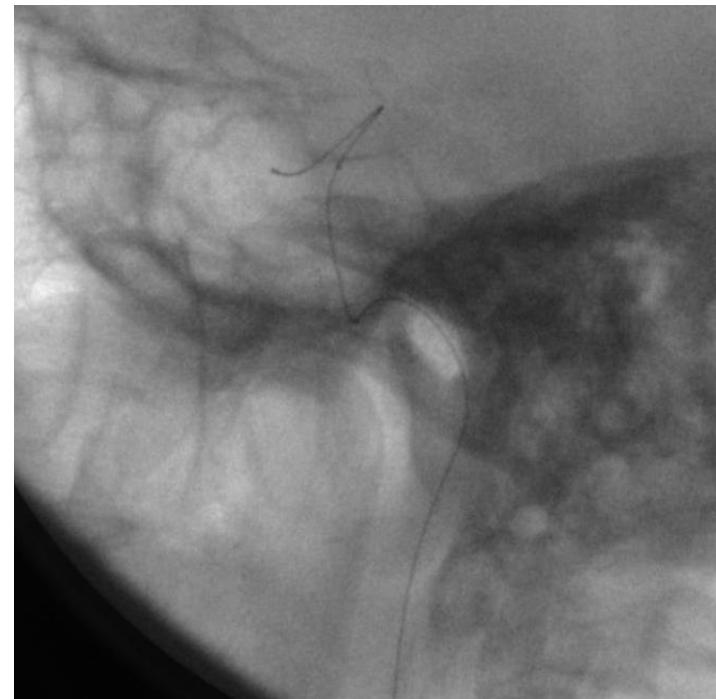
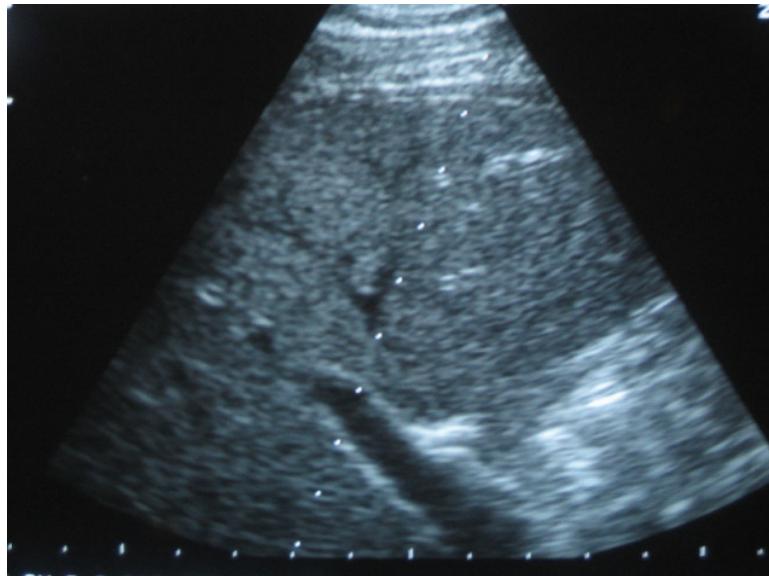


