Fraunhofer MEVIS
PROJECT GROUP IMAGE REGISTRATION

UNIVERSITÄT ZU LÜBECK
INSTITUTE OF MATHEMATICS
AND IMAGE COMPUTING

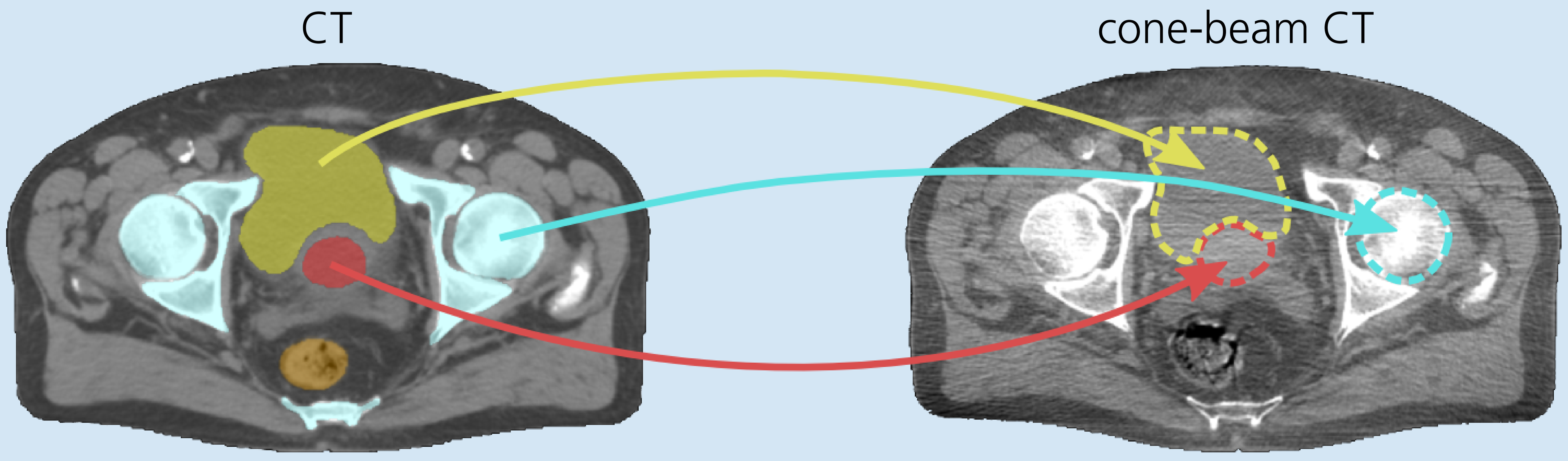
Deformable Registration for Adaptive Radiotherapy with Guaranteed Local Rigidity Constraints

Lars König, Nils Papenberg, Benjamin Haas* and Jan Modersitzki
*Varian Medical Systems Imaging Laboratory GmbH, Baden, Switzerland
lars.koenig@mevis.fraunhofer.de

ALIGNMENT OF CT AND INTRA-SESSION CONE-BEAM CT

In radiotherapy **planning CT images with segmentations are aligned to intra-session cone-beam CT images** to

- decide whether current anatomy makes an adaption of the treatment plan necessary
- calculate total dose accumulation for different body structures.



LOCAL RIGIDITY

As shown in Figure 1, this alignment is a delicate task, because adjacent structures are very sensitive to radiation.

