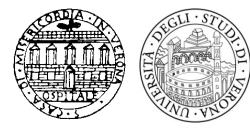
MULTI-MODAL IMAGE INTEGRATION



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ICTP School of Medical Physics for Radiation Therapy TRIESTE – ITALY – 11-22 SEPTEMBER 2023



The Abdus Salam International Centre for Theoretical Physics





School on Medical Physics for Radiation Therapy: Dosimetry, Treatment Planning and Delivery for Advanced Applications

11 - 22 September 2023 An ICTP Meeting Trieste, Italy

Further information: http://indico.ictp.it/event/10205/ smr3871@ictp.it

MULTIMODAL IMAGE INTEGRATION vs. REGISTRATION

- image integration = the use of two or more image sets in the process of (i.e.) treatment planning

 - image registration = the process of making two or more image sets <u>spatially coherent to each other</u>

 - image fusion = the simultaneous visualization of two or more image sets, previously coregistered

IMAGING MODALITIES RELEVANT TO TREATMENT PLANNING

- computed tomography (CT)

- basic modality for treatment planning

- magnetic resonance imaging (MRI)

- multimodality imaging technique
- morphological and functional information

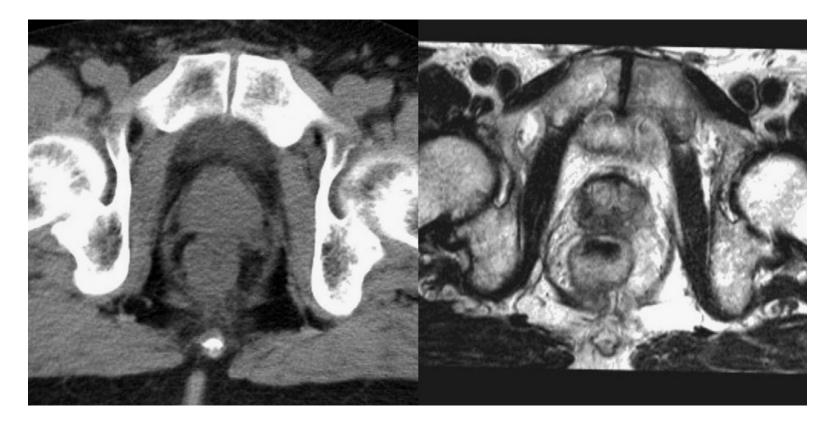
- PET-CT

- low resolution datasets
- CT inherent to modality easy spatial reference
- ultrasound (US)
- emerging modalities (PET-MR etc.)

THE CENTRAL ROLE OF CT IN TREATMENT PLANNING

- CT is the tomographic modality that offers the best **spatial accuracy** (freedom from significant distortion etc.)
- CT information can be directly transformed into a map of attenuation coefficients => useful in dose calculation
- modern in-room verification systems are based on x-ray transmission imaging (e.g. CBCT) => easily registered to CT

MR FOR TREATMENT PLANNING

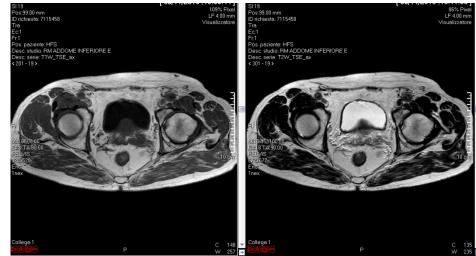


- example: comparison between CT and MR prostate
- better visualization of soft tissue
- no direct correspondence between "gray levels" => may complicate automatic image registration

MORPHOLOGICAL T1- AND T2-BASED IMAGING

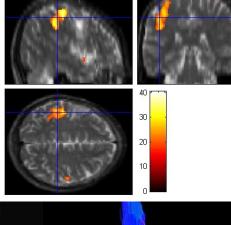
- **T1 and T2** weighting corresponds to imaging with different "modalities"
- T1 enhances muscle-fat T2 enhances water (fluids)
- Paramagnetic contrast agents have more effect on T1-weighted images

