Computer- and robot-assisted Surgery

NCT

NATIONALES CENTRUM
FÜR TUMORERKRANKUNGEN
PARTNERSTANDORT DRESDEN
UNIVERSITÄTS KREBSCENTRUM UCC

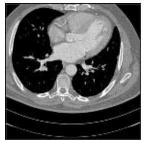
getragen von:
Deutsches Krebsforschungszentrum
Universitätsklinikum Carl Gustav Carus Dresden
Medizinische Fakultät Carl Gustav Carus, TU Dresden
Helmholtz-Zentrum Dresden-Rossendorf

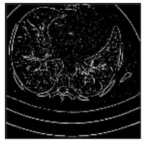
Lecture

Registration

Process chain computer-assisted surgery

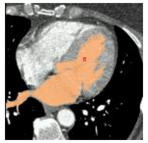
Image acquisition → Pre-processing





Pre-processing ↓

Segmentation



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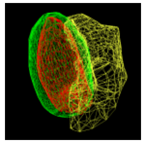
Modeling



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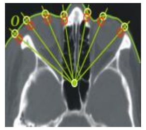
Registration



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Visualization/
Assistance

Overview of the lecture

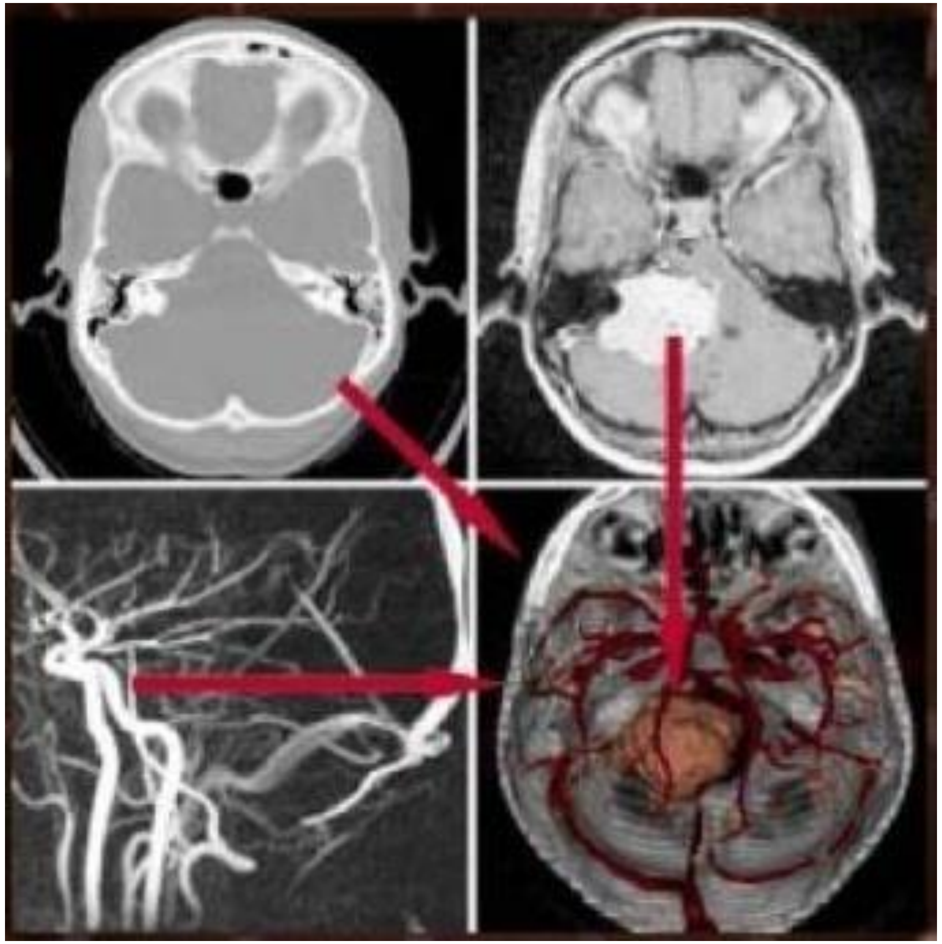
- Registration
  - General definition
  - Classification of registration problems
  - Registration methods:
    - Feature-based rigid registration: Procrustes Analysis
    - Iterative Closest Point
    - Mutual Information
    - Feature-based non-rigid registration using radial basis functions

What is registration?

CT

MRT

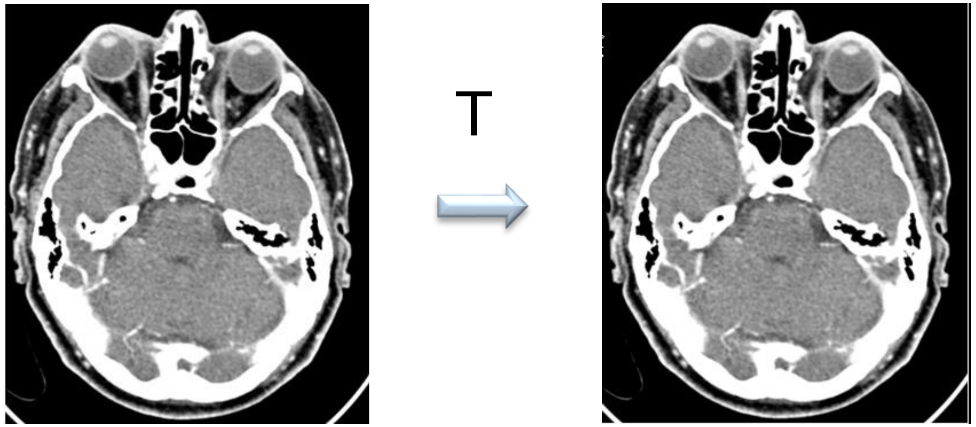
Angiogram



Source: Hajnal et al.

Registration

- **Registration:** Compute a t**ransformation** T, that maps a source dataset A in the best possible manner onto a reference dataset B. The quality of the mapping is defined over a **similarity measure**.

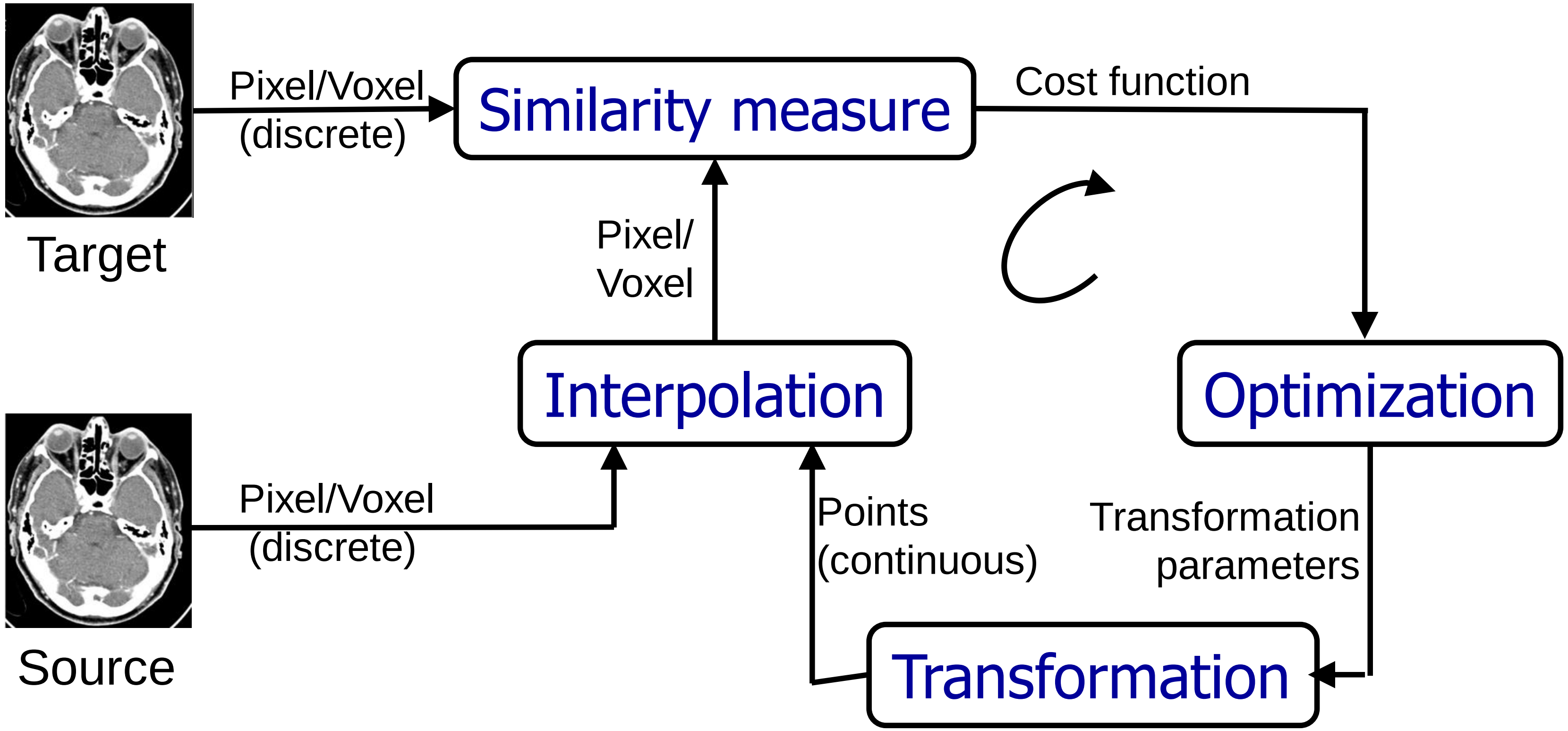


Dataset A Dataset B

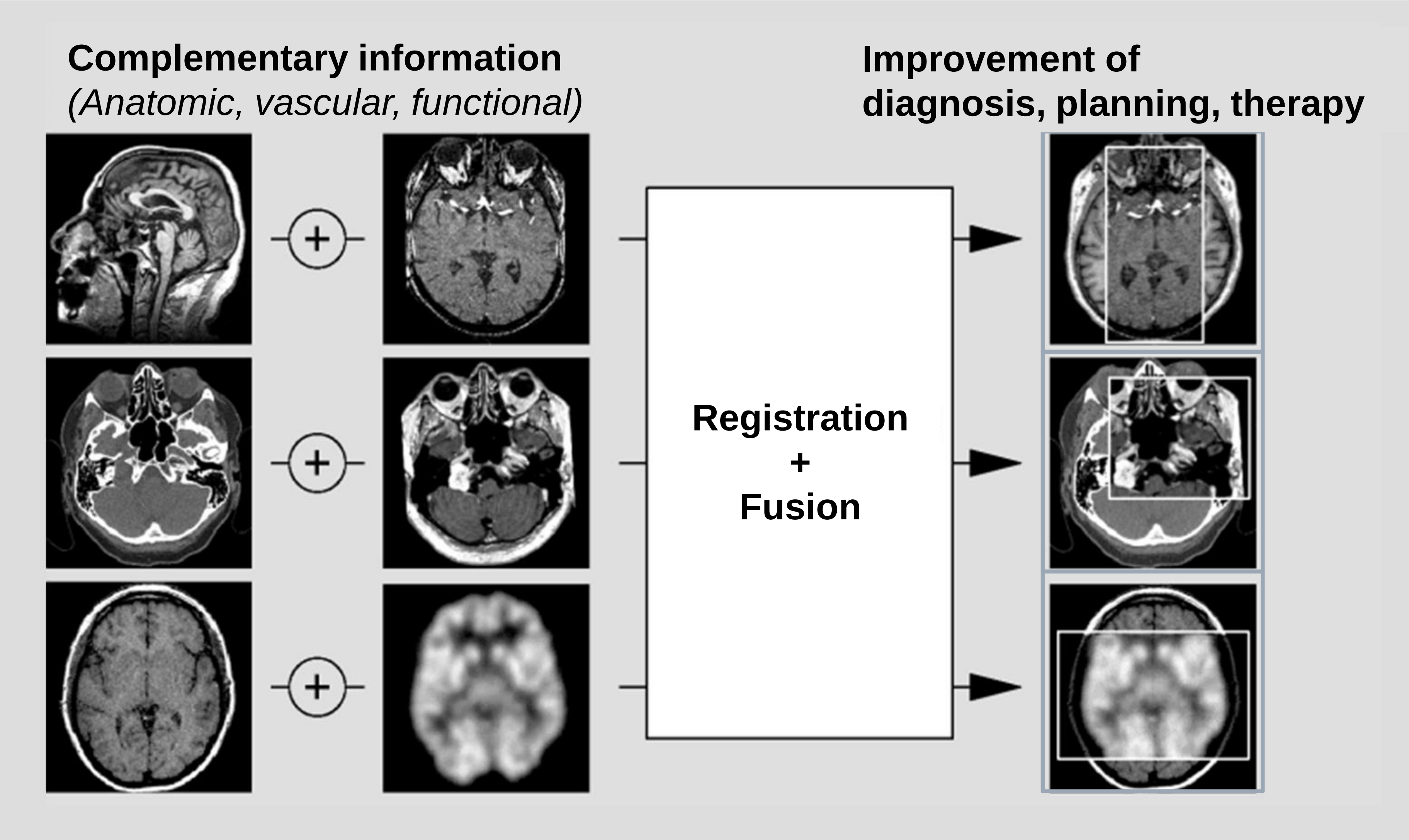
- **Fusion:** Use registration to display source dataset in target dataset

Registration

- Components of a registration algorithm:



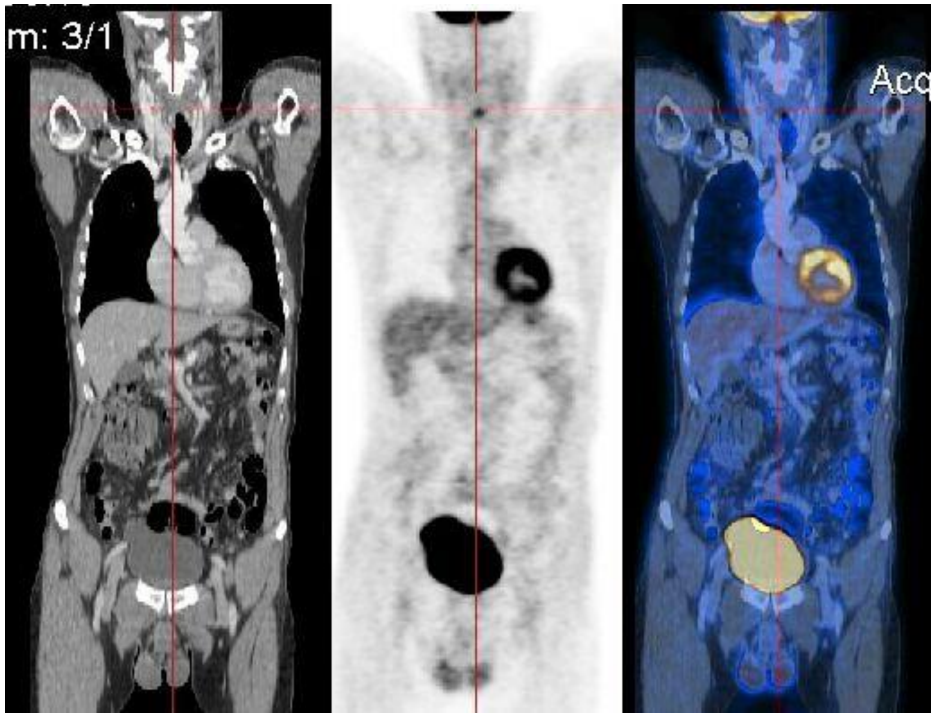
What is registration?



Registration for what?

- Combination of different modalities (MRT, CT, PET,…)
  - Functional information and anatomy
- Follow-Up Screening of patients
  - Movement compensation during dynamic perfusion examinations
  - Monitoring of disease progression
- Combination of pre-operative planning data with intra-operative sensor data
  - Intra-operative usage of tumor resection planning
- Combination of individual anatomies with atlas

Registration for what?



Source: Wikipedia

- Potential:
  - Diagnosis
  - Therapy planning
  - Intraoperative support
  - Evaluation

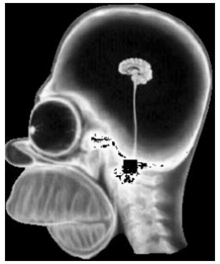
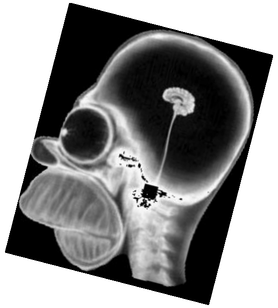
- Problem:
  - How are the different datasets connected with one another?
  - How to compute the transformation?
  - How to measure the quality of a registration?