# **Image registration in image-guided interventions**

**Stefan Klein  
Erasmus MC, the Netherlands  
Biomedical Imaging Group Rotterdam (BIGR)**

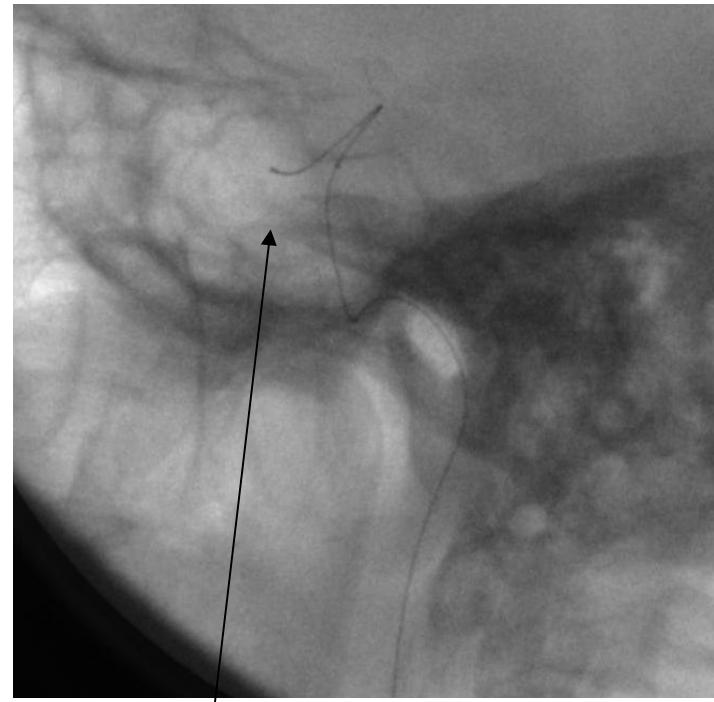
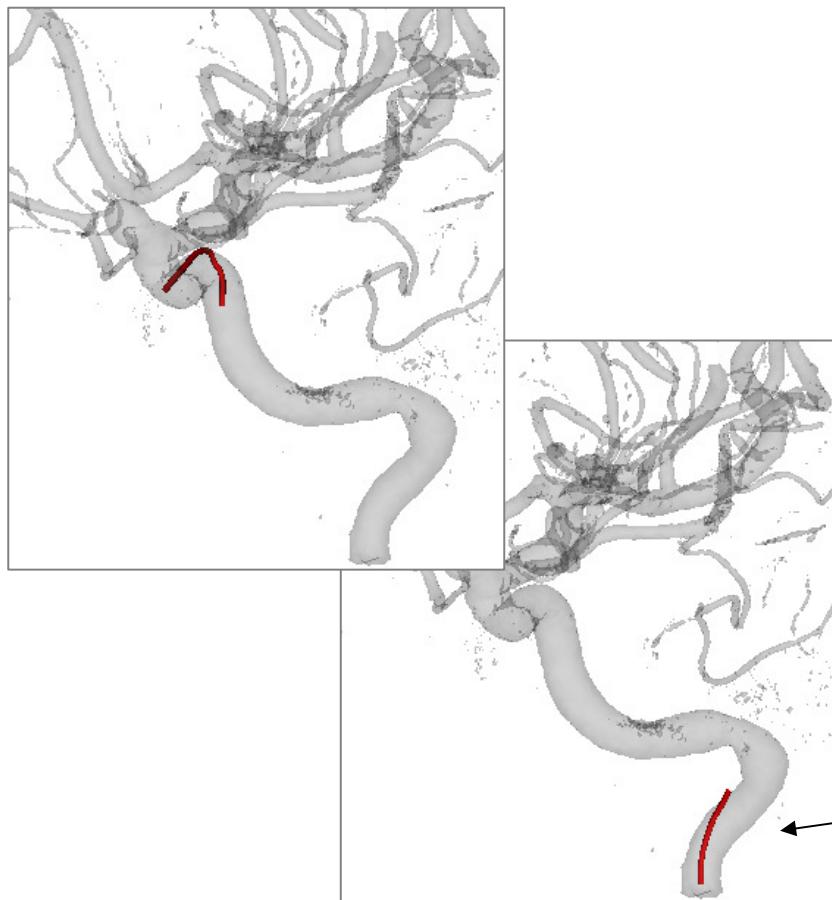
## Intraoperative images