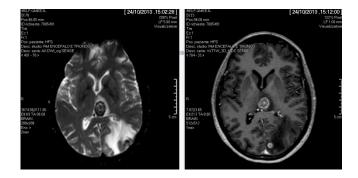
left: T1-weighted MR image right: T2-weighted MR image

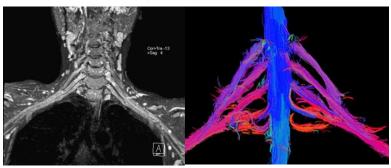


FUNCTIONAL INFORMATION FROM MRI

- MRI can provide valuable **functional information** by means of:
 - diffusion-weighted imaging (DWI) including maps of apparent diffusion coefficient (ADC) and diffusion tensor imaging (DTI) – tractography
 - fMRI based on the BOLD effect
 - arterial spin labeling (ASL)







FUNCTIONAL INFORMATION FROM MRI

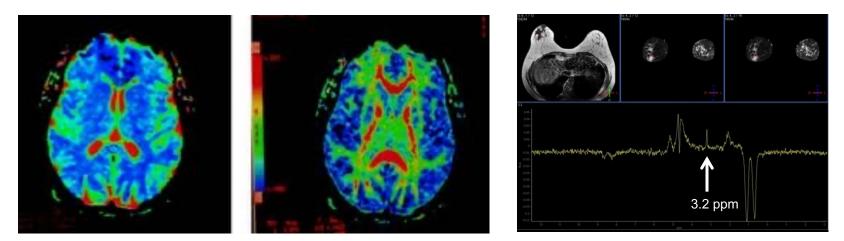
- functional MRI is characterized by **low spatial** resolution (low SNR)

- fMRI is often reported on **anatomical atlases** for reference

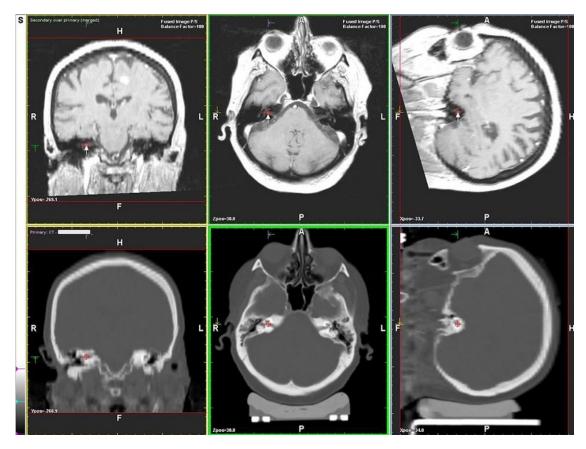
=> registration to CT might be difficult because of poor "common information"

MULTIPARAMETRIC MR IMAGING

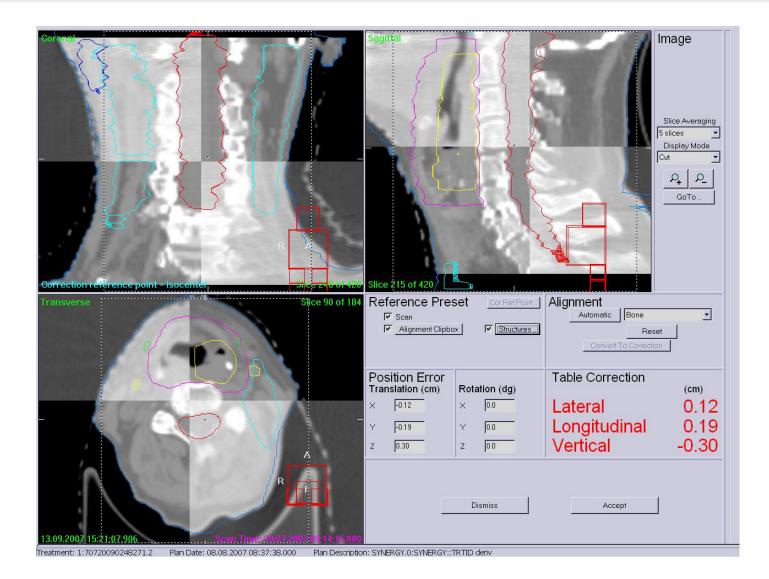
- Special MRI modalities such as **DWI** (ADC) and **spectroscopy** may be integrated for diagnostic purposes (multi-parametric imaging)
- Multi-parametric datasets are usually not employed in the treatment planning process; special attention needed