Registration problems

- **Intra-modality, Intra-subject:**

  same image source, same patient

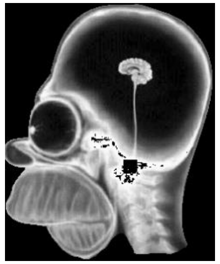
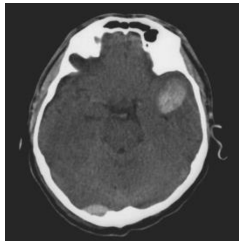
  → Different view angle, monitoring of disease progression

- **Intra-modality, Inter-subject:**

  same image source, different patient

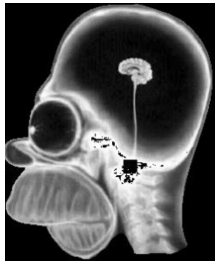
  → Atlas-generation und atlas-based segmentation

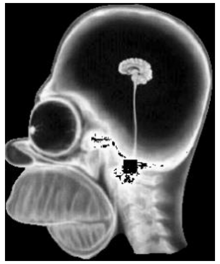
Source: A. Pitiot, ariser.info

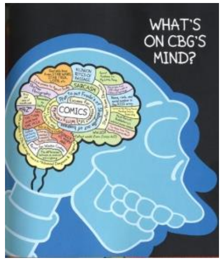
Registration problems

- **Inter-modality, Intra-subject:**
  different image source, same patient
  → Image data fusion, most common mode of registration



- **Inter-modality, Inter-subject:**
  different image source and patient
  → Pathology research





Source: A. Pitiot, ariser.info

Classification

Further classification parameters:

- Dimensionality of the data
- Basis of registration (Marker, landmarks, intensities)
- Type of transformation (Translation, rotation,…)
- Transformation area (global, local)
- Computation/optimization of transformation
- Interpolation
- Interaction (automatic, interactive)
- Objects in the data

Classification

Dimensionality of the data:

- 2D / 2D

  → e.g. registration of two ultrasound images
- 2D / 3D

  → e.g. registration intraoperative X-Ray and pre-operative CT
- 3D / 3D

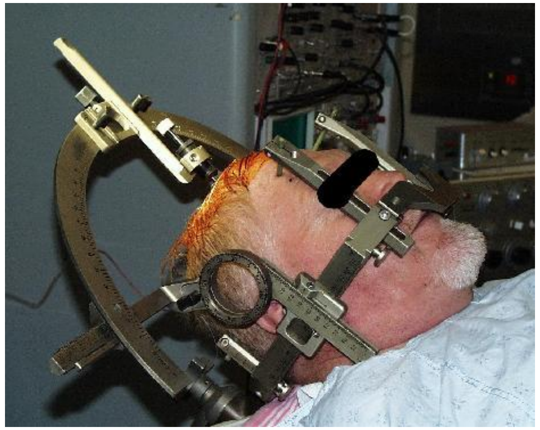
  → e.g. registration of two tomographic datasets
- Time as additional dimension

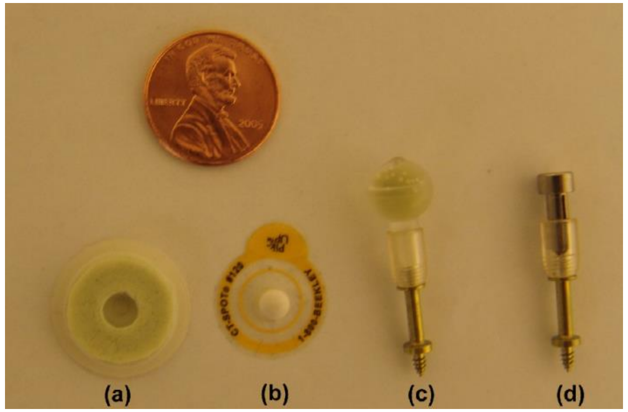
Higher dimensionality implies more complex transformation

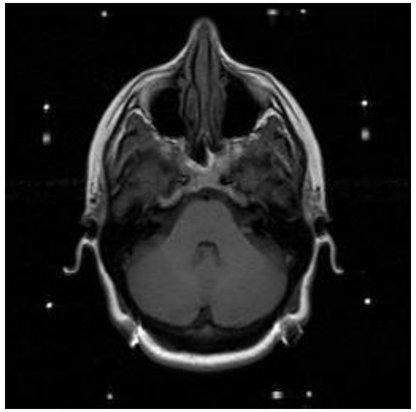
Classification

Basis of registration

- Not image-based features
  - Calibrated coordinate systems, Multimodal scanner
- Extrinsic features
  - Invasive:
    - Stereotactic frame
    - Marker (e.g. screws)
  - Non-invasive
    - Template, Adapter
    - Marker (e.g. skin marker)



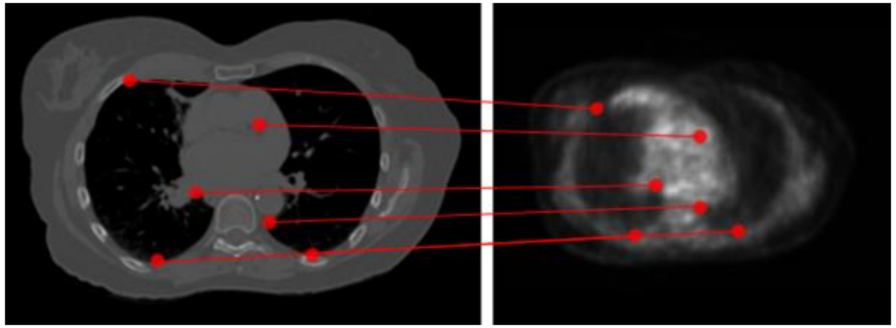


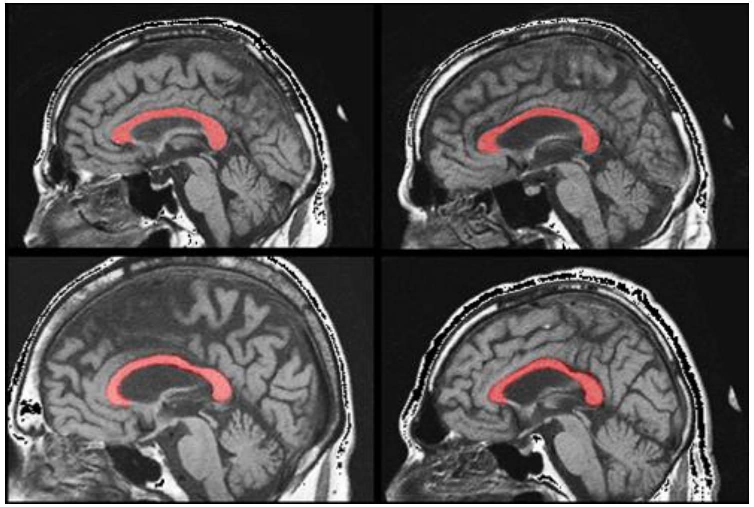


Classification

Basis of registration

- Intrinsic: Only patient data
    - Based on landmarks
        - Anatomic
        - Geometric
        - Structural
    - Based on segmentation
        - Fixed models
        - Deformable models
    - Based on pixel-/voxel properties
        - Grayscale/intensities, gradients
        - Registration of entire image contents
        - (Common in modern deep learning based registration)



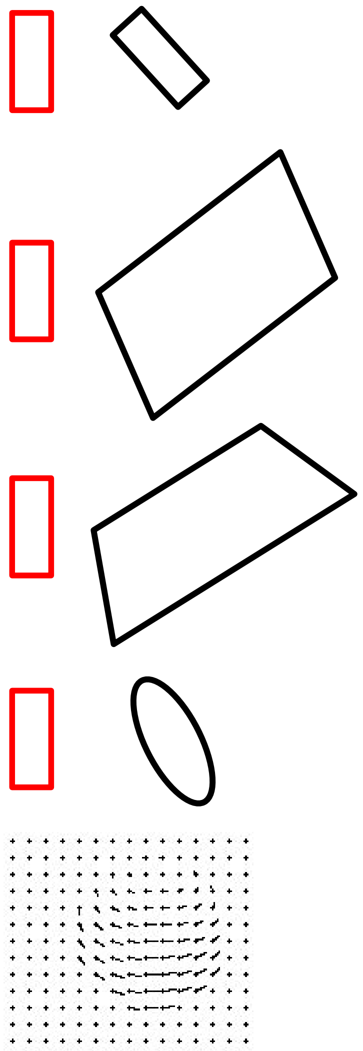


Source: A. Pitiot, ariser.info

Classification

Type of transformation

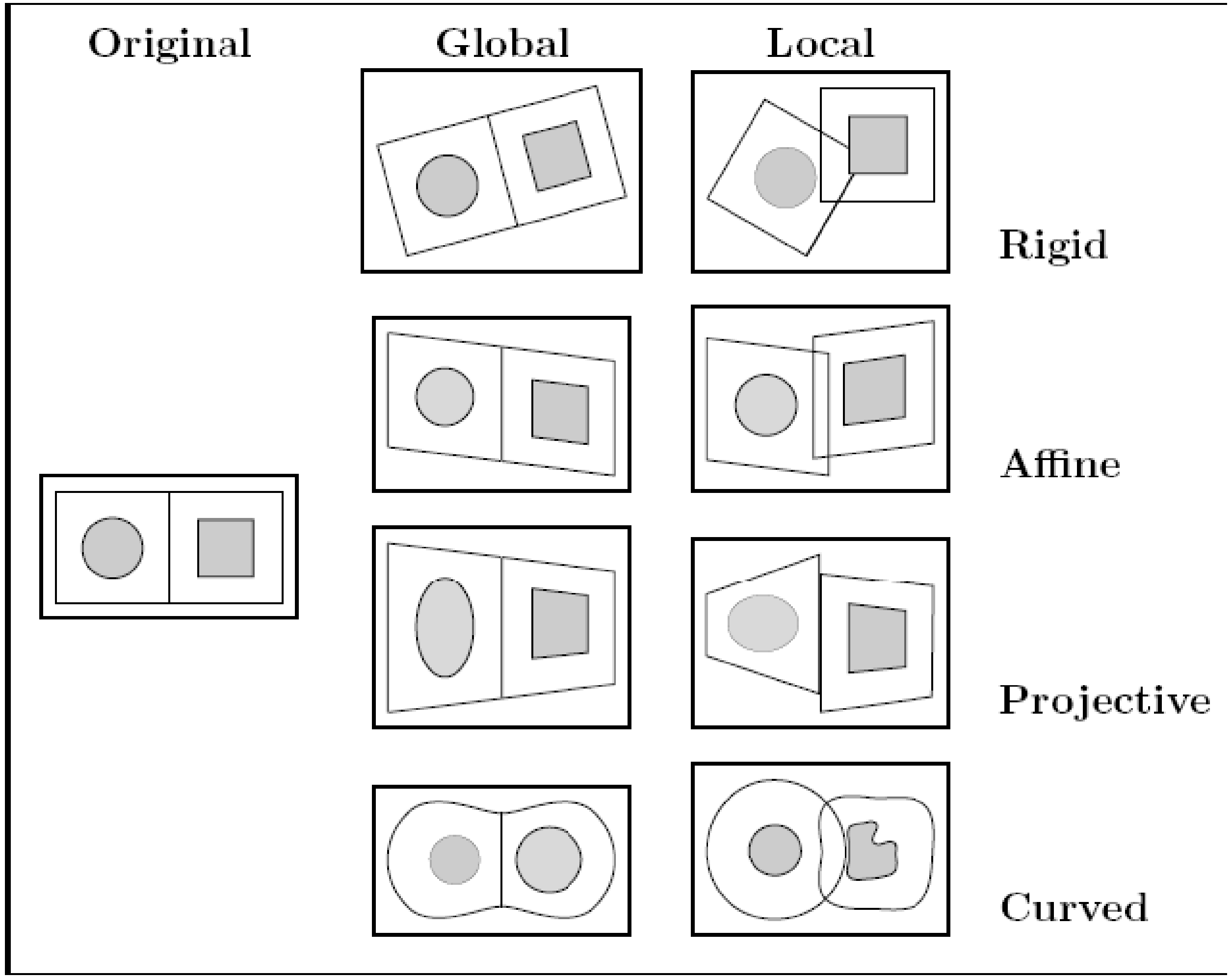
- **Rigid**:
  Only translation and rotation
- Affine:
  additionally scaling and shearing;
  Mapping of parallel lines on parallel lines
- Projective:
  Mapping of lines on lines
- **Non-rigid**/Elastic/"Curved":
  Mapping of lines on curves
- Non-parametric Transformations



Classification

Transformation area

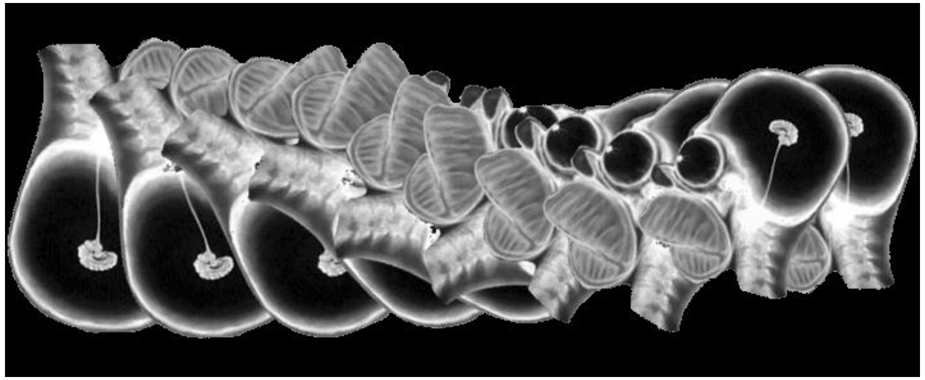
- Global
- Local



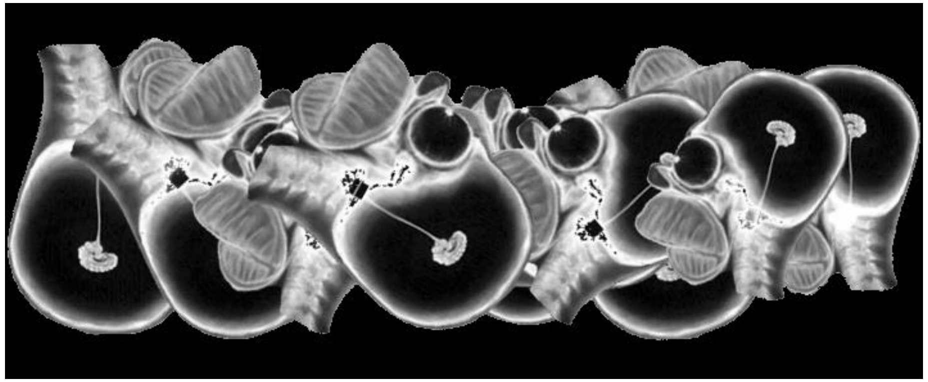
Classification

Computation of the transformation

- Explicit parameter search
- Parameter search (iterative): **Optimization problem**
  - Gradient descent
  - Hill Climbing
  - Simulated Annealing
  - Downhill Simplex
  - …



Gradient descent



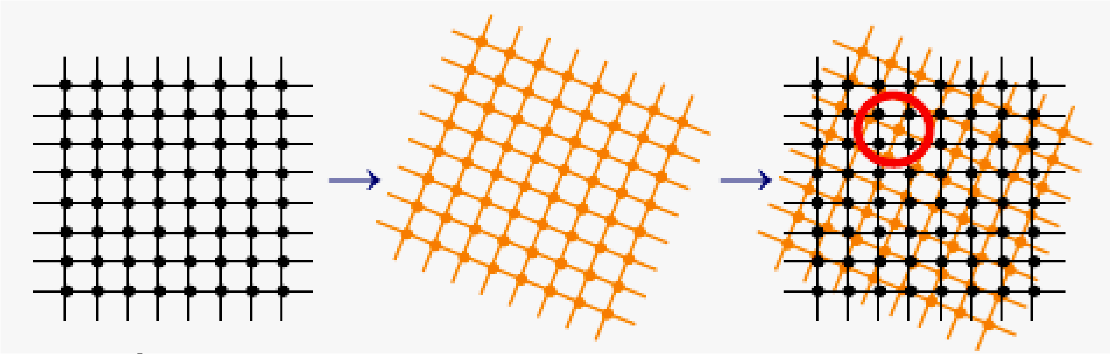
Simulated annealing

Source: A. Pitiot, ariser.info

Classification

Interpolation:

Is required when points in the source are not directly mapped on points in the target via the transformation



Source: N. Navab, CAMP, TUM

Examples:

- Nearest Neighbor Interpolation
- (Bi-)linear Interpolation
- Polynomial Interpolation
- B-Splines

Classification

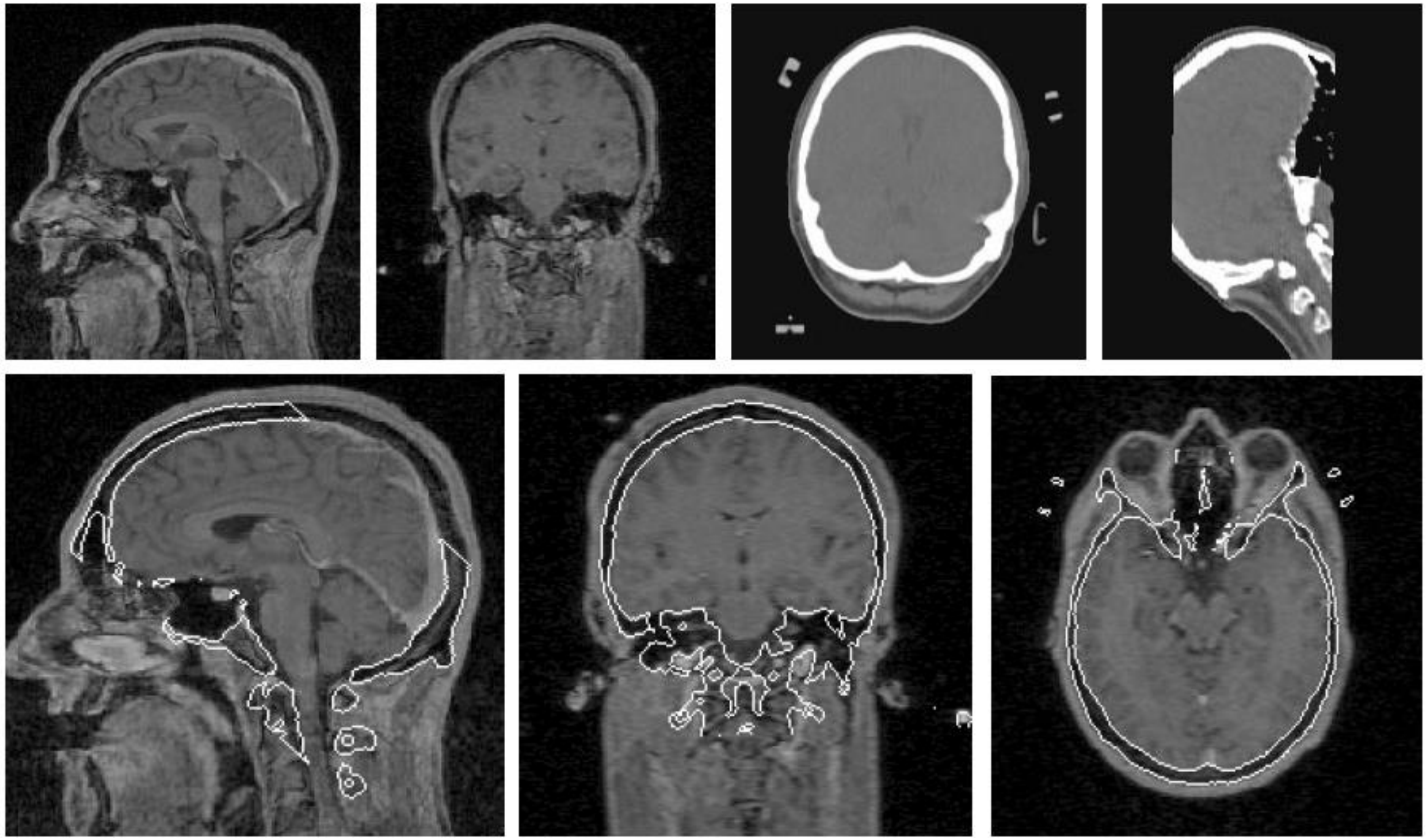
User-interaction

- Interactive
  - With initialization
  - Without initialization
- Semi-Automatic
  - User initialization
  - Correction through user
  - Both
- Automatic