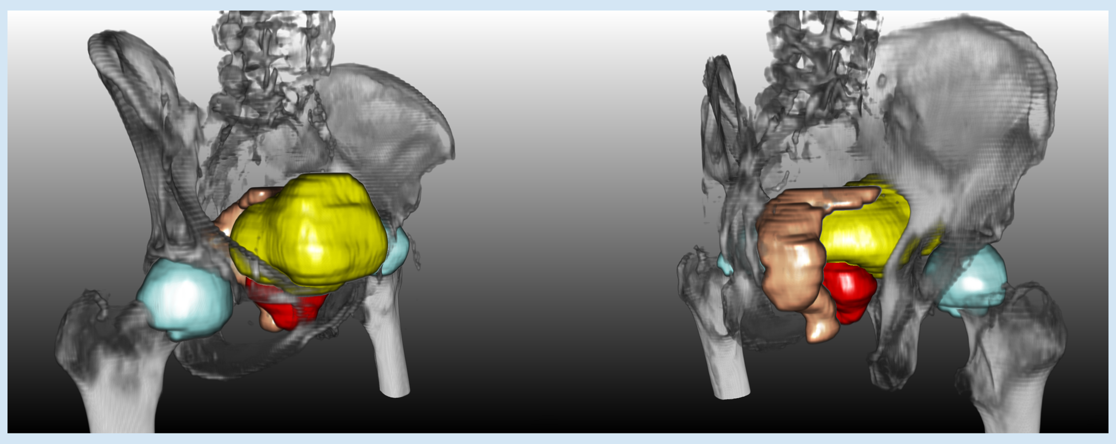


Figure 1: Location of prostate (■) in CT-pelvis scan, along with segmentations of critical structures such as rectum (■), bladder (■) and femurs (■), view from anterior (left) and posterior (right) direction

An exact registration of the images is **hindered by changes related to different anatomy, such as tumor morphology or bladder filling**, see Figure 2.

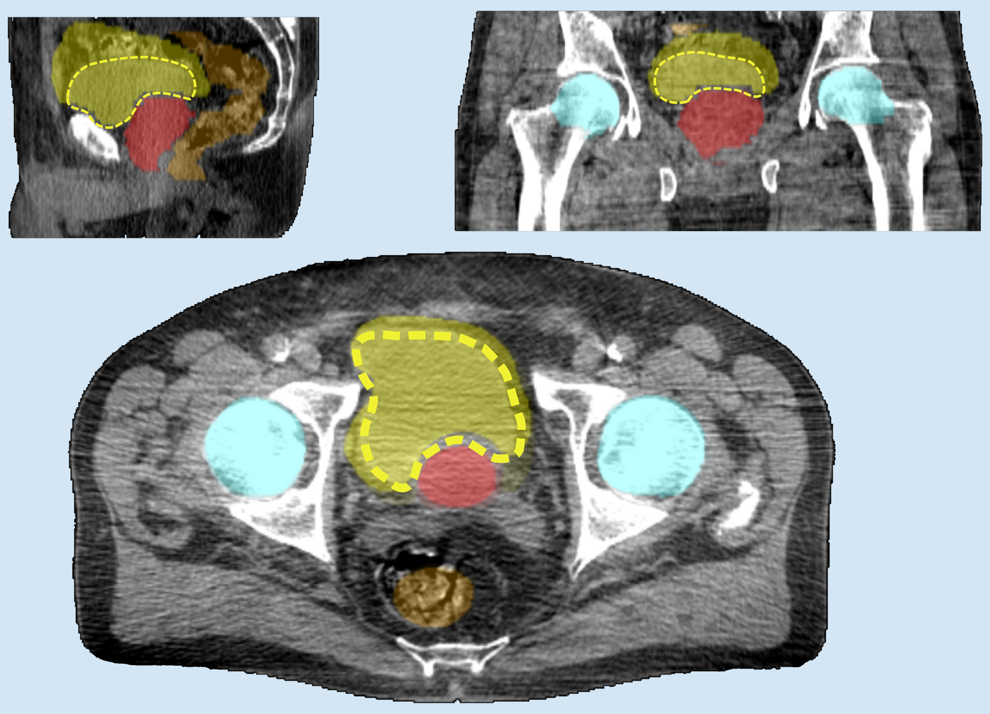


Figure 2: Planning CT segmentation of the bladder (■) visualized on different views of cone-beam CT with outline of cone-beam CT bladder (▬). E.g. different bladder fillings require a non-linear registration

State-of-the-art image registration algorithms do not make use of the fact that e.g. bones or prostate deform rigidly and do either apply a globally rigid transformation, which is not able to capture tissue deformations, or use, like popular Demon approaches, completely nonlinear transformations [1].

MATHEMATICAL MODEL

In our new approach, we

- use a non-Demon nonlinear strategy [2]
- additionally **add anatomical information to the deformation model** [3].