- Strictly rigid transformation in the brain
- 3 translations+3 rotations => 6 parameters



- Diagnostic MRI is usually rotated around the L-R axis compared to CT
- Correction needed might not be evident on axial orientation
- Inferior regions might introduce deformations

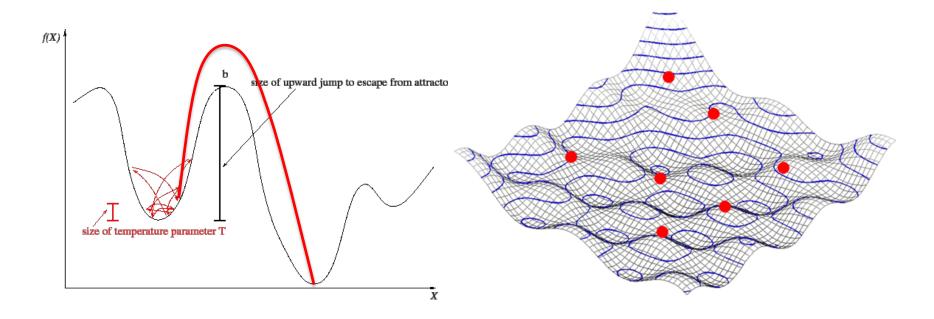


- Use of "clip-boxes" in case of deformations to disregard in the registration process
- Commercially available treatment planning systems and 3rd party software may offer this functionality
- Privilege the anatomical region that has to be coregistered leave any uncontrolled region free

- Obtaining similar (consistent) initial orientation is often essential even in case of automatic transformation – robustness of algorithms to different initial orientation is an issue in general
- Use of patient positioning devices recommended in case of multimodality imaging – example: PETto-CT
- Pay attention to **MR compatibility safety!**

OPTIMIZATION: SEARCH FOR GLOBAL MINIMUM

optimization: simulated annealing - multiresolution



"big steps" necessary to find global minimum of the cost function multiresolution approach: easier to find global minimum but starting situation still important

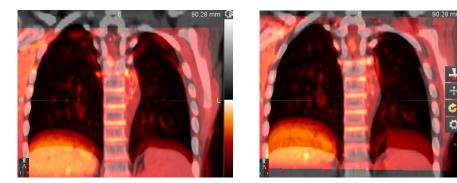
 example of (mild)
 non-convergence in iterative steps

 importance of correct starting position



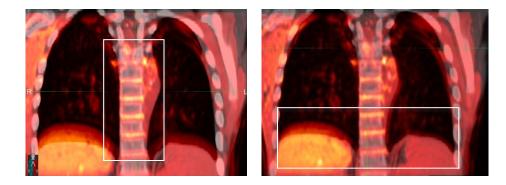
POSSIBLE ERRORS DUE TO LOCAL MINIMA

example of (severe)
 poor robustness
 due to anatomical
 symmetry or
 moving structures



wrong matching of vertebrae (left)