Classification

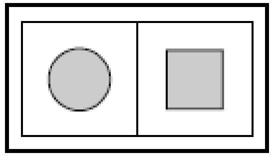
Typical areas of application

- Head
- Thorax
- Lungs
- Liver
- Prostate

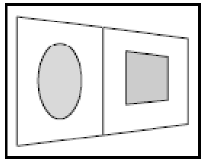


Quelle: Hill et al., **Medical image registration**

Which transformation maps

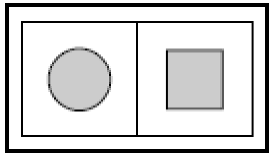


to

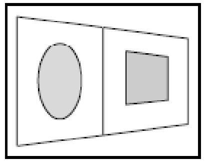


- A: local elastic
- B: global projective
- C: global affine
- D: local affine

Which transformation maps



to



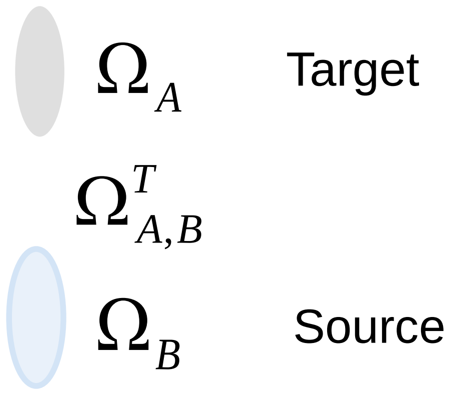
- A: local elastic
- **B: global projective**
- C: global affine
- D: local affine

Registration

Mathematical definition

- Given are the datasets A and B with the corresponding domain Ω

$$A : x_A \in \Omega_A \mapsto A(x_A)$$
$$B : x_B \in \Omega_B \mapsto B(x_B)$$



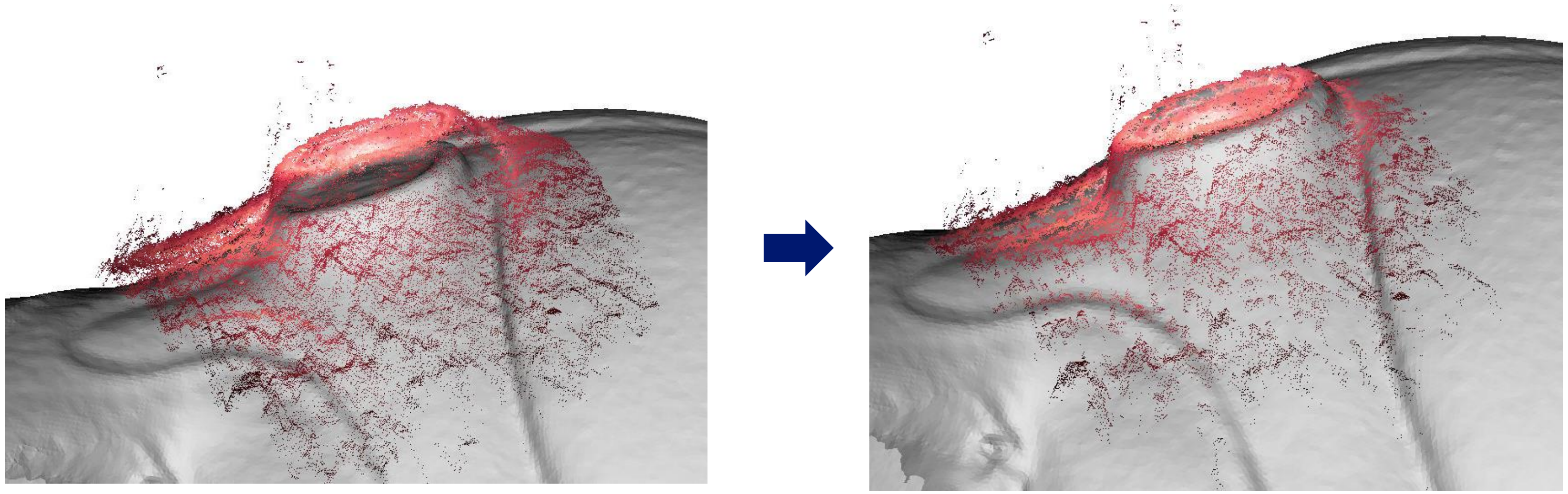
- Unknown: Transformation T

$$T \; : \; x_B \;\mapsto\; x_A \;\Leftrightarrow\; T(x_B) \;=\; x_A$$

$$\Omega^T_{A,B} = \left\{ x_A \in \Omega_A \middle| T^{-1}(x_A) \in \Omega_B \right\}$$

Rigid registration

- Registration of rigid objects that can change position but not shape
- Simplest registration method
- Used in daily clinical routine, e.g. neuro surgery
- Transform data into a common coordinate system



Reminder rigid transformation

- Defined through a rotation ***R*** and translation ***t***:

$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} = R\begin{pmatrix} x_0 \\ y_0 \\ z_0 \end{pmatrix} + t = \begin{pmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{pmatrix}\begin{pmatrix} x_0 \\ y_0 \\ z_0 \end{pmatrix} + \begin{pmatrix} t_x \\ t_y \\ t_z \end{pmatrix}$$

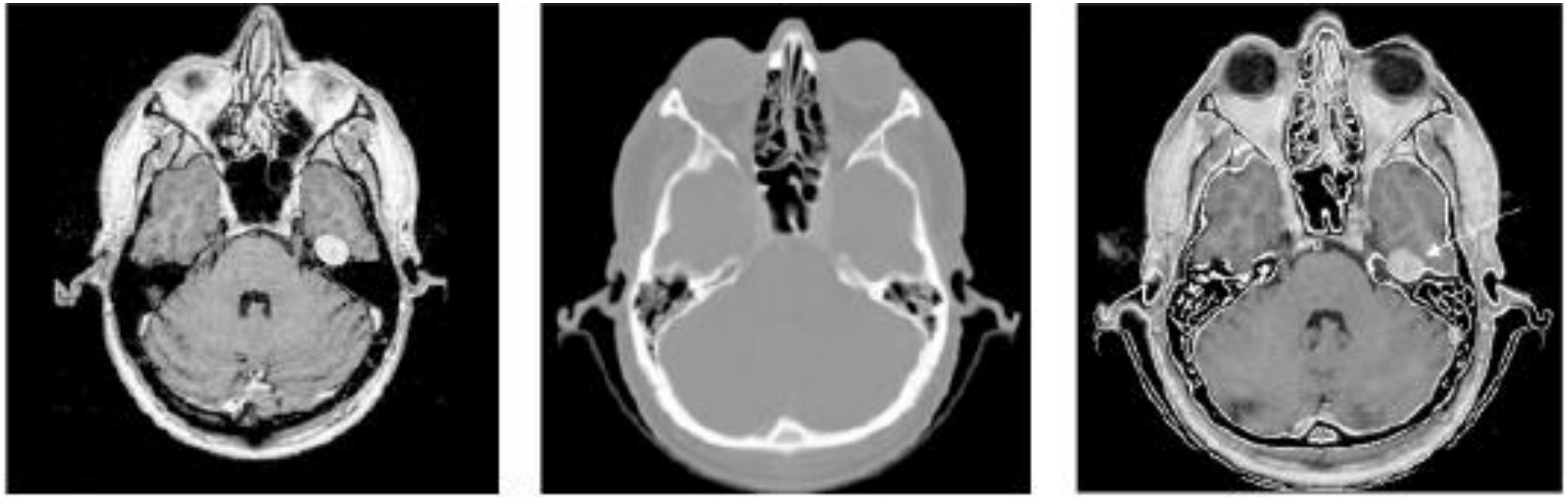
- Representation using homogenous coordinates and transformation matrix

$$\begin{pmatrix} x \\ y \\ z \\ 1 \end{pmatrix} = \left(\begin{array}{cc|c} & R & t \\ \hline 0 & 0 & 1 \end{array}\right)\begin{pmatrix} x_0 \\ y_0 \\ z_0 \\ 1 \end{pmatrix} = A\begin{pmatrix} x_0 \\ y_0 \\ z_0 \\ 1 \end{pmatrix}$$

- Alternative: Representation using quaternions

Non-rigid registration

- Usage for soft-tissue, body-induced movements, e.g. breathing, registration of different patients
- Complex, more difficult to validate
- Fundamental difference to rigid registration: more complex transformation model with more degrees of freedom (100 – 1000 in comparison to 6 for rigid registration in 3D)

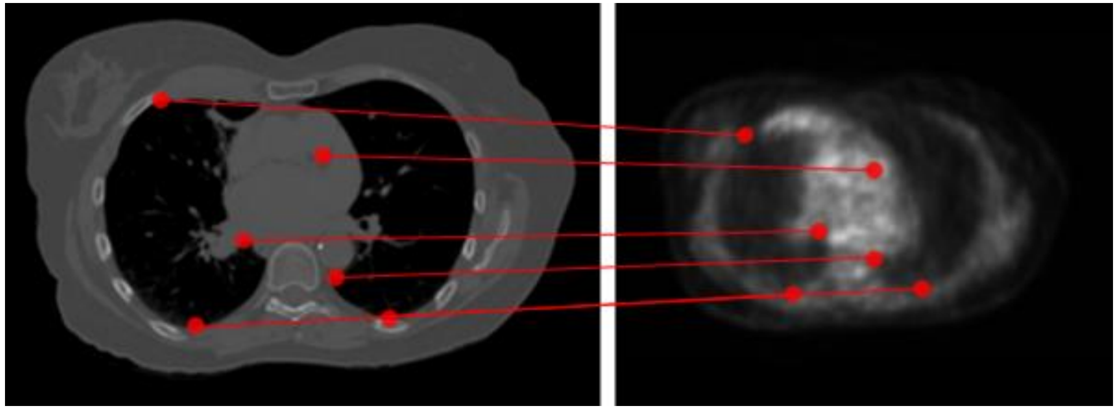


Rigid registration: Point correspondences

- Locate corresponding point features by choosing appropriate feature detectors and descriptors

  → comp. lecture computer vision
- Ideally in 3D: three correspondences are sufficient for an unambiguous computation of transformation
- Problem: Feature positions not exact
- Find an optimal transformation T through minimization of error

  →“Least Squares“-approach



Source: A. Pitiot, ariser.info

Rigid feature-based registration

- Mathematical description (3D case):
  - Given feature dataset $P = \{p_1, \ldots, p_n\}$ (Source)
  - Given feature dataset $Q = \{q_1, \ldots, q_n\}$ (Target)

    $p_i, q_i \in \Re^3$

  - Given correspondences of features $p_i \equiv q_i$

  - Unknown: Transformation T that minimizes the similarity measure

$$\|T(P) - Q\|^2 = \sum_{i=1}^{n} \|Tp_i - q_i\|^2$$

Rigid feature-based registration

Computation of transformation:

- Center the datasets P and Q with their averages $\bar{p}$, $\bar{q}$:

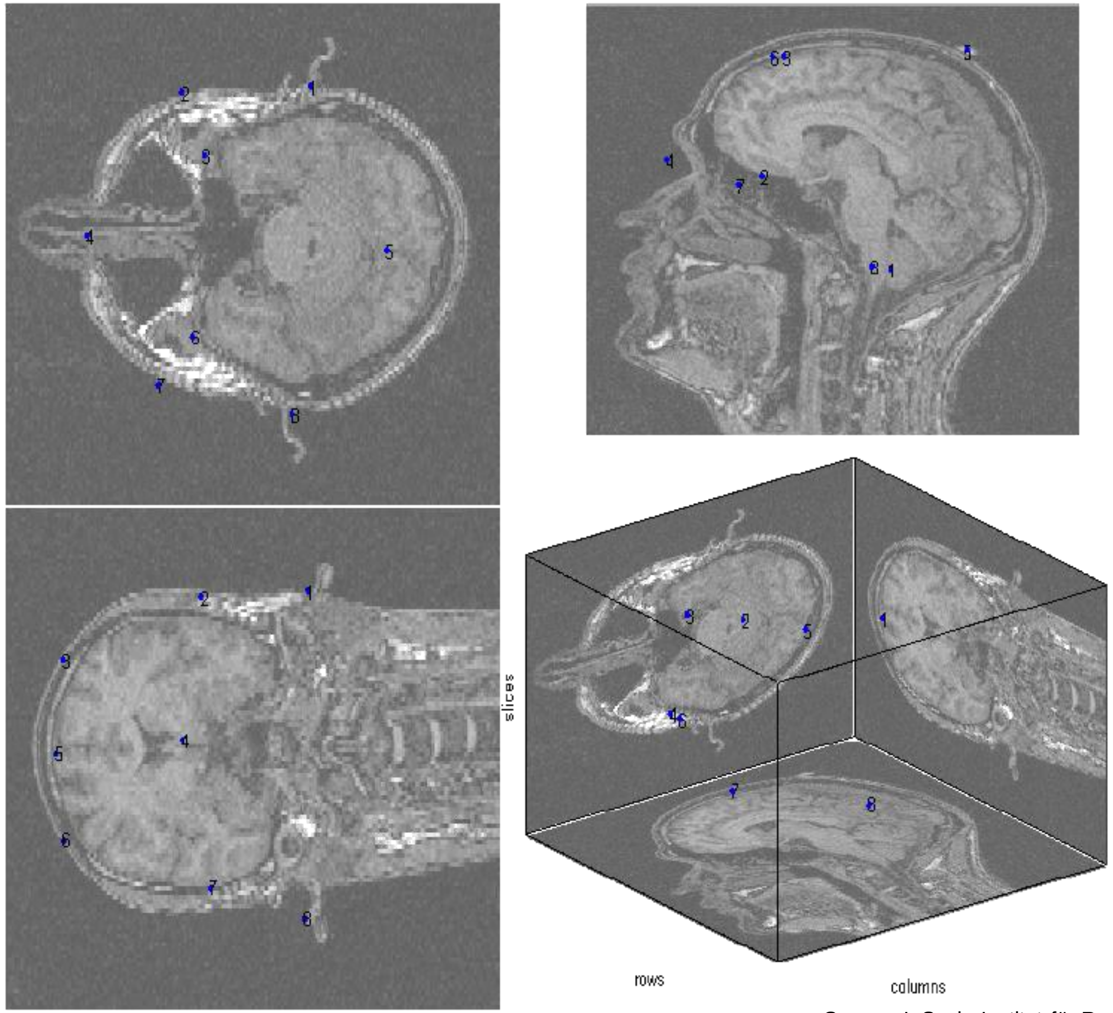
$$p_i \longmapsto p_i - \bar{p} \ , \quad q_i \longmapsto q_i - \bar{q}$$

- Compute the covariance matrices:

$$W = \sum_{i=1}^{n} p_i \, q_i^T = \begin{pmatrix} W_{xx} & W_{xy} & W_{xz} \\ W_{yx} & W_{yy} & W_{yz} \\ W_{zx} & W_{zy} & W_{zz} \end{pmatrix}$$

