article

Evaluation of Deformable Image Registration Methods for Dose Monitoring in Head and Neck Radiotherapy

Bastien Rigaud,[1,2] Antoine Simon,[1,2] Joël Castelli,[1,2,3] Maxime Gobeli,[3] Juan-David Ospina Arango,[1,2] Guillaume Cazoulat,[1,2] Olivier Henry,[3] Pascal Haigron,[1,2] and Renaud De Crevoisier[1,2,3]

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[3]Centre Eugene Marquis, Radiotherapy Department, 35000 Rennes, France

Rigaud et al, 2015

http://www.hindawi.com/journals/bmri/2015/726268/abs/

Dose accumulation

Evaluation

- DIR methods: 10 combinations of method (Demons, FFD), preprocessing (soft tissues enhancement, delineation maps), metric (mean-square, MI)

	Landmark Distance Error (mm)												
	Bones				Soft tissues							Precision (AVG)	Accuracy (AVG SD)
	1	2	3	4, 5	6	7	8	9	10	11, 12	13, 14		
Interobserver variability	1.00	1.24	1.40	2.21	2.43	2.56	1.27	1.36	1.85	2.19	3.15	2.01	1.29
FFD MI filtered CTs	1.18	2.60	1.45	1.62	3.03	2.89	2.64	2.07	2.11	3.85	2.64	2.44	1.30
Demons MI filtered CTs	1.13	2.40	1.72	1.77	2.93	2.97	2.27	2.84	2.89	3.63	2.79	2.54	1.33
Demons MI	1.13	2.36	1.80	1.82	3.03	3.12	2.36	2.79	2.87	3.79	2.82	2.59	1.38
Demons MSE	1.15	2.79	1.81	1.65	3.42	3.21	3.02	2.72	2.58	3.82	3.84	2.81	1.63
FFD MSE filtered CTs	1.32	3.49	1.62	1.91	3.50	3.27	3.63	2.94	2.19	4.06	3.10	2.86	1.54
FFD MI	1.07	3.81	1.93	1.77	3.37	3.52	3.96	3.11	2.07	4.16	3.07	2.92	1.60
Demons MSE filtered CTs	1.35	3.05	1.80	1.82	3.60	3.63	3.13	2.78	2.92	3.80	4.25	3.00	1.64
FFD MSE	1.83	5.13	3.30	2.50	4.07	4.37	5.14	5.05	2.63	5.42	3.48	3.88	2.18
Demons D. maps	2.43	5.51	4.62	2.79	4.40	4.75	5.17	5.97	4.01	6.35	3.41	4.43	2.14
FFD D. maps	2.40	6.03	4.02	3.15	4.42	4.80	5.94	6.37	4.37	6.68	3.55	4.65	2.33
Rigid MSE	3.16	6.26	4.32	4.16	4.85	5.11	6.26	6.57	4.69	6.85	4.53	5.16	2.52

→ Importance of the pre-processing

→ Organs overlap indices not sufficient to evaluate dose accumulation

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Dose accumulation

Evaluation

- DIR methods: 10 combinations of method (Demons, FFD), preprocessing (soft tissues enhancement, delineation maps), metric (mean-square, MI)