modern
 implementations
 are generally
 robust but
 attention is
 necessary



clipboxes used to limit registration to selected regions

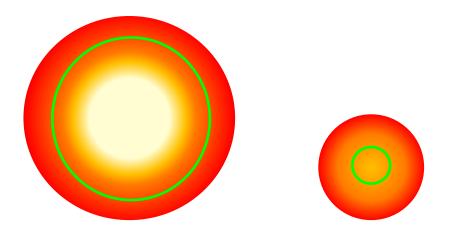
- ¹⁸F-FDG PET-CT imaging is increasingly growing since the introduction of clinical PET-CT scanners (ca. 2000)
- Applications to Radiation Oncology: PET-based volumes of reference (BTV=biological target volume)
- Clinical decisions (including "BTV" delineation) generally based on the Standardized Uptake Volume (SUV)

$$SUV = \frac{c(t)}{A(t)} \cdot bw$$

- c = activity concentration (MBq/kg), A = injected activity (MBq), bw=body weight (kg)
- Importance of **standardization** (patient weight, uptake time, injected activity and correction for decay in the uptake time ...)
- Lesion motion might have negative (even destructive) effects on SUV quantification (see specific module)

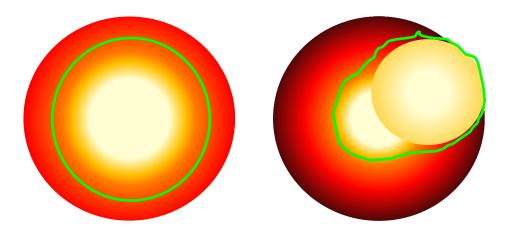
- Use of SUV to define biological volumes of reference suffers from **several limitations**
- **Fixed threshold** (e.g. 2.2): different behaviour for <u>small and large lesions</u>
- Percentage of SUV_{max}: underestimation in case of <u>inhomogeneous uptake</u> and <u>reconstruction artifacts</u> (e.g. Gibbs artifact in resolution-modeling reconstruction - PSF)
- Tumor motion is an additional bias

- threshold-based contouring (e.g. SUV=2.2)



 small lesions might be underestimated due to small SUV values – large lesions might be overestimated

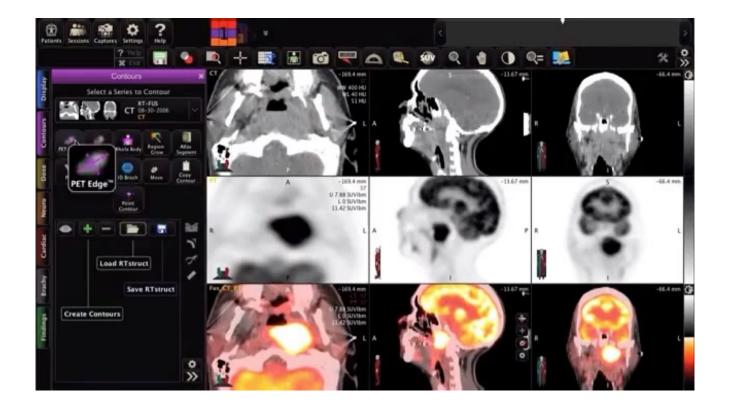
- percentage-based contouring (e.g. 40% of SUV_{max})



 inhomogeneous lesions tend to be underestimated because of high SUV spots

- -more refined algorithms are based e.g. on the maximum gradient (gradient-based) or on *objectrecognition* or *classification* algorithms
- there is no recognized "best-in-class" algorithm so far – a critical approach is always necessary when using commercially-available systems
- new algorithms might be more robust with respect to motion artifacts etc. – more research needed

- example of gradient-based algorithm



PET-CT REGISTRATION TO CT

- PET-CT has an **inherent CT dataset** that might be used for treatment planning if the required parameters and conditions are used
- PET-CT can be registered to a different (setup) CT usually through CT-CT (intra-modality) registration whose transformation is then applied to the PET dataset
- Multi-modality PET-to-CT registration is feasible but should be avoided (poor "common information")