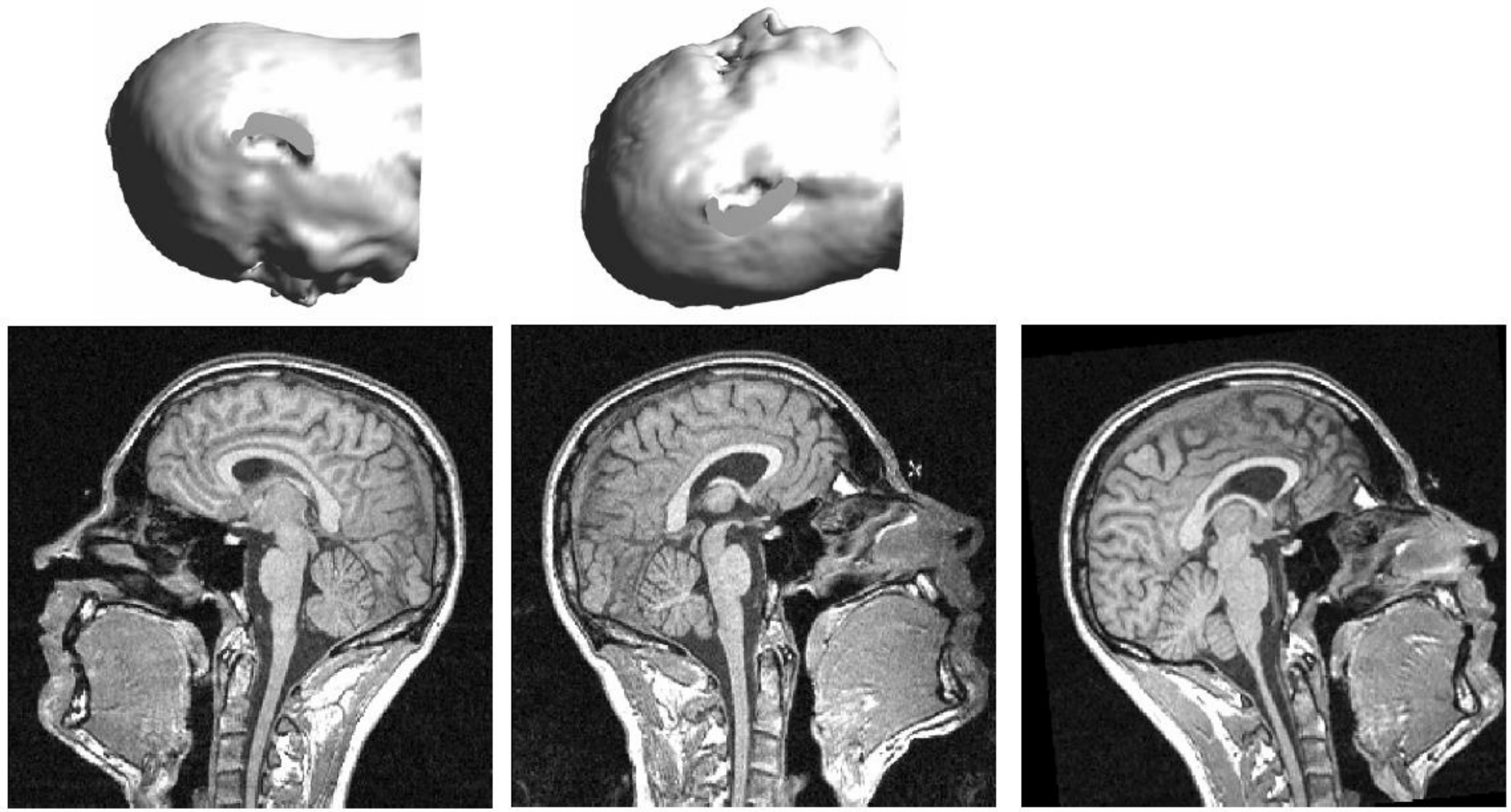
- Singular value decomposition: $W = USV^T$
- Rotation matrix: $R = U \begin{pmatrix} 1 & & \\ & 1 & \\ & & \det(UV^T) \end{pmatrix} V^T$
- Translation : $t = \bar{q} - R\bar{p}$

Rigid feature-based registration



Source: I. Sack, Institut für Radiologie, Charite Berlin

Rigid feature-based registration



Ventral position | Dorsal position | Registered dorsal position

Quelle: I. Sack, Institut für Radiologie, Charite Berlin

Feature-based registration

- Similarity measure: Fiducial Registration Error

$$\varepsilon^2 = \frac{1}{N}\sum_{i=1}^{N} \|Tp_i - q_i\|^2$$

- Assessment:
  - Anatomical or artificial markers available:
    - Fast method, robust, widely used for multimodal registration, easy to implement
  - Problems:
    - Accurate detection (Interpolation), often user interaction necessary, difficult detection of markers (e.g. PET), unambiguous matching of features necessary, only little (error prone) image information is used
    - Artificial marker are often at distance from target structure

Surface registration

- Search for edges/surfaces instead of single features
- Prerequisite: high contrast for automatic segmentation
- Problem:
  Data with functional
  information (PET, fMRI,
  SPECT)

Surface registration

Iterative Closest Point (ICP)

- Most commonly used registration algorithm
- Principle: Iterative registration of data points $f_i \in F_A$ of a set *A* with a representation F_B of surface *B* without prior known correspondences
    1. Find correspondences
    2. Compute transformation
    3. Iterate, until stopping condition is fulfilled
    - Applicable for different representations of surfaces:
        - Point set
        - Triangular mesh $v_i \in F_B$
        - Implicit und parametrized surfaces

Iterative Closest Point

Process (two point sets):

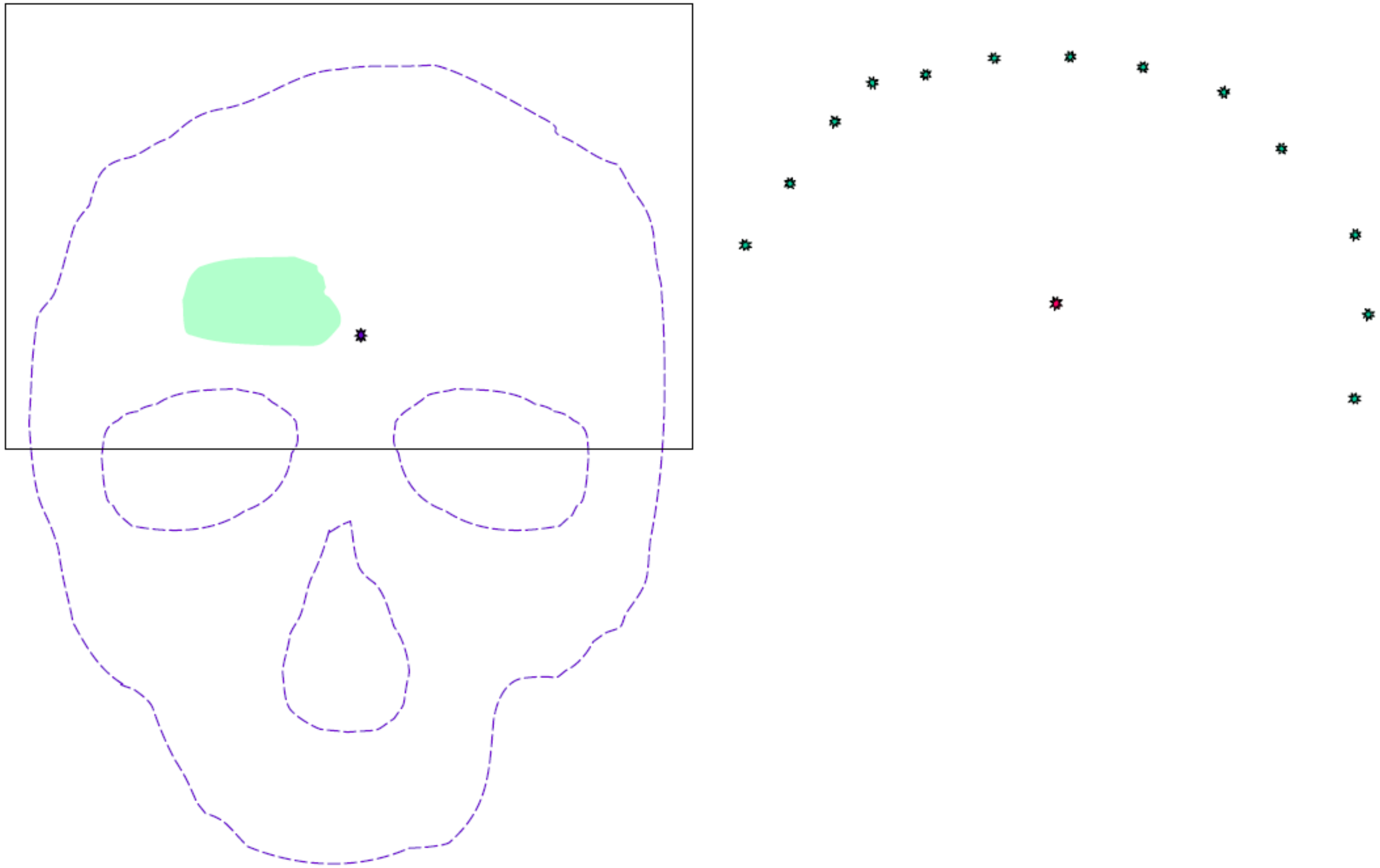
- Start: Initial Transformation T_0
- For each iteration : k
  - For each point $f_i \in F_A$ locate $v_i \in F_B$, that is closed to the resulting point
  - Compute T_{k+1} so that D is minimized (see feature-based registration) :

$$D_{k+1} = \sum_i \left\| v_i - T_{k+1} \cdot f_i \right\|^2$$

- Stopping criteria:
  - Threshold on error of last iteration
  - Maximum number of iterations