	Landmark dose (Gy)															
				Bones							Soft tissues				Precision (AVG)	Accuracy (AVG SD)
	1	2	3	4	5	6	7	8	9	10	11	12	13	14		
Planned dose	44.47	35.13	54.87	64.91	63.64	8.84	44.50	64.74	21.60	66.87	66.91	63.95	39.71	41.37	48.68	10.35
Cumulated dose difference*	1.95	1.96	1.68	1.96	1.71	3.09	2.87	2.55	2.52	1.93	0.69	1.12	5.17	4.25	2.39	2.40
	Landmark Cumulated Dose Error (Gy)															
Interobserver variability	0.41	0.23	0.29	0.38	0.67	0.26	0.28	0.31	0.41	0.77	0.14	0.61	1.68	3.14	0.68	0.75
FFD MI filtered CTs	0.36	0.60	0.43	0.58	0.69	0.43	0.41	0.59	0.63	0.74	0.91	0.48	2.63	2.41	0.85	0.93
Demons MI filtered CTs	0.40	0.39	0.60	0.57	0.71	0.33	0.45	0.41	1.09	0.75	0.69	0.78	2.74	2.46	0.88	0.95
Demons MI	0.33	0.39	0.57	0.54	0.69	0.38	0.48	0.47	1.11	0.90	0.73	0.80	2.56	2.33	0.88	0.92
Demons MSE	0.41	0.52	0.42	0.48	0.88	0.40	0.43	0.56	0.85	1.38	0.74	0.75	3.15	2.96	0.99	1.22
FFD MSE filtered CTs	0.49	0.69	0.52	0.59	0.86	0.55	0.38	0.83	0.95	0.83	0.98	0.57	2.37	3.09	0.98	1.09
FFD MI	0.31	0.63	0.47	0.53	0.53	0.48	0.61	0.82	1.09	0.84	0.85	0.85	2.45	2.68	0.94	1.02
Demons MSE filtered CTs	0.41	0.52	0.42	0.48	0.88	0.40	0.43	0.56	0.85	1.38	0.74	0.75	3.15	2.96	0.99	1.25
FFD MSE	0.34	1.16	1.13	1.27	1.02	0.45	0.92	1.34	1.88	1.26	1.06	1.86	2.75	3.91	1.45	1.60
Demons D. maps	0.99	1.29	3.11	1.19	1.24	0.53	0.94	1.28	1.76	2.39	1.29	2.22	3.05	5.14	1.89	2.14
FFD D. maps	0.95	1.56	1.24	0.94	1.53	0.53	1.00	1.54	2.66	2.90	1.32	2.54	2.99	4.87	1.90	2.18
Rigid MSE	0.94	1.67	1.20	2.78	1.80	0.59	1.02	1.71	3.35	3.99	1.35	2.61	3.44	4.27	2.19	2.60

	geometrical error		dose error
Carotid bifurcation:	3.8 mm	→	0.7 Gy
Parotid glands:	2.6 mm	→	2.5 Gy

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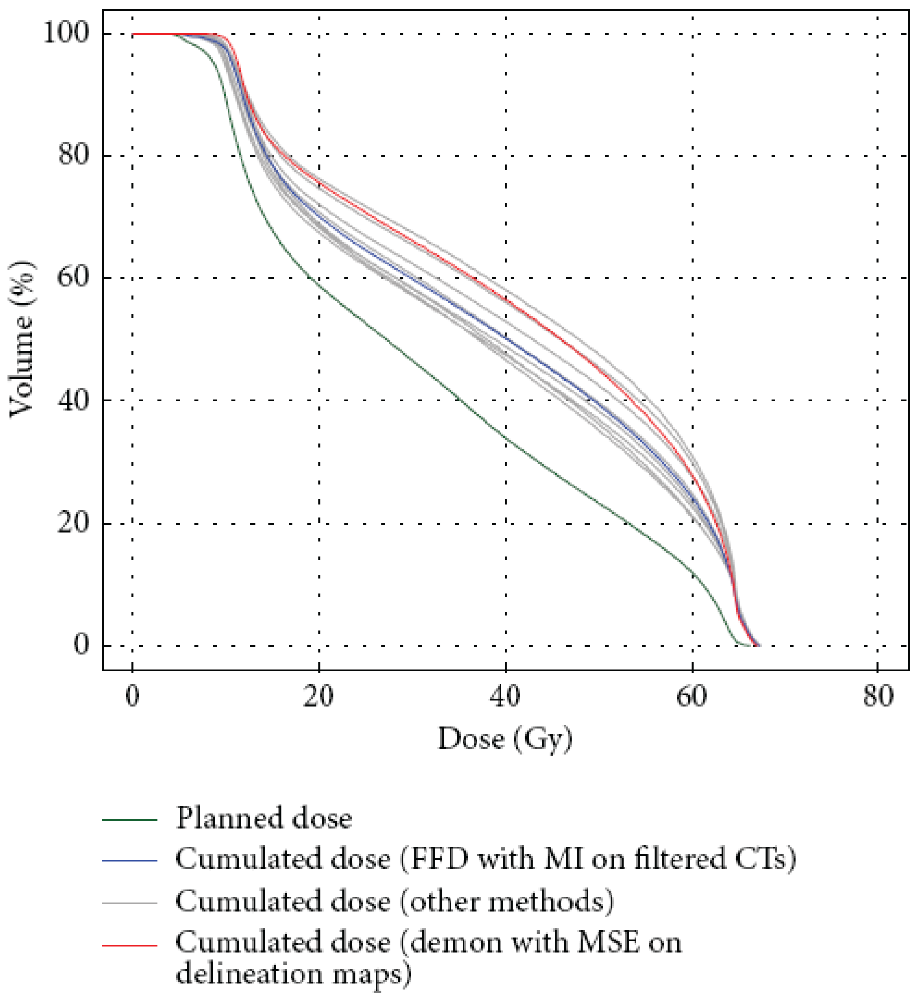
Dose accumulation