IMAGE REGISTRATION - METHODS

- Spatial coherence between different imaging modalities used for treatment planning may be a key factor for treatment success
- Manual registration methods must be avoided when coregistering 3D datasets
- Automatic methods are implemented on modern treatment planning systems for rigid registration
- Deformable registration is seldom implemented and requires careful evaluation of results – however necessary for adaptive strategies (dose accumulation)

IMAGE REGISTRATION – transformation types

- **Rigid registration** described by 6 parameters
 - three translations and three rotations corresponding to the principal axes in 3D
- Deformable registration affine 12 parameters
 - 3 translations + 3 rotations + 3 scaling f. + 3 shear factors

- Deformable registration – local

- locally rigid registration free to deform on a large scale
- B-splines (B-cubic-splines)
- locally affine
- biomechanical models (finite elements method FEM)
- elastic or visco-elastic models

- ...

STRUCTURE OF A (DEFORMABLE) REGISTRATION ALGORITHM

$$\widehat{T} = \arg_T \max(sim(I_{Ref}, I_{fl} \circ T) + \lambda Reg(T))$$
similarity measure

 regularization term (deformable only)

- similarity measures vary as a function of the nature of coregistration (intramodality, multimodality ...)
- the regularization term charges a penalty on improbable transformations

SIMILARITY MEASURES

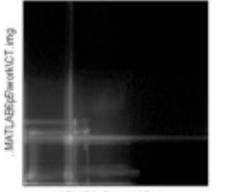
- Least-squares distance (set of **fiducial points**)
- Least-squares distance (**surfaces**)
- Intra-modality problem (e.g. CT-to-CT): cross-correlation (or mutual information, see below)
- Multimodality problem (e.g. MR-to-CT): maximization of the mutual information index/ normalized mutual information (NMI)

SIMILARITY MEASURE

- cross correlation
 - fast and robust method
 - only intramodality or
 "similar" (e.g. CT CBCT)

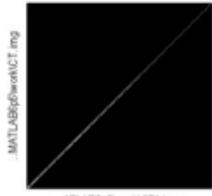
Normalised Cross Correlation

X1 = 1.000*X -0.000*Y +0.001*Z +0.004 Y1 = 0.000*X +1.000*Y +0.000*Z -0.033 Z1 = -0.000*X -0.000*Y +1.000*Z +0.016 Original Joint Histogram



ATLABEp5/work/iCT1.img

Final Joint Histogram

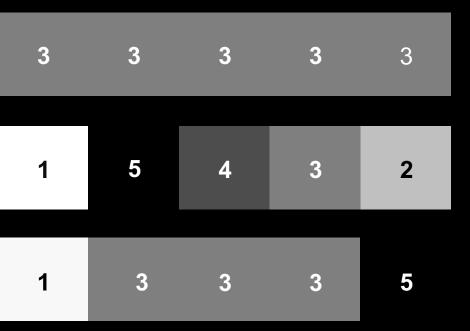


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$$R = \frac{\sum_{(i,j)\in T} (I_{fl}(i,j) - \overline{I}_{fl})(I_{ref}(i,j) - \overline{I}_{ref})}{\sqrt{\sum_{(i,j)\in T} (I_{fl}(i,j) - \overline{I}_{fl})^2} \sqrt{\sum_{(i,j)\in T} (I_{ref}(i,j) - \overline{I}_{ref})^2}}$$

IMAGE ENTROPY (INFORMATION)

$$H = \sum_{i} p_{i} \log \frac{1}{p_{i}}$$



 \Rightarrow **H** = **0** "PREDICTABLE" MESSAGE – no information added at each step