Iterative Closest Point

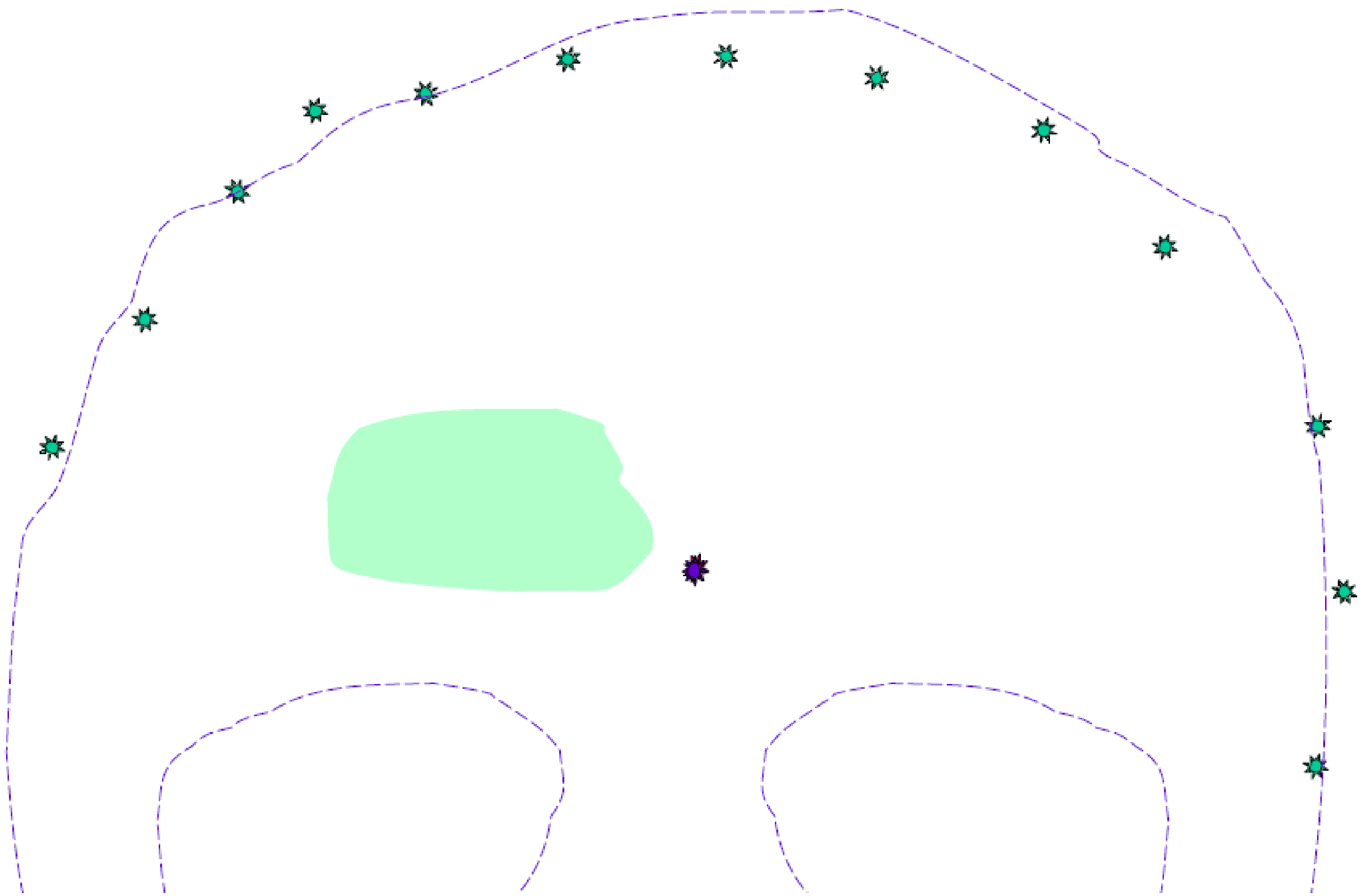
Data to register



Source: R. Taylor, JHU

Iterative Closest Point

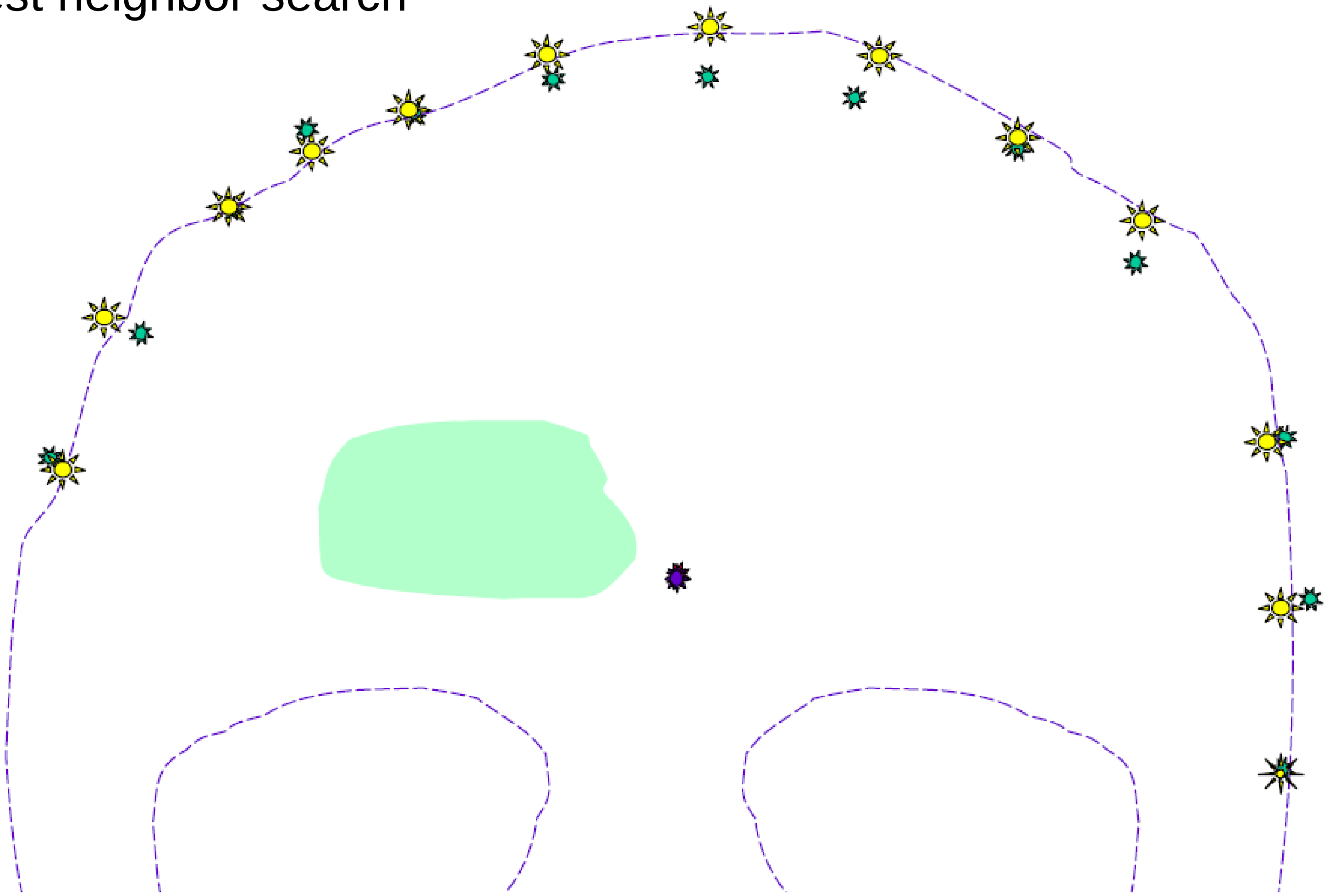
Initial registration



Source: R. Taylor, JHU

Iterative Closest Point

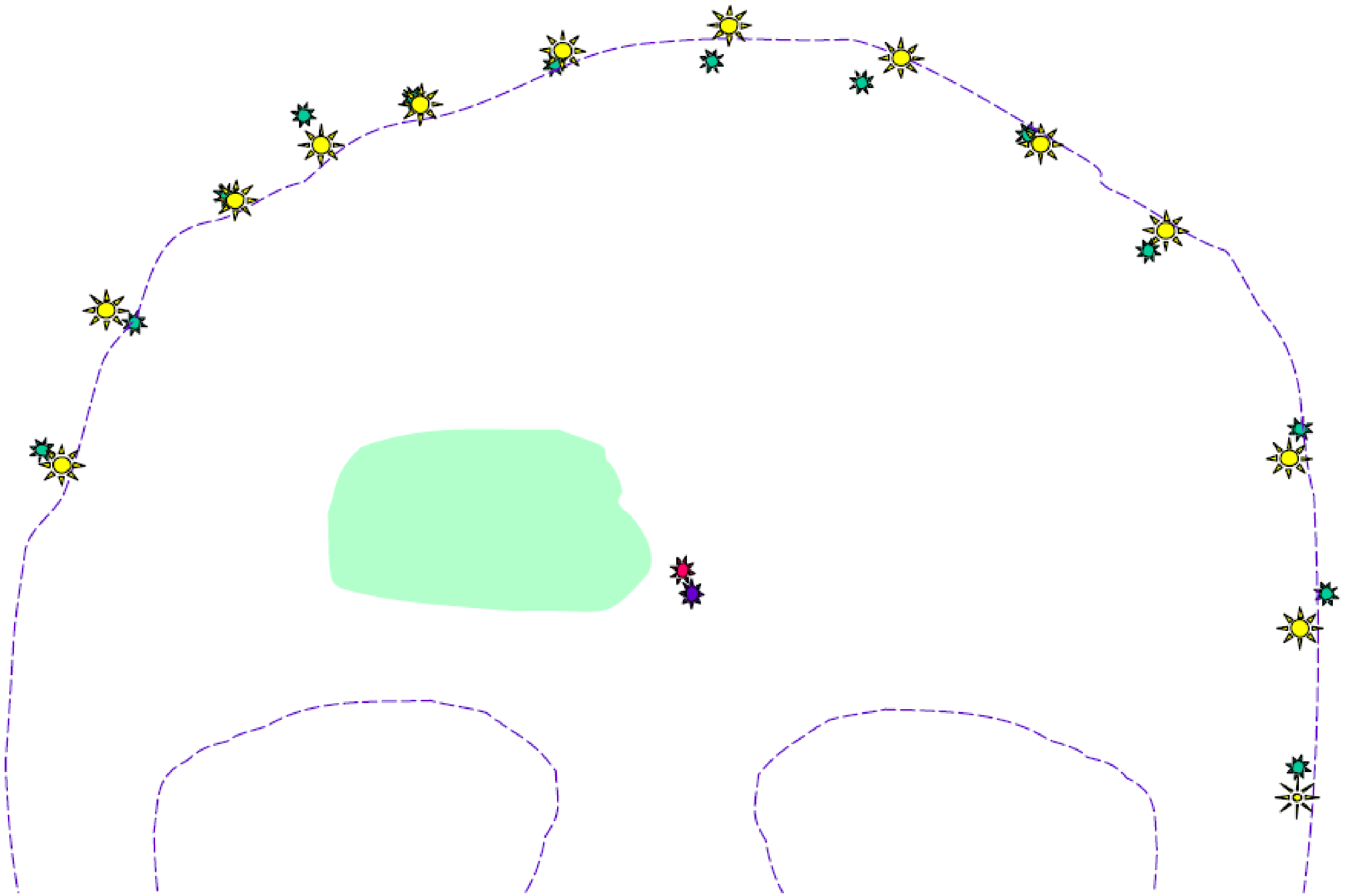
Nearest neighbor search



Source: R. Taylor, JHU

Iterative Closest Point

Recomputation and application of transformation

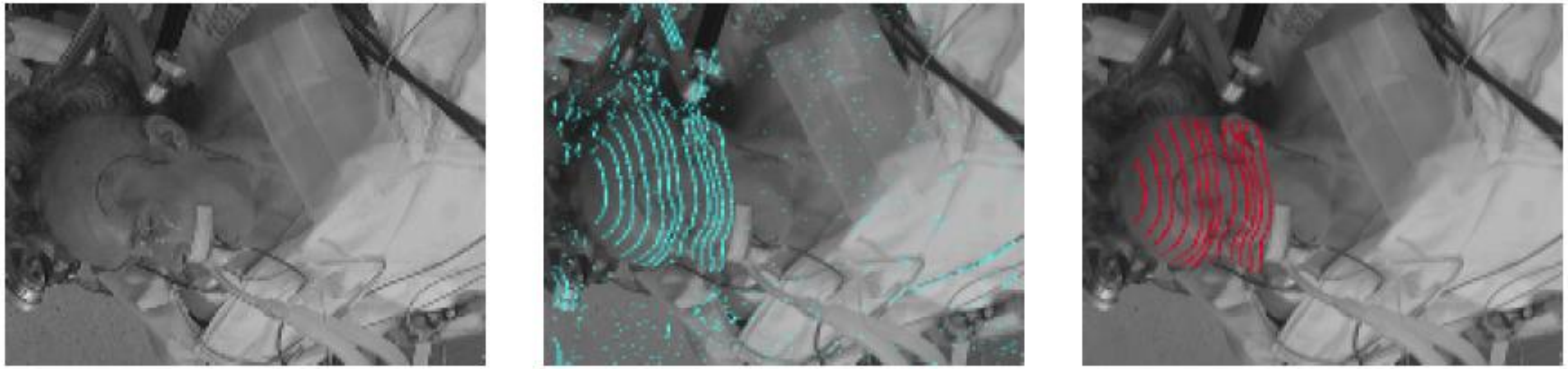


Source: R. Taylor, JHU

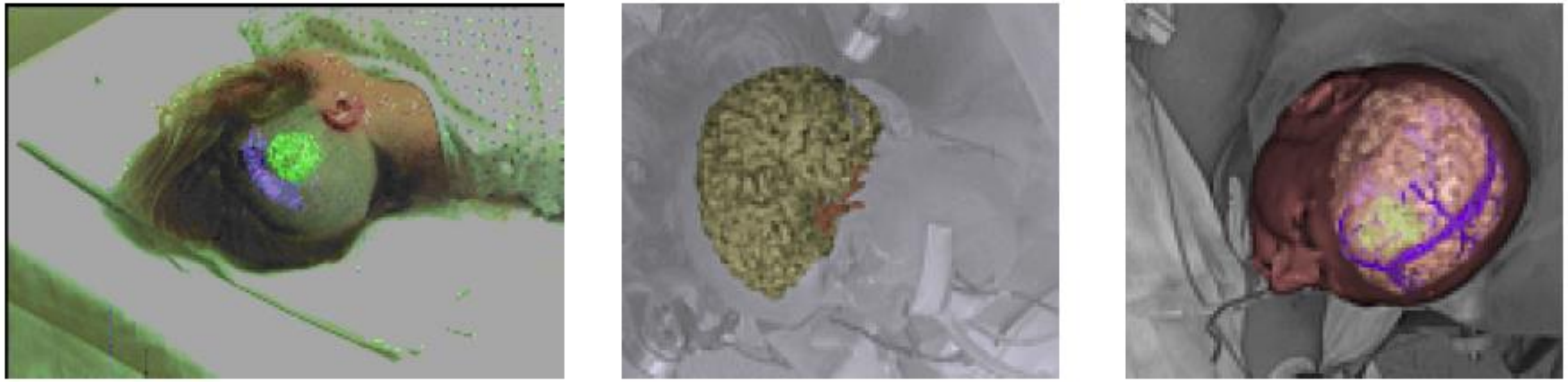
Iterative Closest Point

Source: **MIT AI Lab/**
Brigham and Women's Surgical Planning Laboratory

3D surface with laser scanner

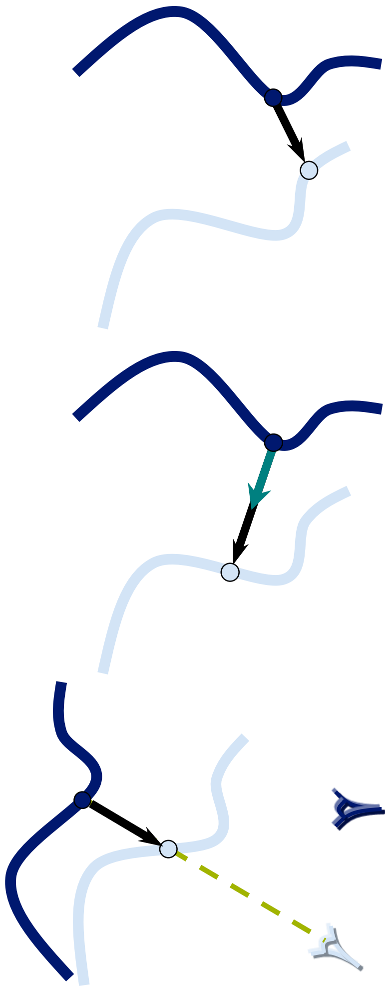


Registration (ICP) with pre-operative data



Iterative Closest Point Evaluation

- Applicable to points, lines and other forms of representations
- Uses only geometric information
- Only simple mathematical operations necessary
- Correspondence analysis costly and error prone
  - Optimized NN-search algorithm, K-D Tree
  - Alternative selection criteria of points
- Convergence in local minimum possible
  - good initial transformation required
  - multiple start transformations
  - different method for optimization
- Reacts sensitively to outliers
  - Weighting of correspondences,
  - outlier detection



Which of the following points regarding the Iterative Closest Point – Algorithm is incorrect?

A: Computation of transformation is mathematically simple

B: Sensitive in regards to outliers

C: Always converges to optimal solution

D: Uses only geometric information

Which of the following points regarding the Iterative Closest Point – Algorithm is incorrect?

A: Computation of transformation is mathematical simple

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C: Always converges to optimal solution

D: Uses only geometric information

Break?

Registration via intensities

- Registration based on voxel-/pixel-intensities (not on single features or point coordinates)
- Components
  - Similarity measure: function of intensities
  - Optimization
  - Interpolation
- Distinction:
  - Monomodal (Direct dependency of intensities)
  - Multimodal (Statistical dependency of intensities)

Registration via intensities

Intra-Modality (Monomodal):

- Deterministic similarity measures:
  - Sum of Squared Difference:

$$SSD(A,B) = \frac{1}{N} \sum_{x_A \in \Omega_{A,B}^T} (A(x_A) - B_T(x_A))^2$$

  - Sum of Absolute Difference:

$$SAD(A,B) = \frac{1}{N} \sum_{x_A \in \Omega_{A,B}^T} |A(x_A) - B_T(x_A)|$$

  - Normalized Cross Correlation:

$$NCC(A,B) = \frac{\sum_{x_A} (A(x_A) - \overline{A(x_A)})(B_T(x_A) - \overline{B_T(x_A)})}{\sqrt{\sum_{x_A} (A(x_A) - \overline{A(x_A)})^2 \sum_{x_A} (B_T(x_A) - \overline{B_T(x_A)})^2}}$$

Registration via intensities

Inter-Modality (multimodal): Non-linear relationship between intensities of images

- Same tissue type will have different intensity values
- Different tissue contrast
- Difference in image noise levels

Registration via intensities

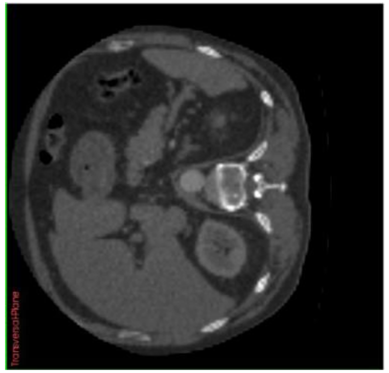
Information and entropy

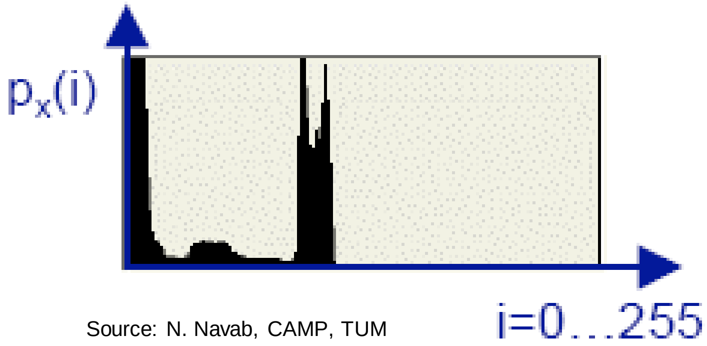
- Information is registration metric

  Goal: Information reduction
- Intensities of image are interpreted as random variables

$p_A(i)$ = Probability that a pixel in dataset A will have intensity i

- Probability destruction must be estimated
  - Histogram





Source: N. Navab, CAMP, TUM

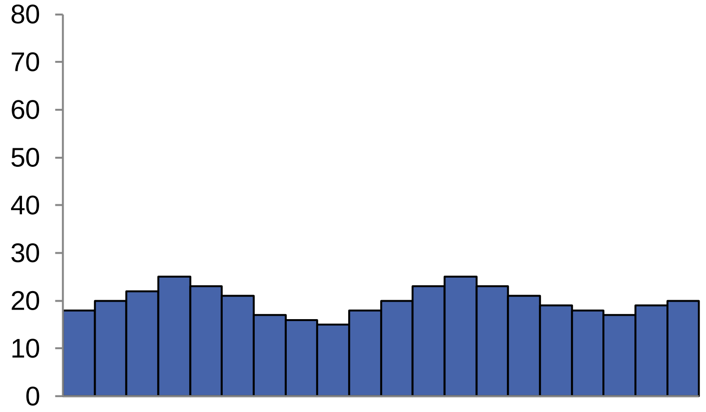
Registration via intensities

Information and entropy

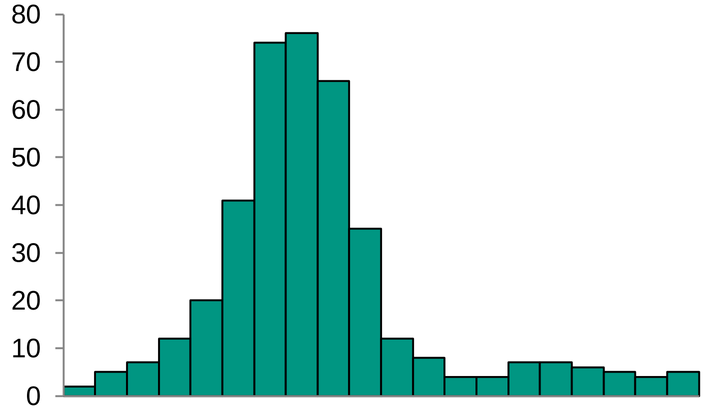
- Entropy describes information content of a signal:

$$H(A) = -\sum_i p_A(i) \log p_A(i)$$

- The more unpredictable, the higher the entropy
- For images: Entropy is large, when images are strongly textured; small, when image constant (a few, dominant intensities)



→ H(A) high



→ H(A) low

Registration via intensities

Information and entropy

- **Joint entropy**: $$H(A,B) = -\sum_{i,j} p_{AB}(i,j) \log p_{AB}(i,j)$$

$p_{AB}(i,j)$ = Probability that a pixel will have intensity i in image A and intensity j in image B

- It applies: $H(A,B) \leq H(A) + H(B)$

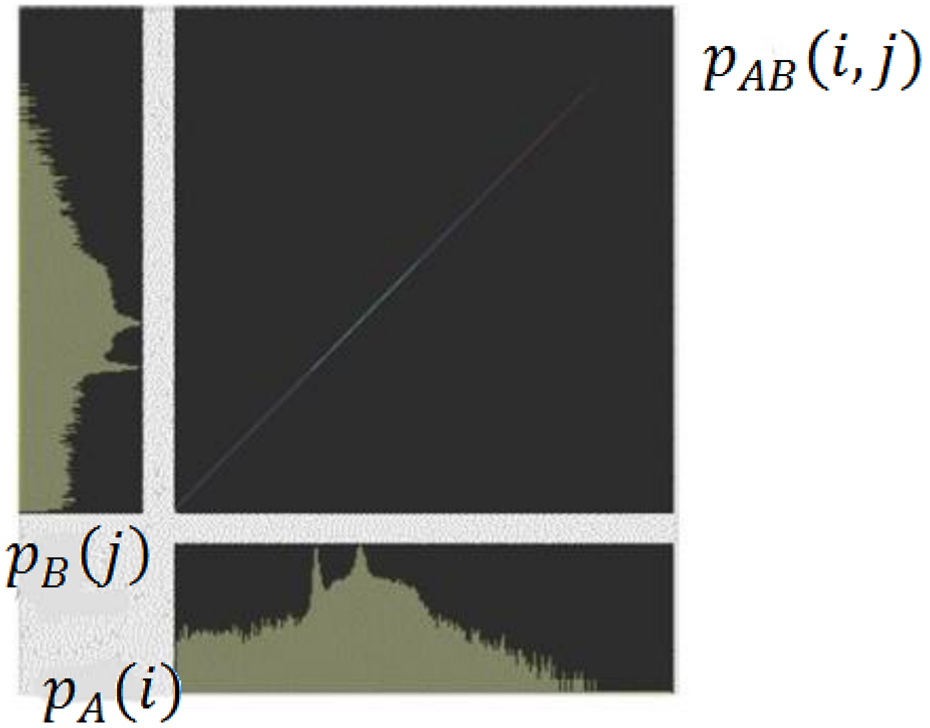
- If image A and B are independent, then

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

Registration via intensities

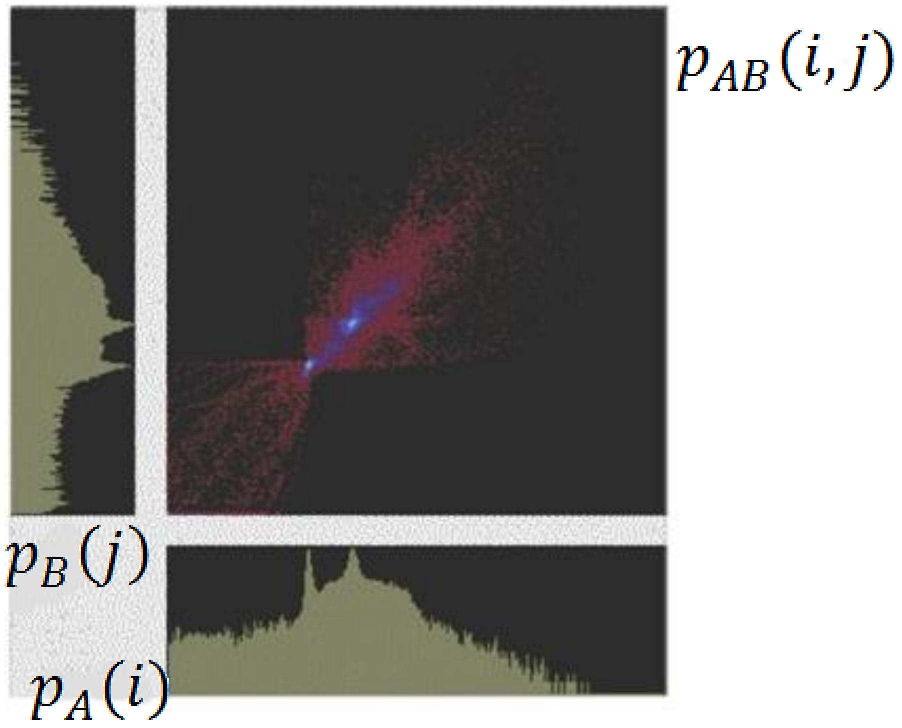
Overlay of images: Distribution in 2-dim. Histogram
→ Joint entropy