Given two images $R, T : \Omega \subset \mathbb{R}^3 \to \mathbb{R}$, find a transformation y such that the deformed image $T(y)$ is similar to R. To add further information **we require an additional constraint $C(y)$ to be fulfilled on a set $\Sigma \subset \Omega$, e.g. obtained from a segmentation**. Using a local rigidity constraint $C(y, \theta, b)$ this setup can be written as an optimization problem

$$J(y) = D(y) + S(y) \to \min, \text{ s.t.}$$
$$C(y, \theta, b)(x) = y(x) - (Q(\theta)x + b) = 0 \ \forall x \in \Sigma,$$

where D is a distance measure and S is a regularizer term that ensures a smooth solution. The distance measure can be formulated as

$$D(y) = \frac{1}{|y(\Omega)|} \int_{y(\Omega)} \left(T(y^{-1}(\hat{x})) - R(\hat{x})\right)^2 d\hat{x},$$

which can be transformed to

$$D(y) = \frac{1}{|y(\Omega)|} \int_{\Omega} \left(T(x) - R(y(x))\right)^2 |\det \nabla y(x)| \, dx,$$

with $|y(\Omega)| = \int_{y(\Omega)} d\hat{x} = \int_{\Omega} |\det \nabla y(x)| \, dx$.

This Lagrangian framework avoids tracking of constraint regions, i.e. Σ is not dependent on y and the constraints are differentiable. The minimization problem is then solved by using SQP-Methods with the resulting KKT-System

$$\begin{pmatrix} H & \nabla C^\top \\ \nabla C & 0 \end{pmatrix} \begin{pmatrix} \delta\tilde{y} \\ \delta\lambda \end{pmatrix} = -\begin{pmatrix} \nabla J + \nabla C^\top \lambda \\ C \end{pmatrix},$$

where $\delta\tilde{y} = (\delta y, \delta\theta, \delta b)^\top$ and H is the Hessian of the Lagrange function of J.

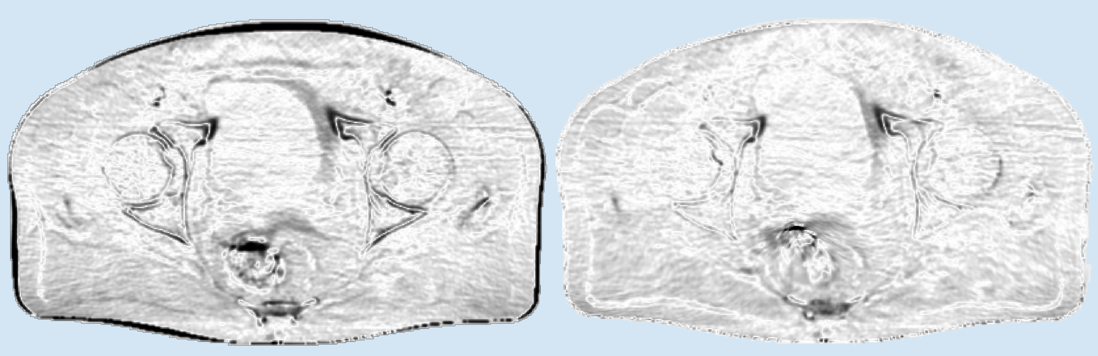


Figure 3: Difference image before (left) and after registration (right)

RESULTS

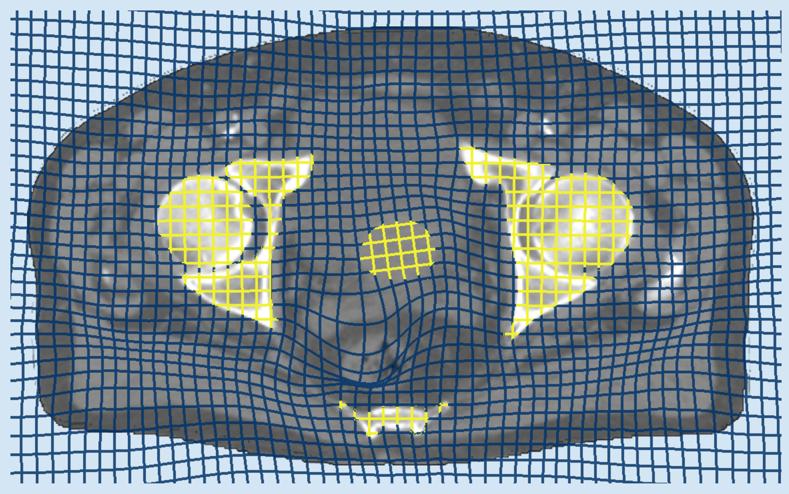


Figure 4: CT with deformation grid (■), rigid areas (■)

Since our approach is based on a hard numerical constraint, **local rigidity can be guaranteed and no additional parameters are required**.

As an example, the two images shown above are registered with the described method. The cone-beam CT was acquired by a clinical partner* using a Varian TrueBeam device. Figure 3 shows the difference between CT and cone-beam CT before and after registration.