Evaluation



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Conclusions (take home messages)

- Registration finds place in many clinical applications
- Is challenging, since it involves different methodological steps
- Implementation depends on the application
- Feature extraction seems to work better than pure intensity based
- Validation is a bottleneck

Take home message

- Validation
  - It is challenging
  - Which method to be used?
  - Depends on the applications and the experimental setup
  - Computational trade off
  - There is no ground truth (annotated data)

Registration is a dynamic research activity

- Conferences..
  - Conferences In Registration
  - MICCAI.. Medical Image Computing and Computing Assisted Interventions (19% of publications).
  - IEEE-ISBI, SPIE..
  - ESTRO/ASTRO
- Journals
  - IEEE Transactions on Medical Imaging (370 entries)
  - Medical Image Analysis
  - Neuroimage
- Software and libraries

Additional references

- Mutual information
  - Viola, P. and Wells, W.. Alignment by maximization of mutual information. In Proceedings of the 5th International Conference of Computer Vision, June 20 –23, 1995.
  - Collignon A, Maes F, Delaere D, Vandermeulen D, Suetens P, MarchalG, Automated multi-modality image registration based on information theory. IPMI June 26, 1995.
  - Viola, P. Alignment by maximization of Mutual Information. MIT PhD Thesis, June 1995.
- Validation
  - Klein, NeuroImage 2009: “Evaluation of 14 nonlinear deformation algorithms applied to human brain MRI registration” http://www.mindboggle.info/papers/index.php
  - KRISTY K. BROCK, PH.D., ON BEHALF OF THE DEFORMABLE REGISTRATION ACCURACY CONSORTIUM “RESULTS OF A MULTI-INSTITUTION DEFORMABLE REGISTRATION ACCURACY STUDY (MIDRAS)” Int. J. Radiation Oncology Biol. Phys., Vol. 76, No. 2, pp. 583–596, 2010
- Attributes vectors for image registration
  - Shen, D. and Davatzikos, C., HAMMER: hierarchical attribute matching mechanism for elastic registration, IEEE Transactions on Medical Imaging, 2002
  - M. Wacker and F. Deinzer. Automatic robust medical image registration using a new democratic vector optimization approach with multiple Measures, MICCAI, 2009
  - …

Resources (open source)

– http://www.itk.org/

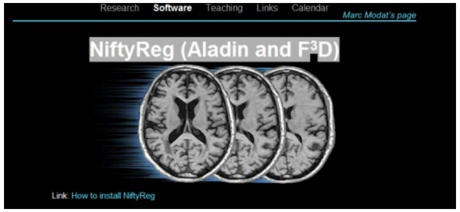
– http://elastix.isi.uu.nl/

– http://www.doc.ic.ac.uk/~dr/software/index.html

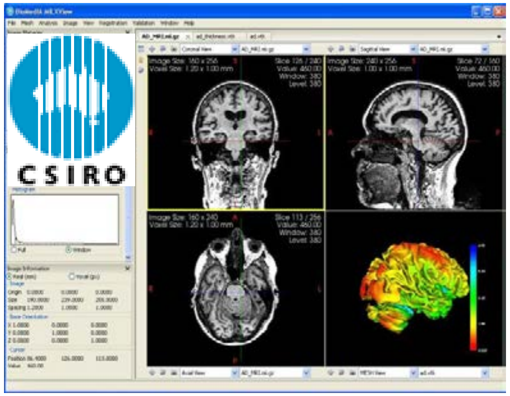
– http://www.picsl.upenn.edu/ANTS/

Resources (open source)

- NiftyReg (Aladin and F3D), UCL, UK
  - http://www.cs.ucl.ac.uk/staff/m.modat/Marcs_Page/Software.html