A, B identical



→ H(A,B) low

A, B slightly moved

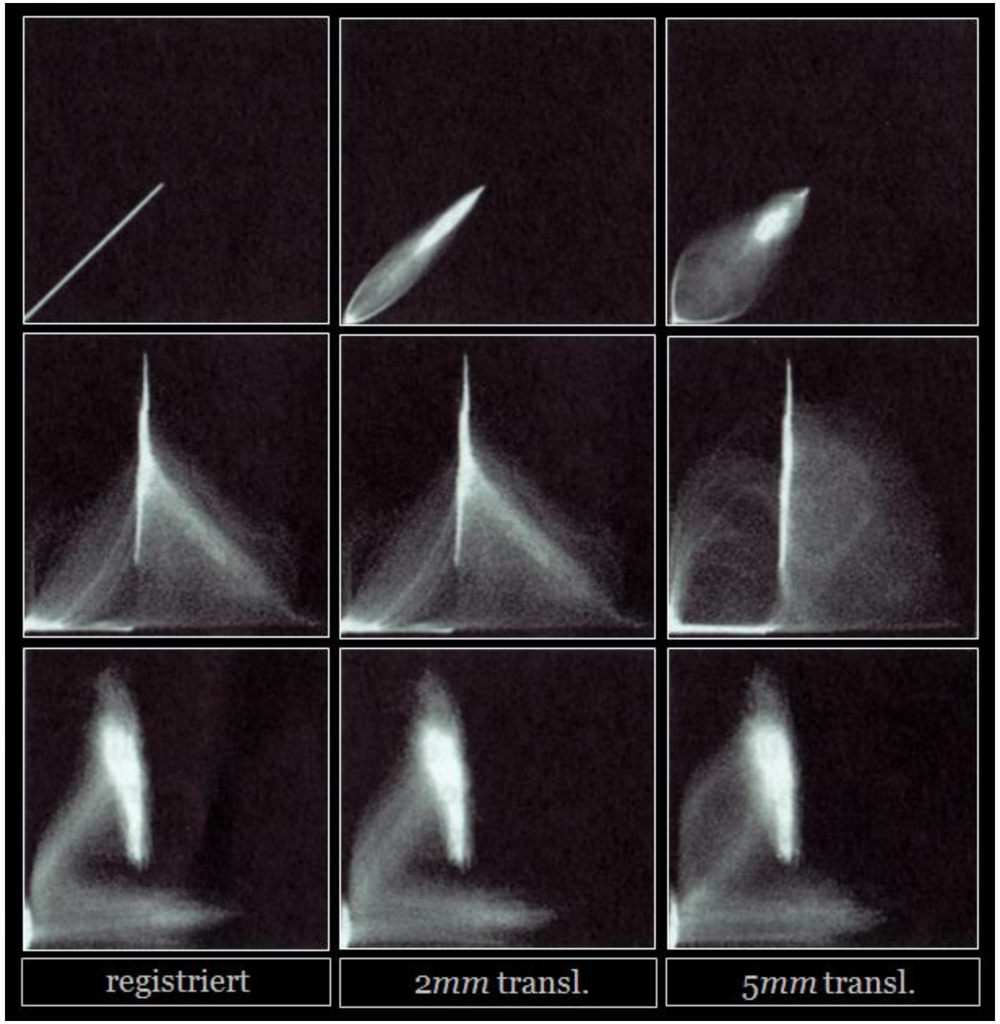


→ H(A,B) high

Source: N. Navab, CAMP, TUM

Registration via intensities

Joint histogram



MR-MR

MR-CT

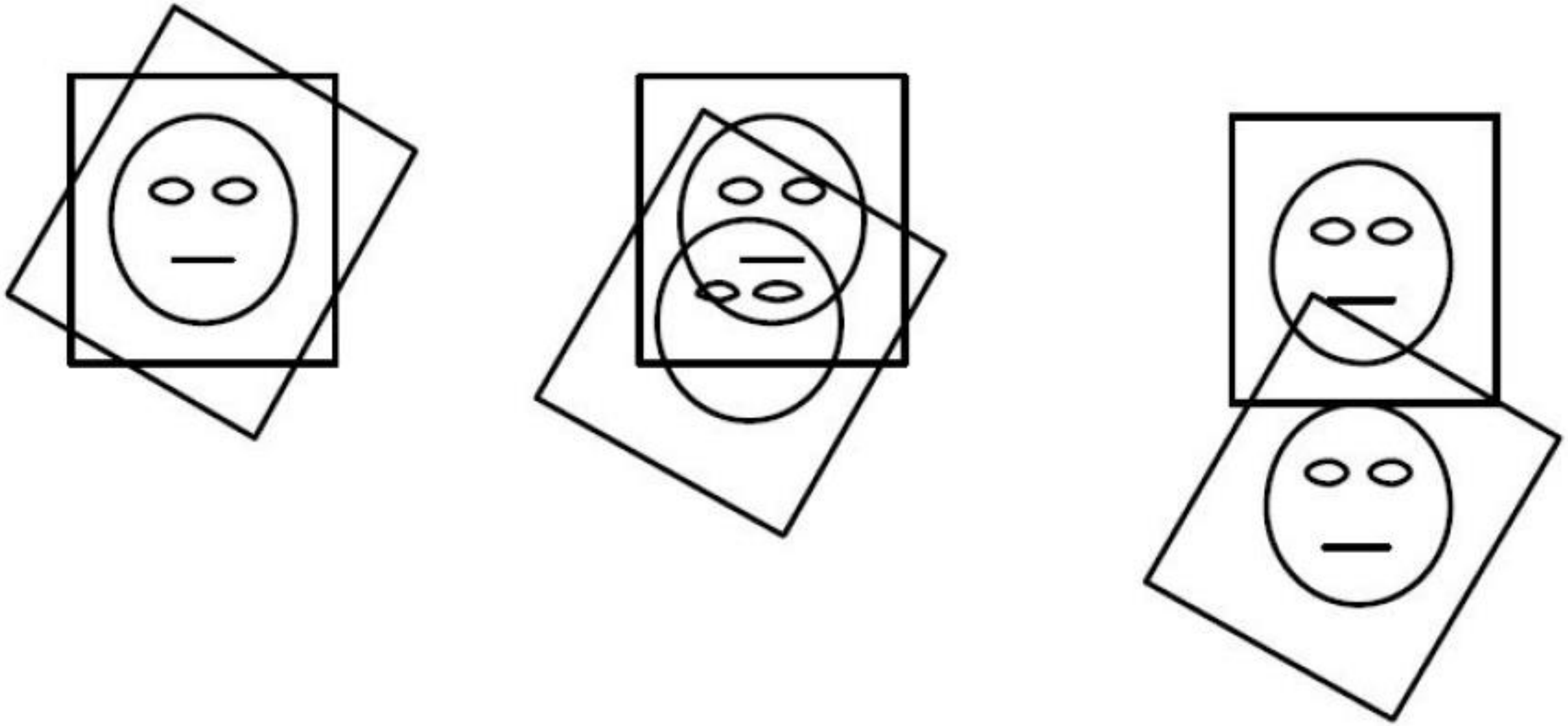
MR-PET

Source: Hill et al., **Medical image registration**

Registration via intensities

Joint entropy as similarity measure:

- Issue with overlap



Entropy low | Entropy high | Entropy low

Registration via intensities

Mutual Information

- Measures the correlation of two overlaid signals:

$$MI(A,B) = H(A) + H(B) - H(A,B)$$
$$= \sum_i \sum_j p_{AB}(i,j) \log \frac{p_{AB}(i,j)}{p_A(i)p_B(j)}$$

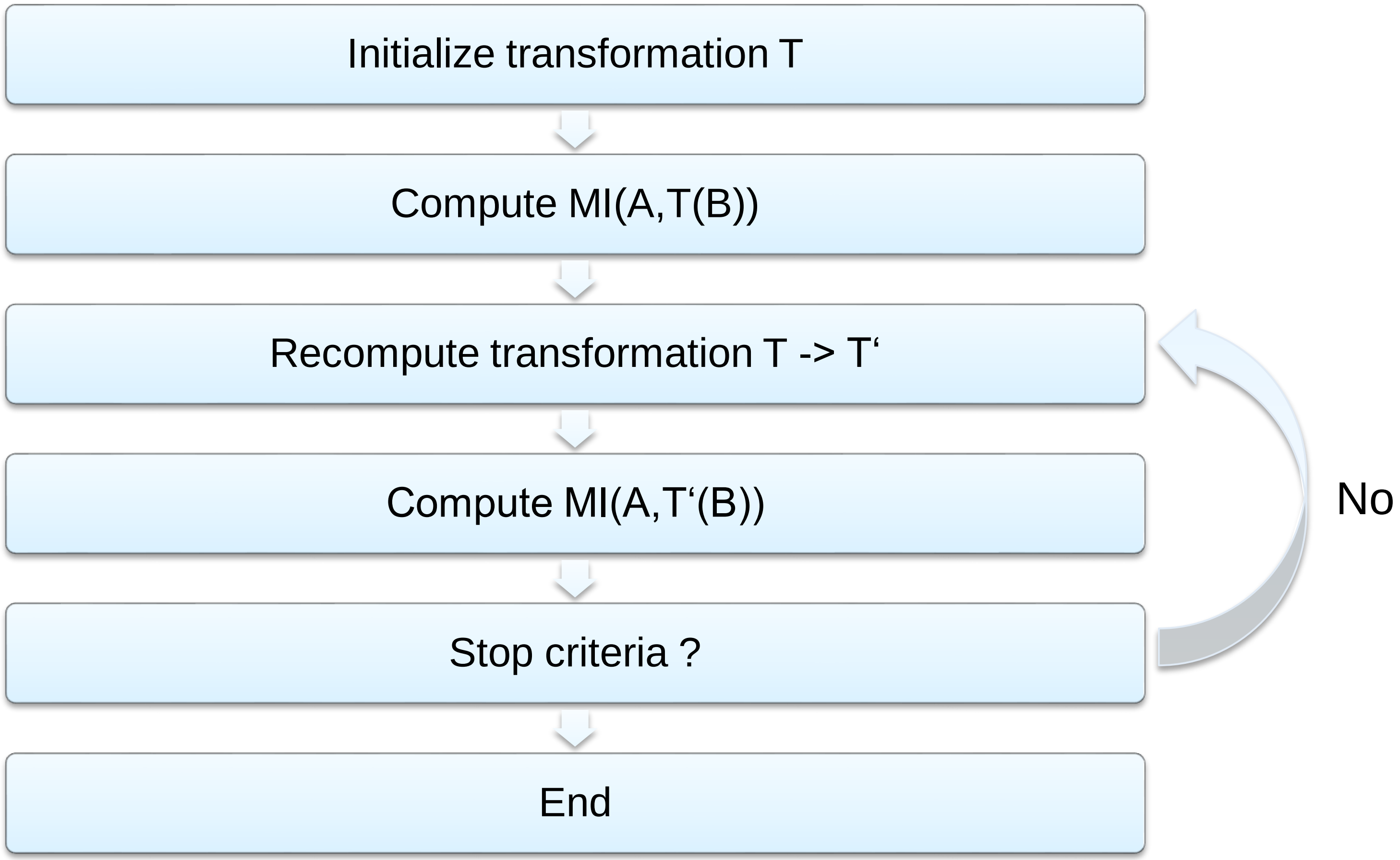
- Maximum when overlay is optimal: H(A) and H(B) high, H(A,B) low
- Problem: Still dependent on overlapping area (small intensity range, noise)
- Solution: Normalized MI

$$NMI(A,B) = \frac{H(A) + H(B)}{H(A,B)}$$

Useful for multimodal registration!

Registration via intensities

Mutual Information-algorithm: Search iterative for maximum



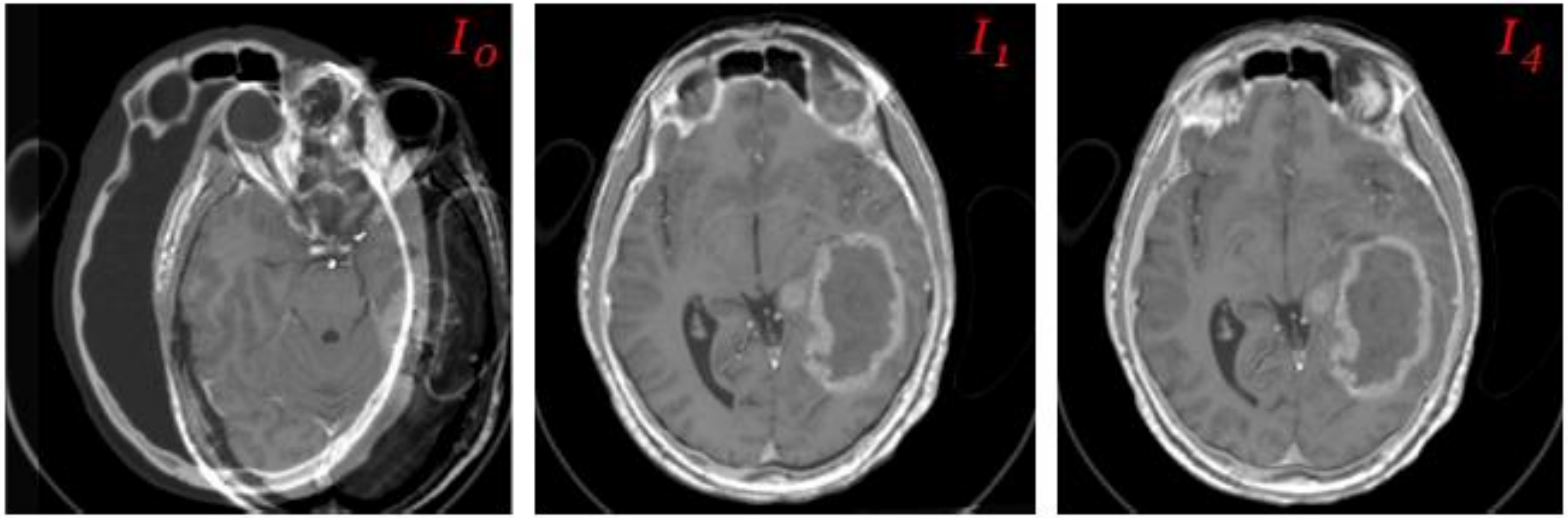
Registration via intensities

Registration with Mutual Information:
Non-linear optimization problem

- Multiple options for computing T‘ from T and the current overlap
- Gradient descent:
    - Compute locally the derivative of MI(A,T(B)) for the parameters of T
    - Adapt first the parameters of T that have the largest (positive) change in MI

Registration via intensities

Registration after multiple iterations



Registration via intensities

Mutual Information pros/cons:

- No linear dependencies between intensities required
- Co-occurrence of the most probable intensity values is maximized
- Uses only textural and structural information, no geometric
- Well suited for multimodal registration
- Bad for 2D-3D
- Local minimum possible
- Computationally more expensive than simpler similarity measures
- Application: 3D-3D registration, e.g. CT-MRT

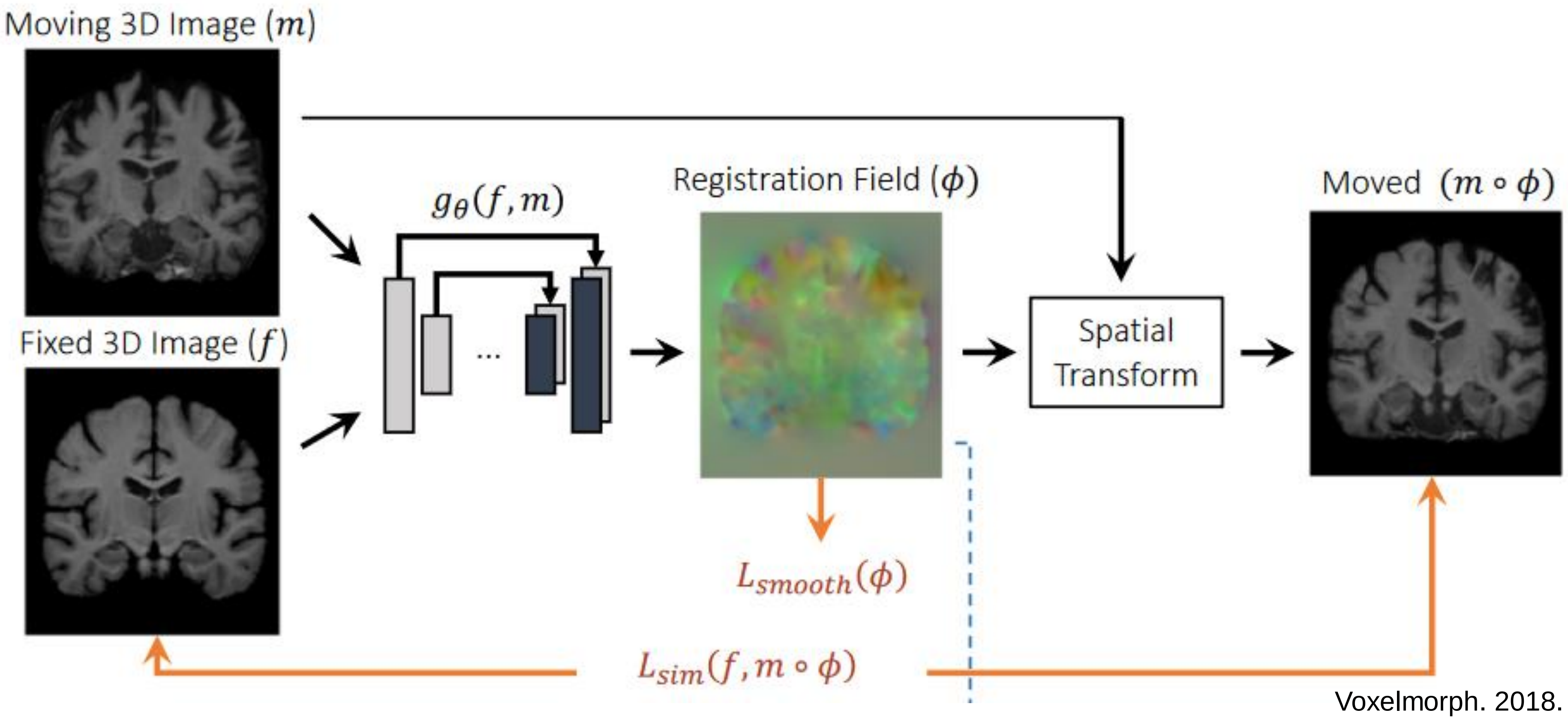
What is true in the overlap?