As Figure 4 illustrates, the new scheme combines the **best of two worlds: it deforms selected structures rigidly but embedded in a global, smooth and nonlinear way.**

Compared to an entirely nonlinear registration (Figure 5) our method shows its superiority. The implausible deformation of bones and prostate is prevented, while the bladder and other tissue experience a nonlinear deformation.

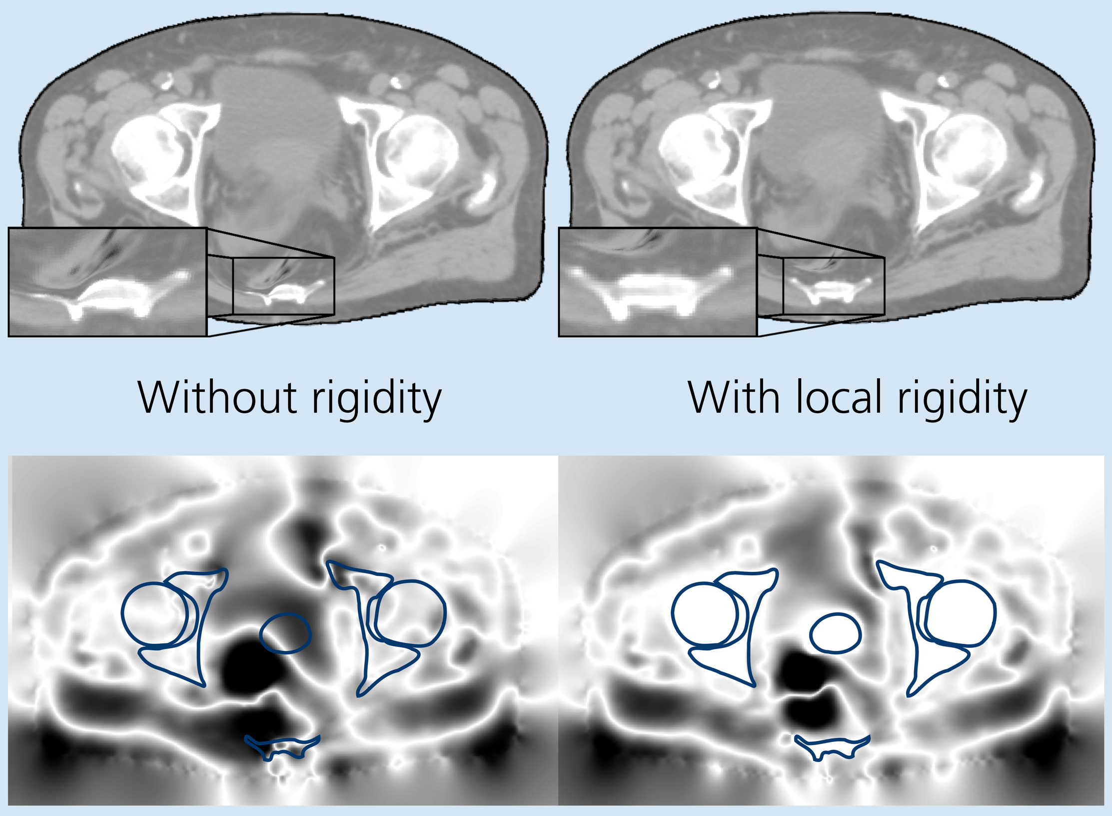


Figure 5: Top row: Deformed CT. Bottom row: local volume change from no change (□) to severe change (■)

REFERENCES

[1] S. Thörnqvist, J. B. Petersen, M. Høyer, L. N. Bentzen, and L. P. Muren, "Propagation of target and organ at risk contours in radiotherapy of prostate cancer using deformable image registration," *Acta Oncologica*, vol. 49, no. 7, pp. 1023–1032, 2010.
[2] J. Modersitzki, *FAIR: Flexible Algorithms for Image Registration*, vol. 6, Society for Industrial and Applied Mathematics (SIAM), 2009.
[3] E. Haber, S. Heldmann, and J. Modersitzki, "A computational framework for image-based constrained registration," *Linear Algebra Appl.*, vol. 431, 2009.

*Image data courtesy of Inselspital Bern

ZUKUNFTSprogramm Wirtschaft
Investition in Ihre Zukunft
financed by the European Union,
European Regional Development Fund (ERDF)