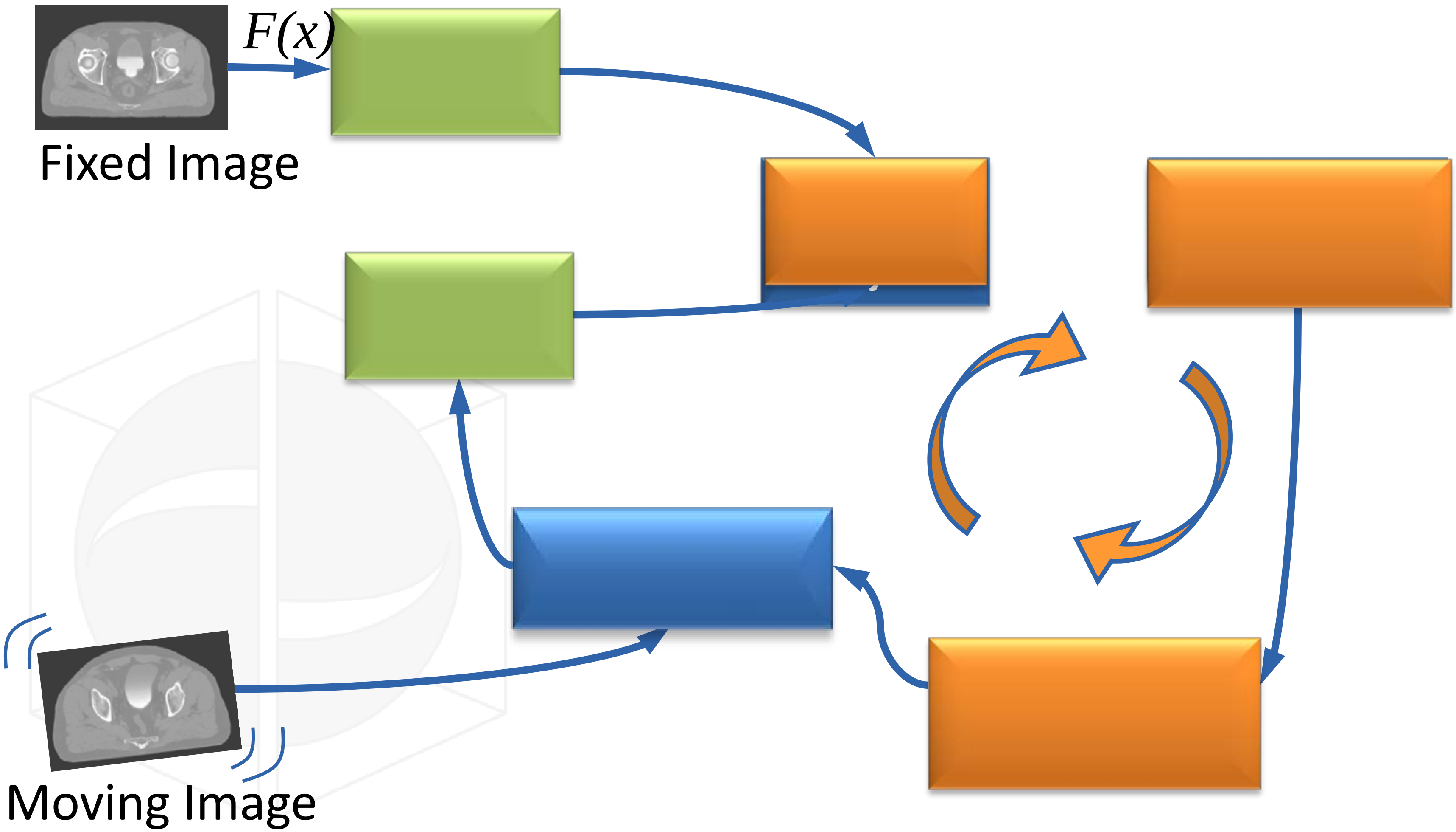


- Milxview, CSIRO, Australia
  - http://research.ict.csiro.au/software/milxview



- Slicer 3D
- VV

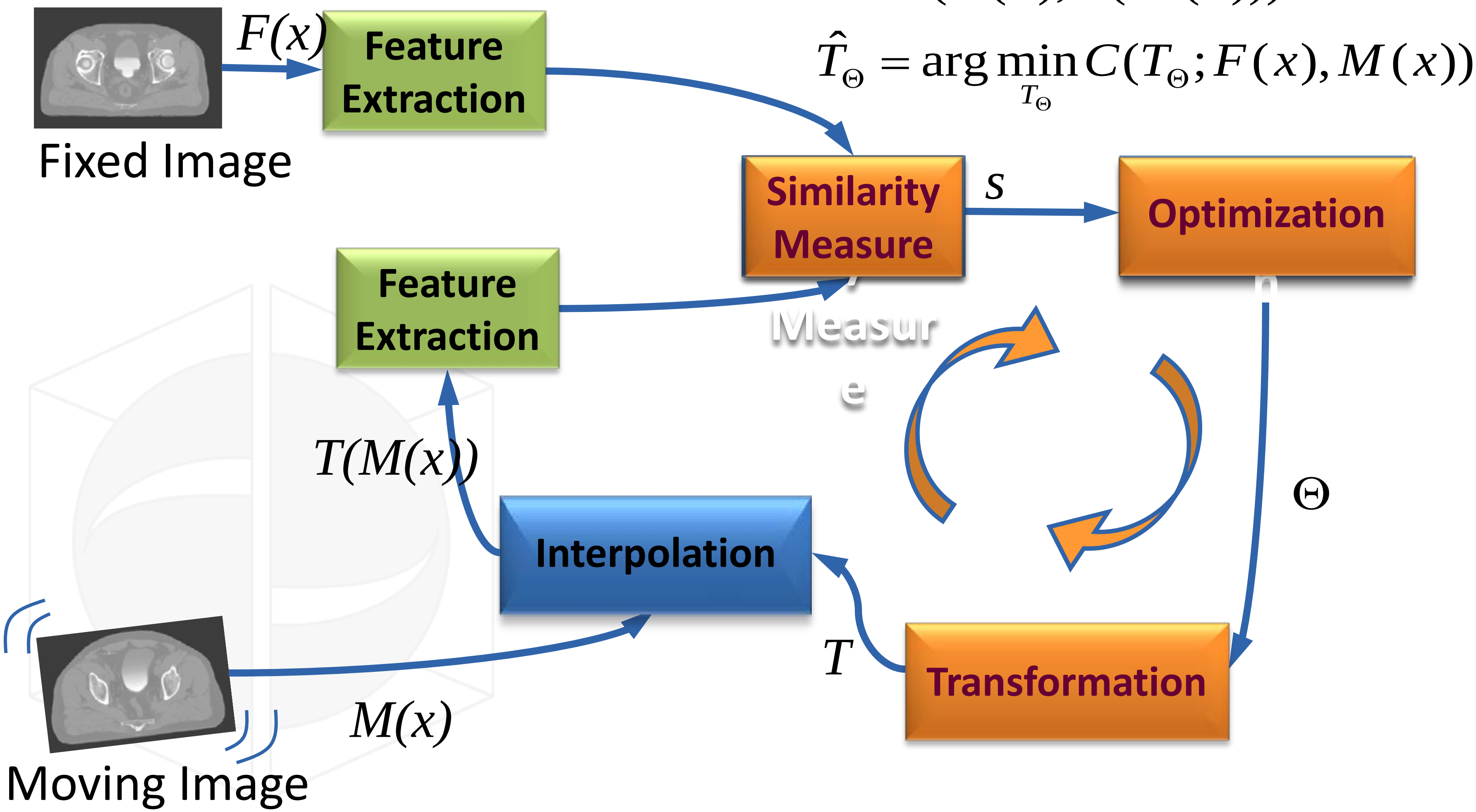
Computerized registration framework



Computerized registration framework

$$C = s(F(x), T(M(x)))$$

$$\hat{T}_\Theta = \arg\min_{T_\Theta} C(T_\Theta; F(x), M(x))$$



Acknowledgments

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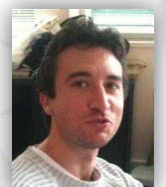
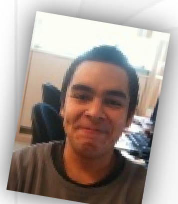



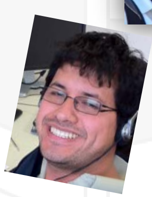








Thanks

FONDATION ARC POUR LA RECHERCHE SUR LE CANCER
Reconnue d'utilité publique

Région BRETAGNE

Centre Eugène Marquis RENNES

CominLabs

Institut de Recherche en Santé Publique GIS-IReSP

plan cancer 2009 2013

Action 3.5

Instituts thématiques

Inserm

Institut national de la santé et de la recherche médicale

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