- A: high single entropies, low joint entropy
- B: low single entropies, high joint entropy
- C: low single entropies, low joint entropy
- D: high single entropies, high joint entropy

What is true in the overlap?

- **A: high single entropies, low joint entropy**
- B: low single entropies, high joint entropy
- C: low single entropies, low joint entropy
- D: high single entropies, high joint entropy

Registration via Intensities using Deep Learning



Voxelmorph. 2018.

Losses:

- Similarity measure L_{sim} compares transformed and target image (SSD, SAD, MI, …)
- Smoothness measure L_{smooth} penalizes large gradients in displacement field

Registration via Intensities using Machine Learning

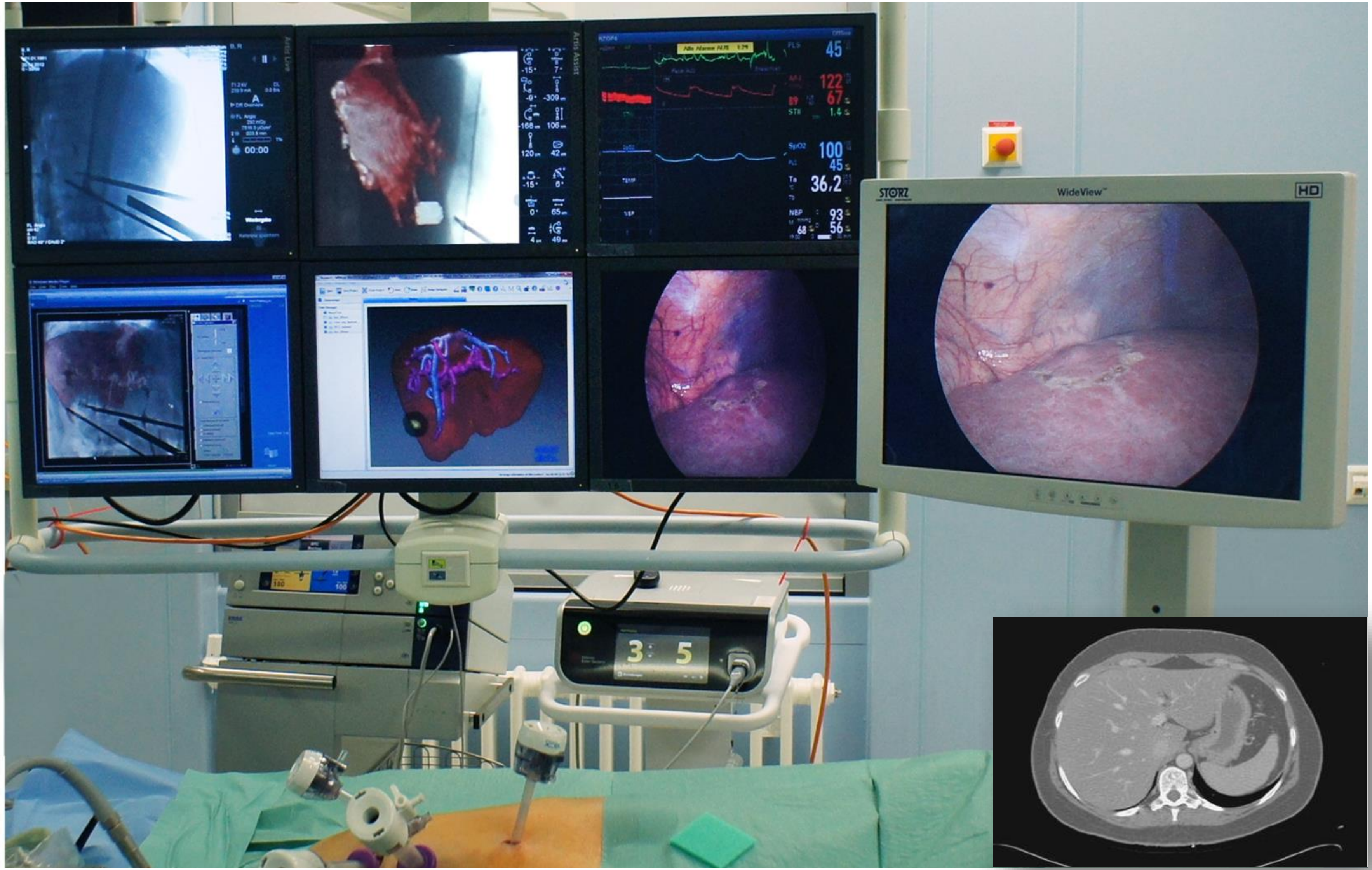
Key components:
- Differentiable similarity measure
- Differentiable spatial transformer layer

Training:

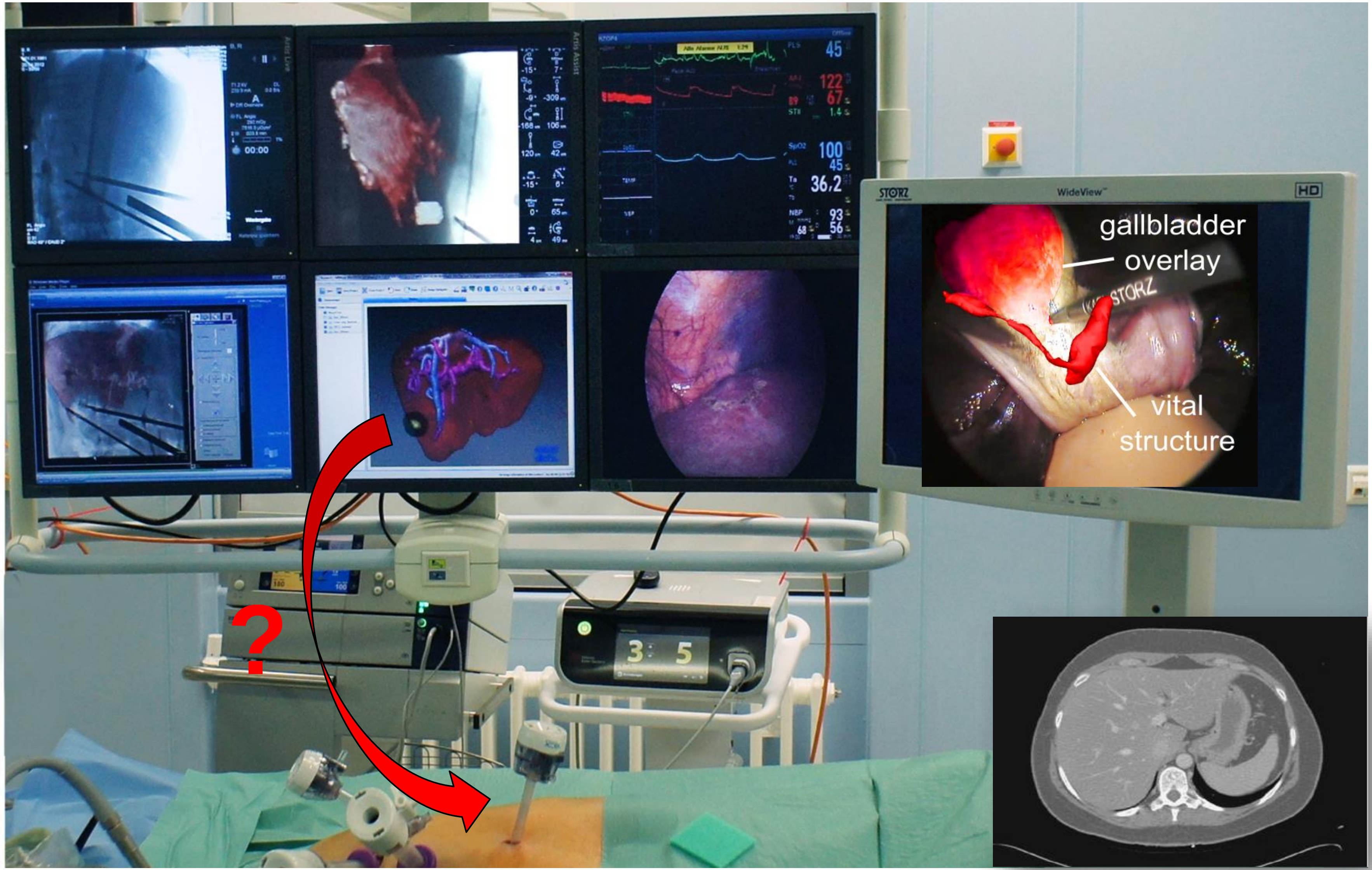
- Unsupervised training possible
- Optional additional supervision:
  - Comparison of segmentation maps
  - Usage of individual known correspondences

Result is a very fast registration method for intra-modal and inter-modal registration

Intra-operative registration

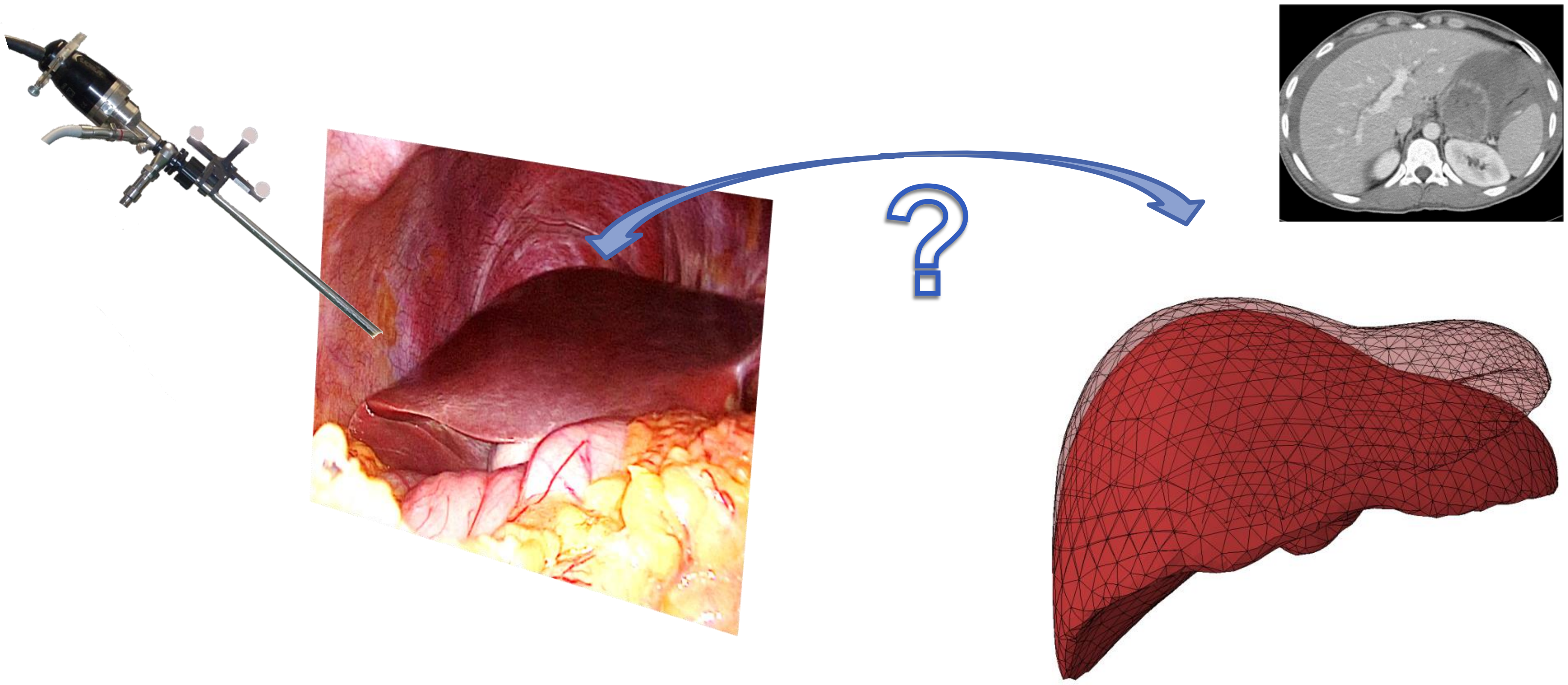


Intra-operative registration



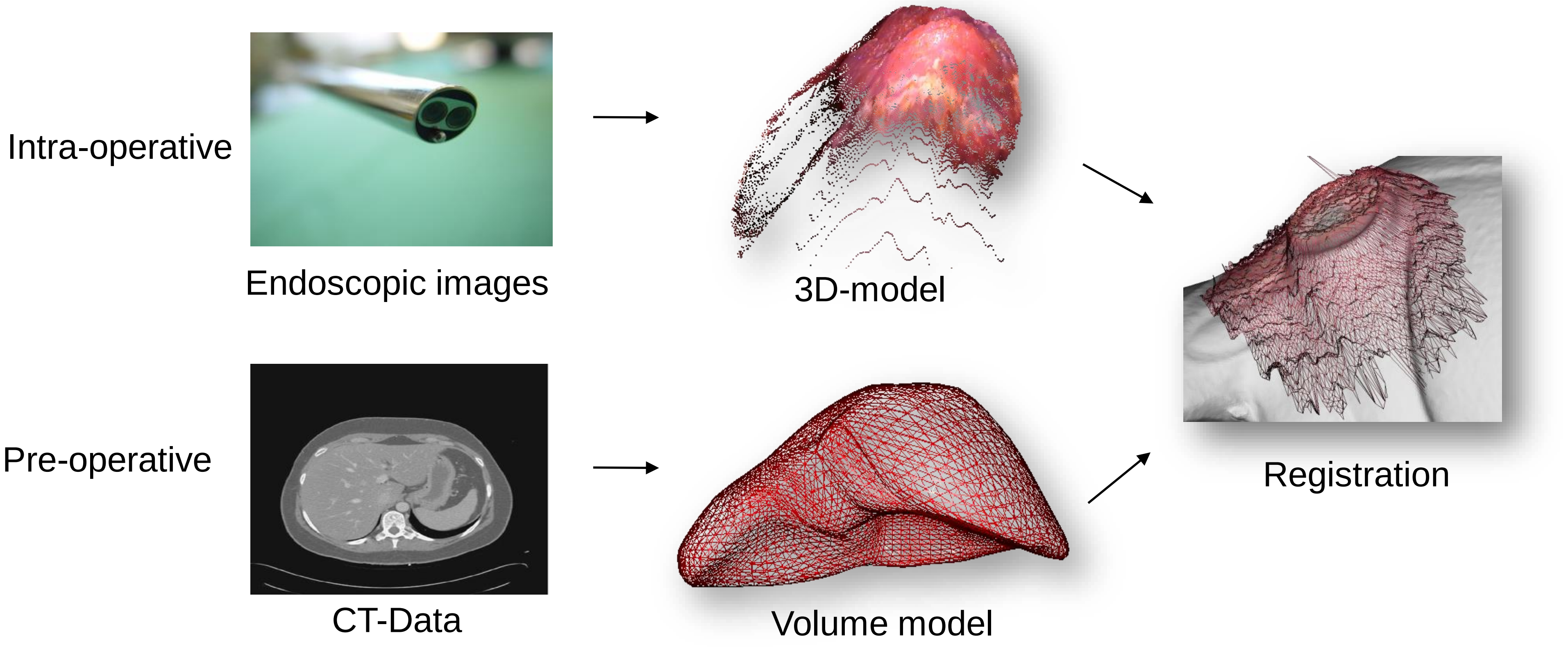
Intra-operative registration

Planning based on pre-operative images
Changes of the operation site before and during surgery
→ Pre-operative plan becomes invalid
→ Intra-operative adaptation of the plan

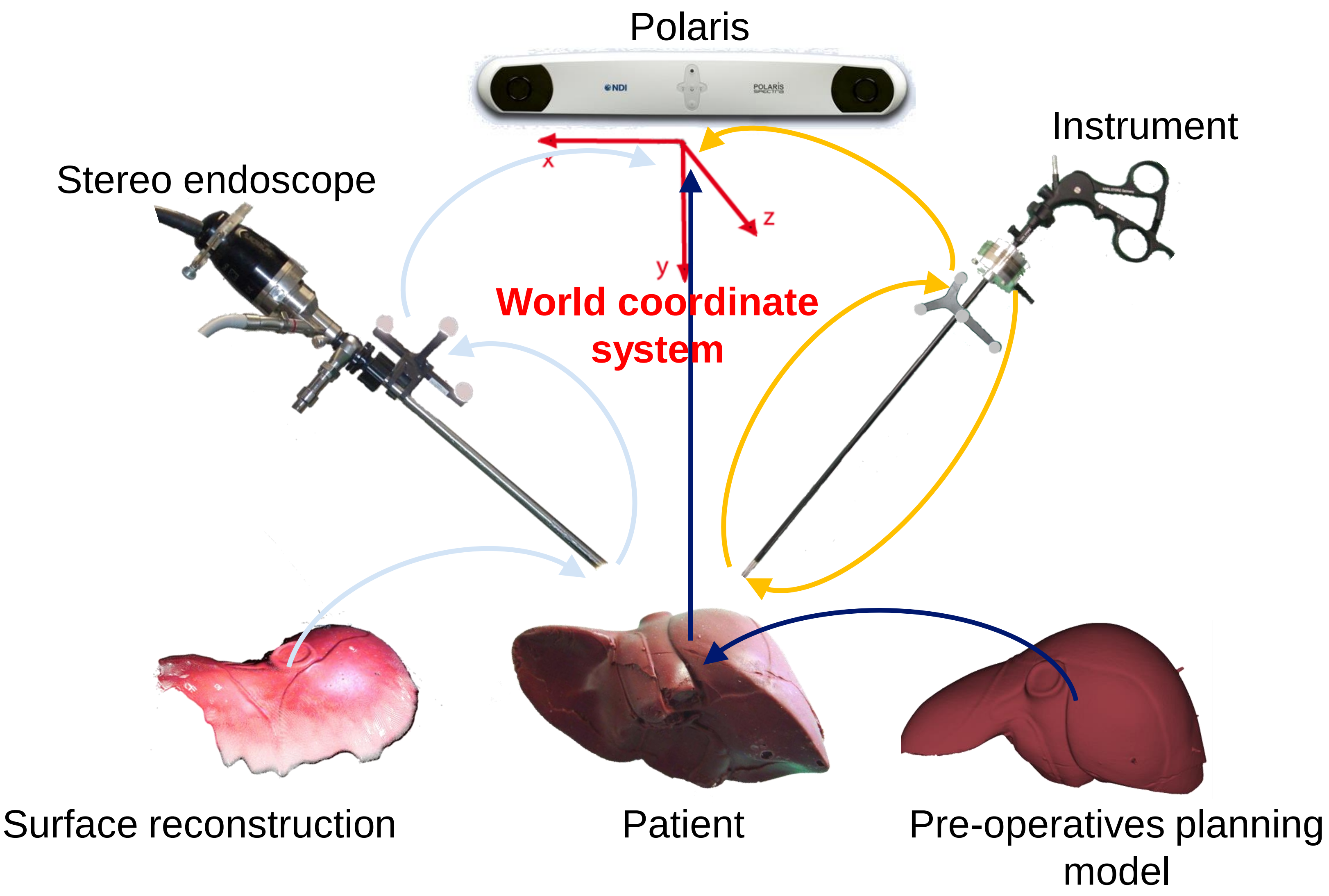


Intra-operative registration

- Generate intraoperative model via endoscope
- Registration with pre-operative model