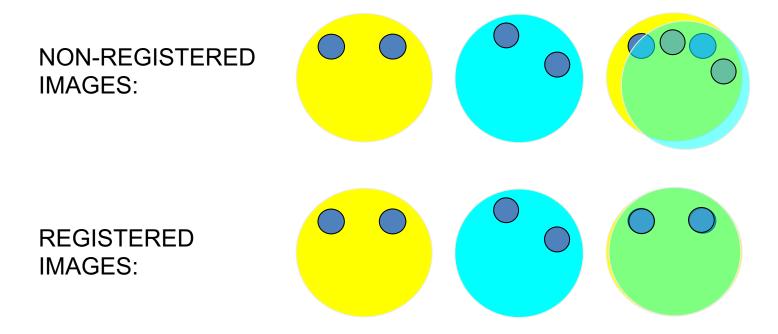
p(1)=0.2 p(2)=0.2 p(3)=0.2 p(4)=0.2 p(5)=0.2 \Rightarrow **H** = **1.61** "UNPREDICTABLE" MESSAGE – new information added at each step

p(1)=0.2 p(3)=0.6 p(5)=0.2 $\Rightarrow H = 0.95$ INTERMEDIATE CASE

The MUTUAL INFORMATION index

Subtraction of the "joint entropy" ("false" information) => maximization of the mutual information index

$$I(A,B) = H(A) + H(B) - H(A,B)$$



STRUCTURE OF A (DEFORMABLE) REGISTRATION ALGORITHM

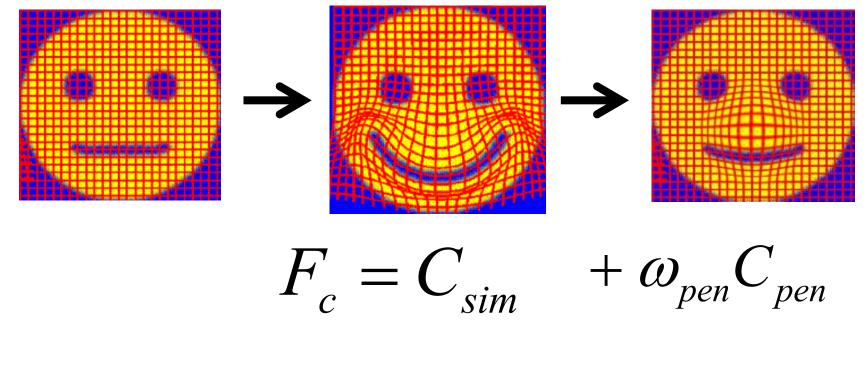
$$\widehat{T} = \arg_{T} \max(sim(I_{Ref}, I_{fl} \circ T) + \lambda Reg(T))$$

$$similarity measure$$

 regularization term (deformable only)

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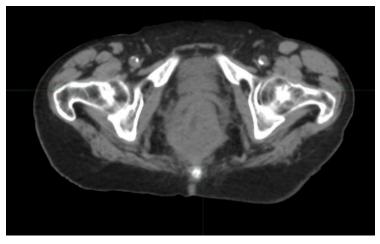
STRUCTURE OF A (DEFORMABLE) REGISTRATION ALGORITHM

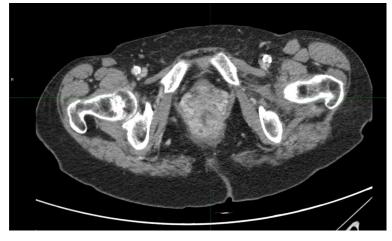


Regularization term:

 $1 + J_{\tau}J_{\tau}^{T}; \quad 1 + \det(J_{\tau}); \quad \mathbf{K}$

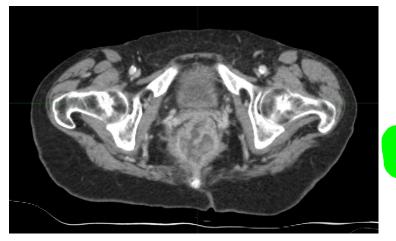
deformable registration - regularization