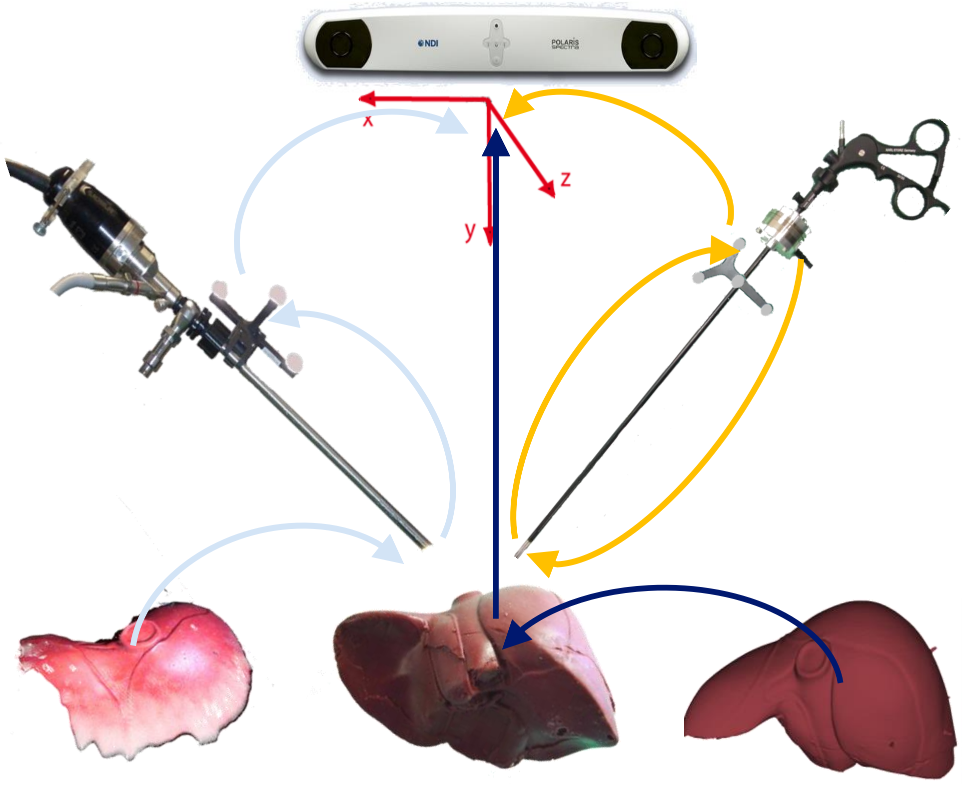


Intra-operative registration



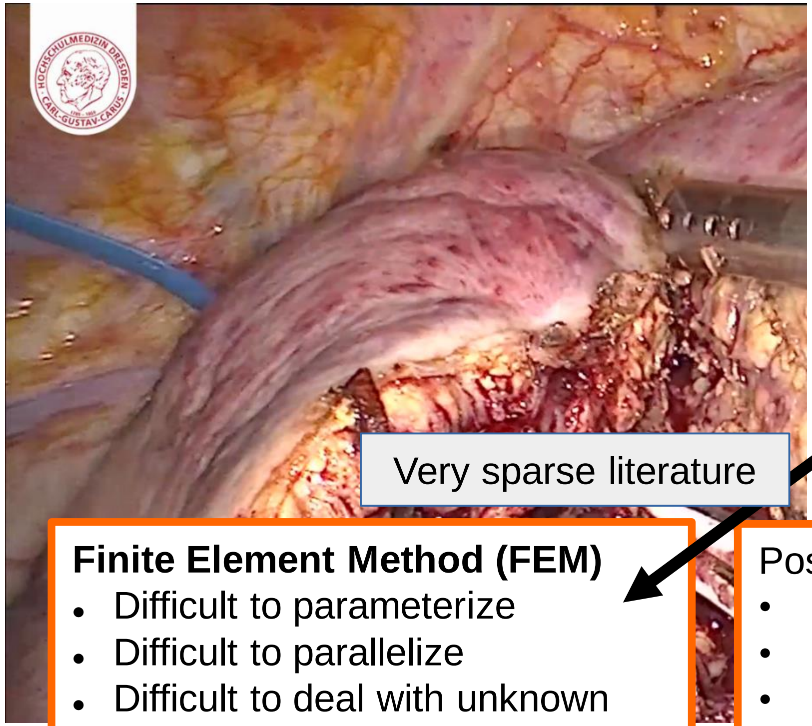
Intra-operative registration

- Fusion of the different sensors and the generated models
- Data is transformed into a single coordinate system
- Rigid and non-rigid registration



Feature-Based approach very difficult here!

Soft-tissue registration



Very sparse literature

Finite Element Method (FEM)
- Difficult to parameterize
- Difficult to parallelize
- Difficult to deal with unknown boundaries

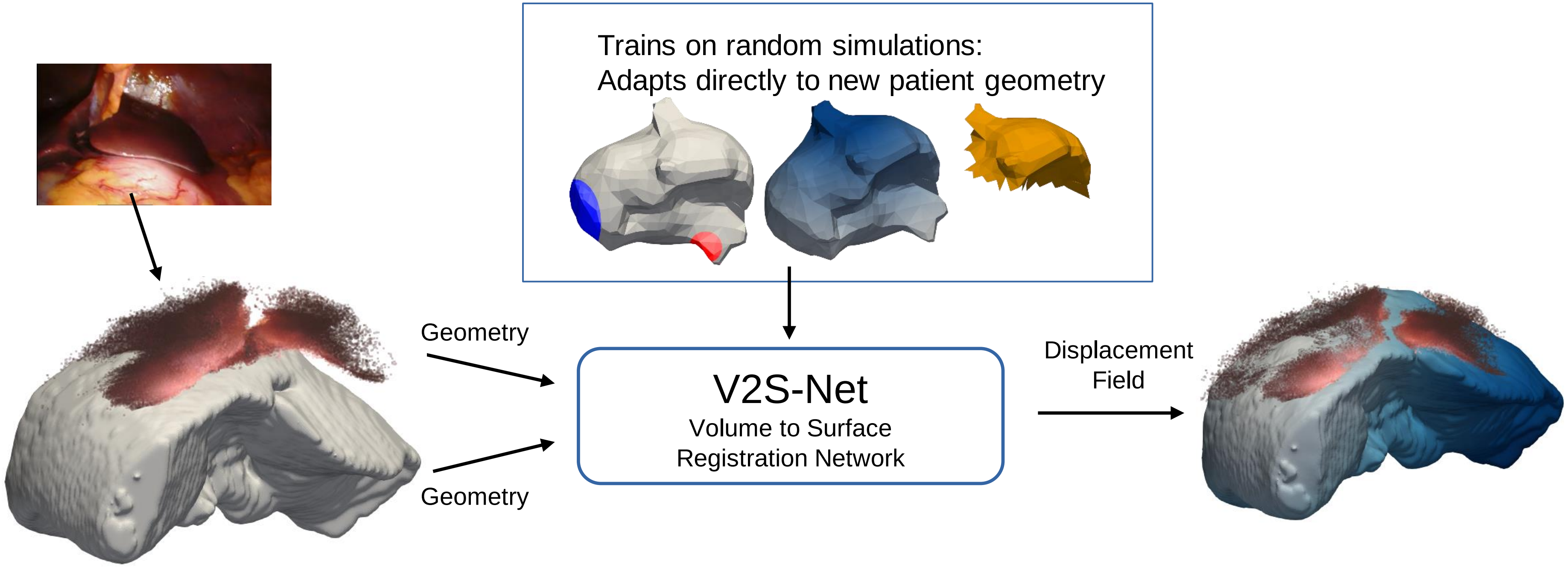
Visible:
- Extremely noisy
- Sparse correspondences

Invisible:
- Unseen boundaries
- Unknown boundary conditions
- Uncertain boundary conditions

Possible solution:
- **Learn** tissue deformation
- **Learn** to match surfaces
- **Learn** to deal with different input modalities

➢ **Data-driven** biomechanical models

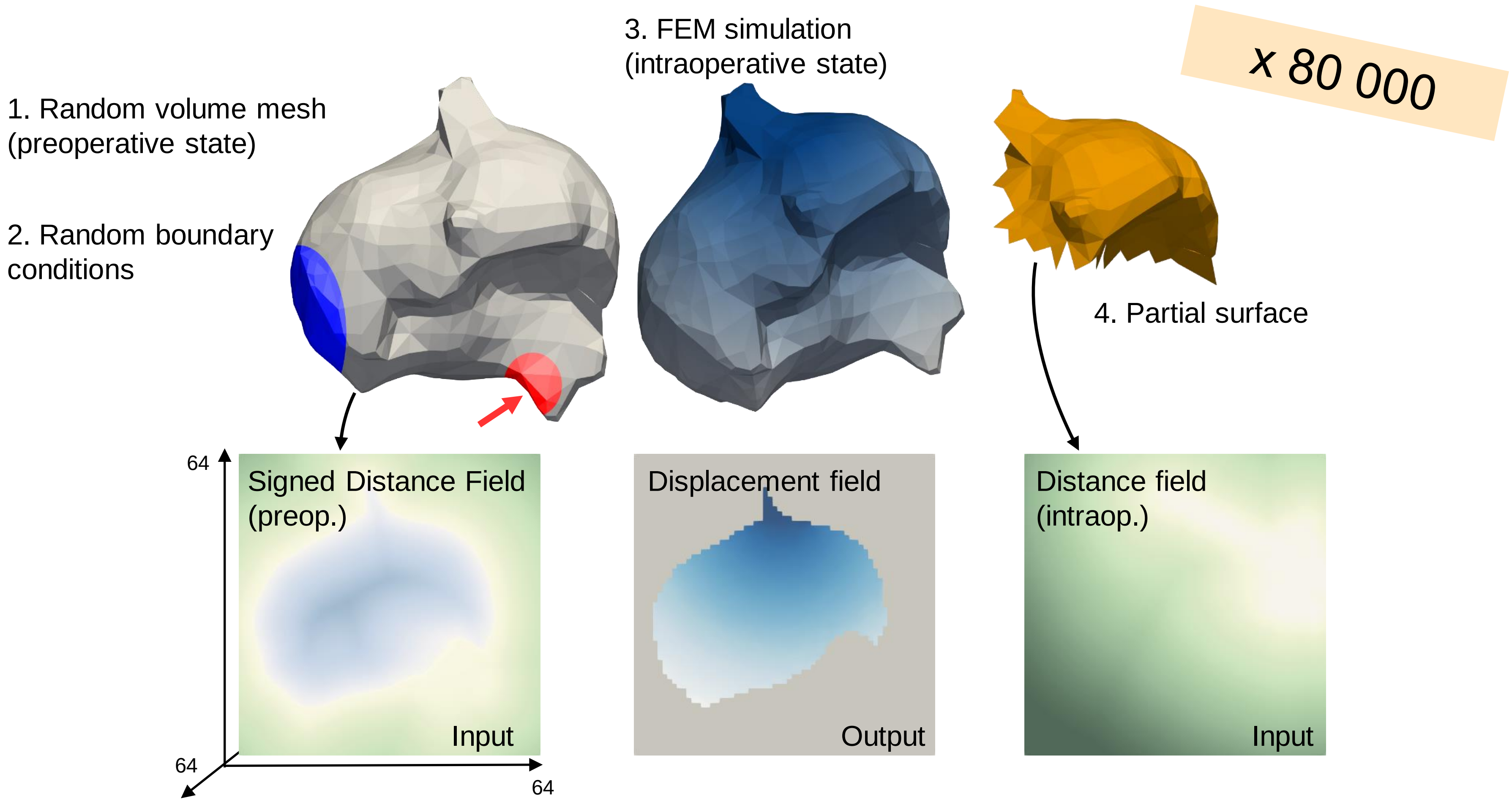
CNN based registration



Works directly on geometry:
No known correspondences

Pfeiffer,..., Speidel IJCARS (IPCAI) 2019 : Learning soft tissue behavior of organs for surgical navigation with convolutional neural networks
Pfeiffer, …, Speidel MICCAI 2020: Non-Rigid Volume to Surface Registration using a Data-Driven Biomechanical Model

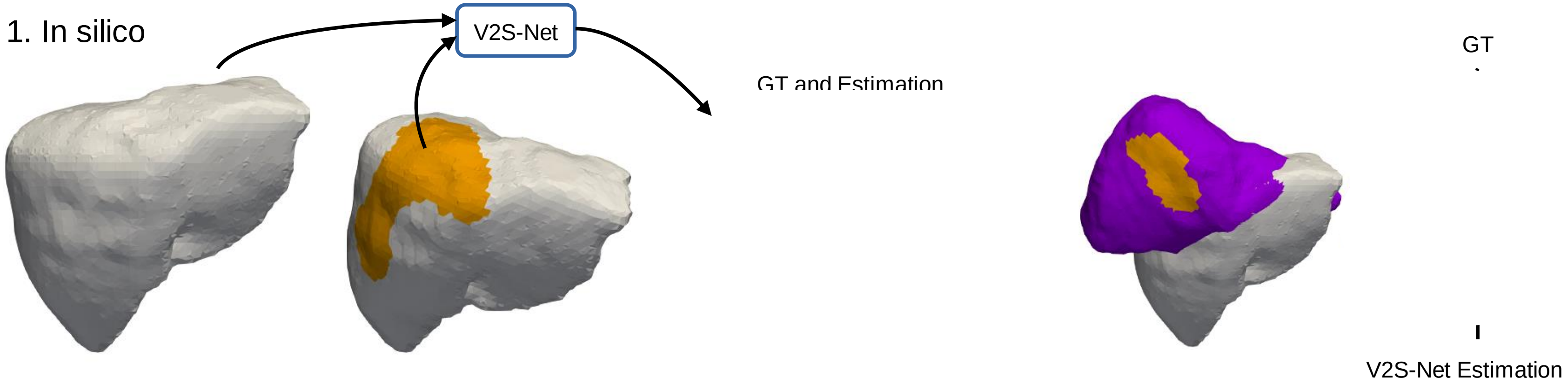
Synthetic Training Data



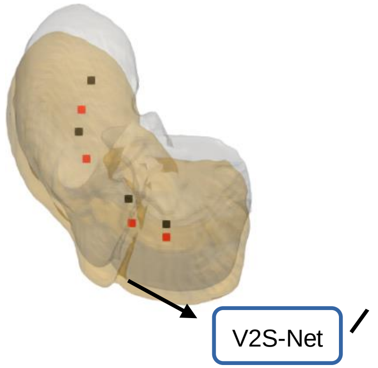
NCT

Experiments

1. In silico

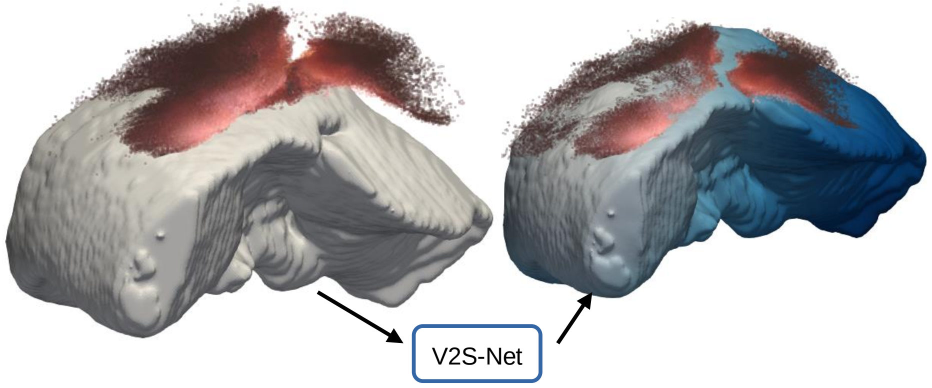


2. In human (CT breathing motion)



Avg. Displacement: 21.4 mm
vg. Error: 5.7 mm

3. Laparoscopy (qualitative)



NCT

Assessment of registration methods

- How can the accuracy of a registration method be measured?
  - Phantom-/animal trials, simulations, offline trials with patient data, comparison with gold standard, comparison with manual registration of experts
- What accuracy is required?
- Metrics:
  - **FRE** (Fiducial registration error): How well are corresponding features mapped onto one another?
  - **FLE** (Fiducial localization error): How well can the features be located?
  - **TRE** (Target registration error): How well can target structures (e.g. tumors) be mapped onto one another?
- Further criteria: Robustness, degree of user interaction, runtime

Literature

- Hajnal et al.: “Medical Image Registration”
- Hill et al.: “Medical Image Registration”. Physics in Medicine and Biology, 2001.
- Maintz et al.: “A Survey of Medical Image Registration”.
- Crum et al.: “Non-rigid image registration: theory and practice”
- Zitova et al: “Image registration: a survey”
- Modersitzki: “Numerical methods for image registration“.