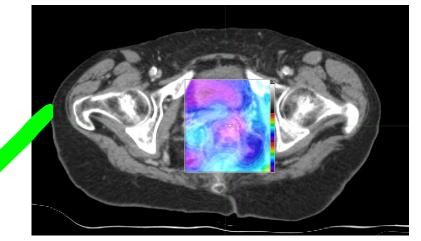


target

source



deformed



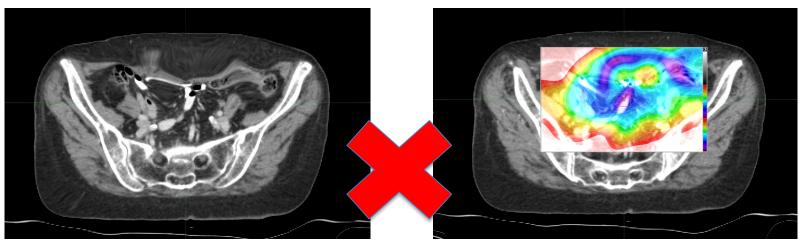
deformation map

deformable registration - regularization





source

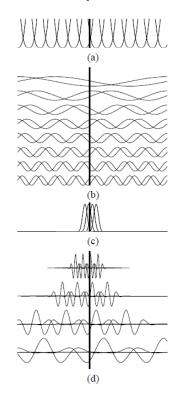


deformation map

deformed

DEFORMABLE REGISTRATION - LUNG

-**B-spline-based** deformable registration -continuous and differentiable functions -simple implementation – calculation speed -critical aspects in "anatomic discontinuities "





DEFORMABLE REGISTRATION - LUNG

-**regularization**: conditions on the transf. Jacobian -for example $D \cdot D^T = 1$ or J+1 = 0 etc.

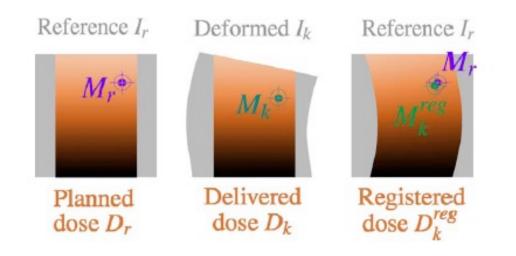
$$J(\mathbf{x}; \boldsymbol{\phi}) = \det(\mathbf{D}) \quad \text{with } \mathbf{D} = \begin{pmatrix} \frac{\partial T_x^c}{\partial x} & \frac{\partial T_x^c}{\partial y} & \frac{\partial T_x^c}{\partial z} \\ \frac{\partial T_y^c}{\partial x} & \frac{\partial T_y^c}{\partial y} & \frac{\partial T_y^c}{\partial z} \\ \frac{\partial T_z^c}{\partial x} & \frac{\partial T_z^c}{\partial y} & \frac{\partial T_z^c}{\partial z} \end{pmatrix}.$$

-corresponds to volume preservation -false in general in the lung => alternative condition mass preservation

Y Yin, EA Hoffman, CL Linb, "Mass preserving nonrigid registration of CT lung images using cubic B-spline". Med. Phys. 36(9), 4213-4222 (2009).

IMAGE REGISTRATION – beyond multimodality image integration for treatment planning

-Dose tracking – dose accumulation in Adaptive Radiation Therapy



G Janssens, J Orban de Xivry, S Fekkes, A Dekker, B Macq, P Lambin, W van Elmpt, "Evaluation of nonrigid registration models for interfraction dose accumulation in radiotherapy". Med. Phys. 36(9), 4268-4276 (2009)

TAKE HOME MESSAGES

1. Image registration is the process that makes two or more image sets **spatially coherent to each other**

2. Applications to Radiation Oncology include treatment planning and treatment verification/adaptation

3. Rigid transformation is to be preferred, **if possible**, but deformations shall be considered as potential sources of error

4. Deformable registration is powerful (sometimes necessary) but difficult to control – expert judgment needed!

5. ... see following module for other considerations on image registration applied to motion management ...