## Diagnostic images

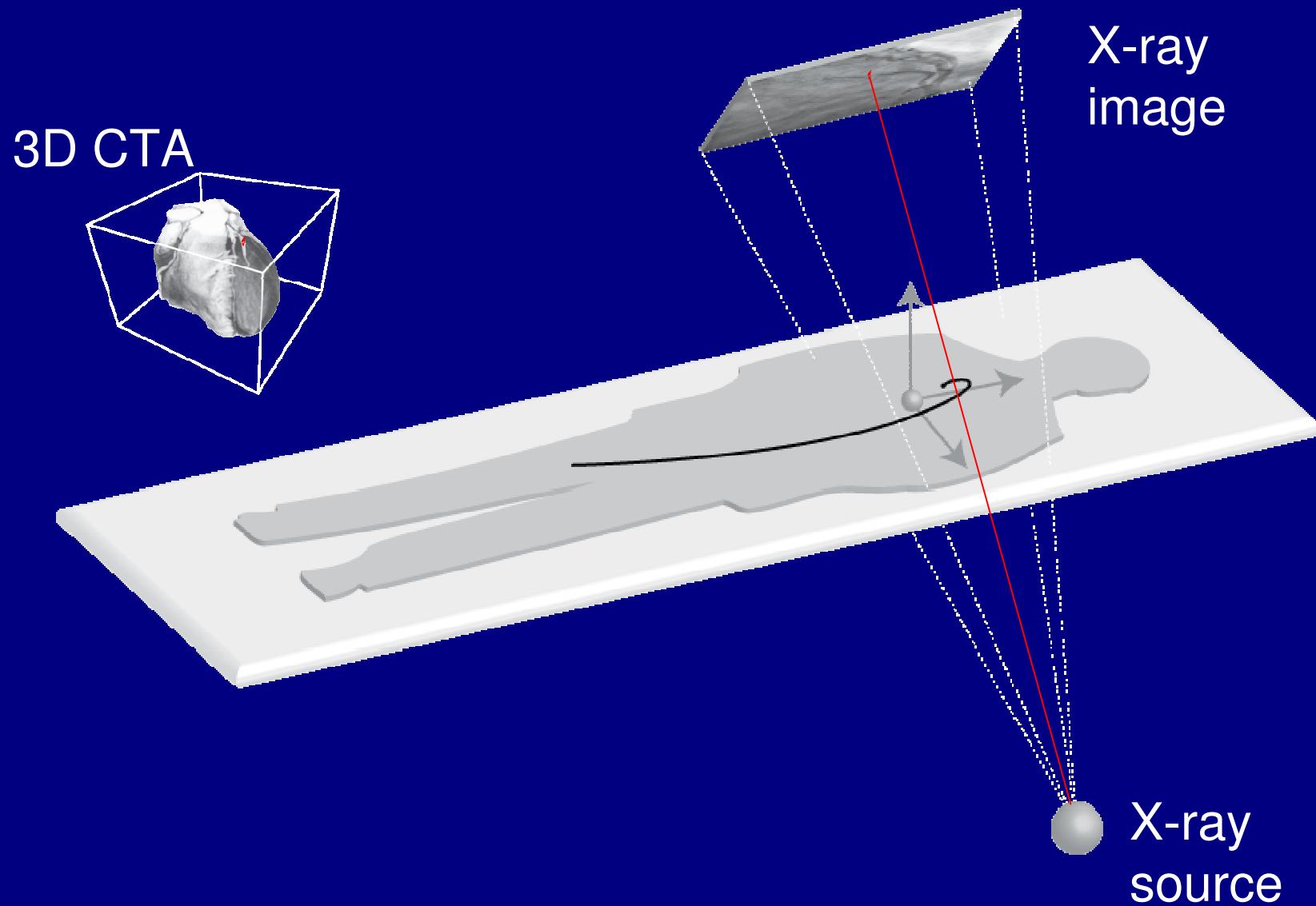


## Registration in IGI: fuse information!

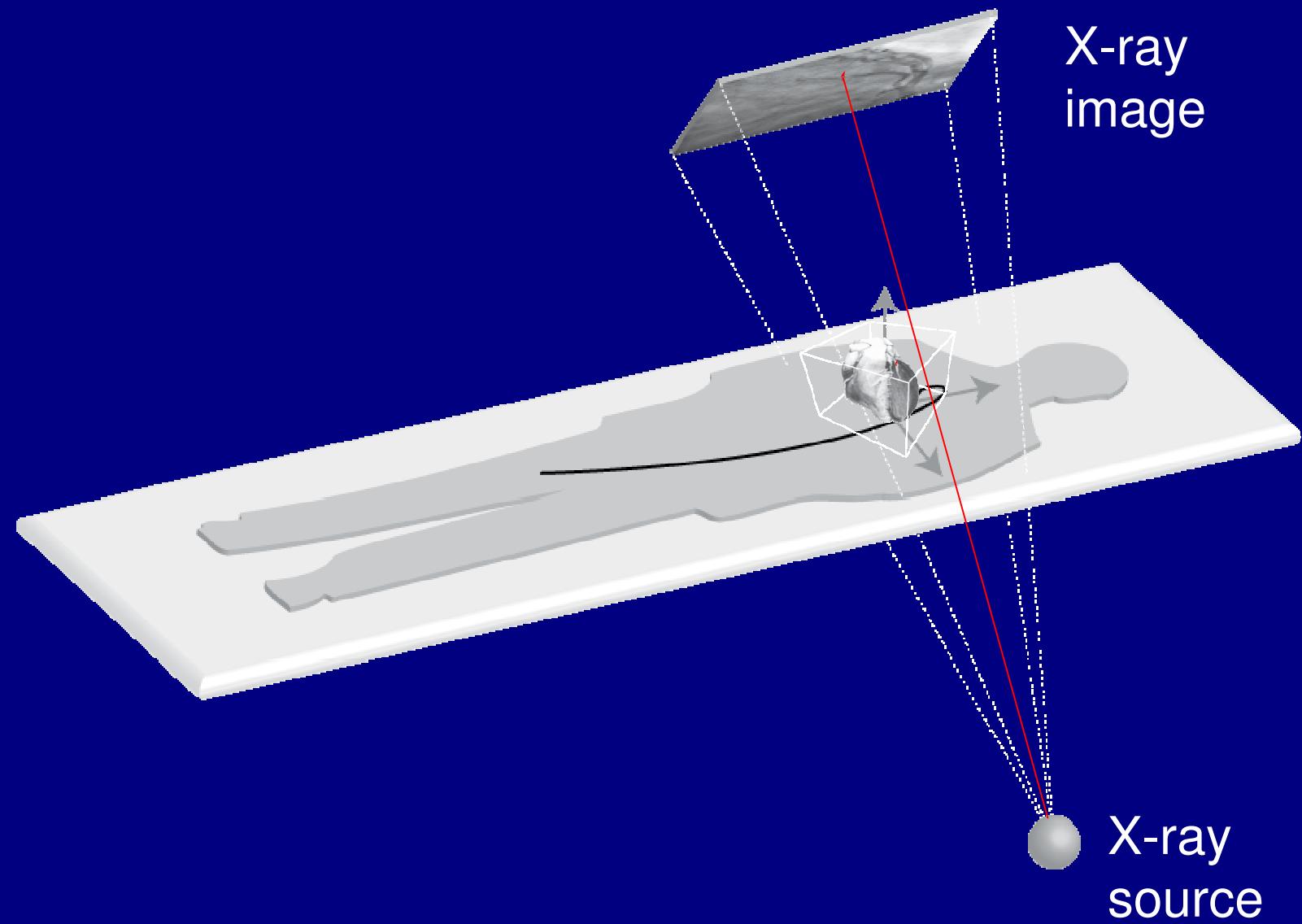


Guide-wire

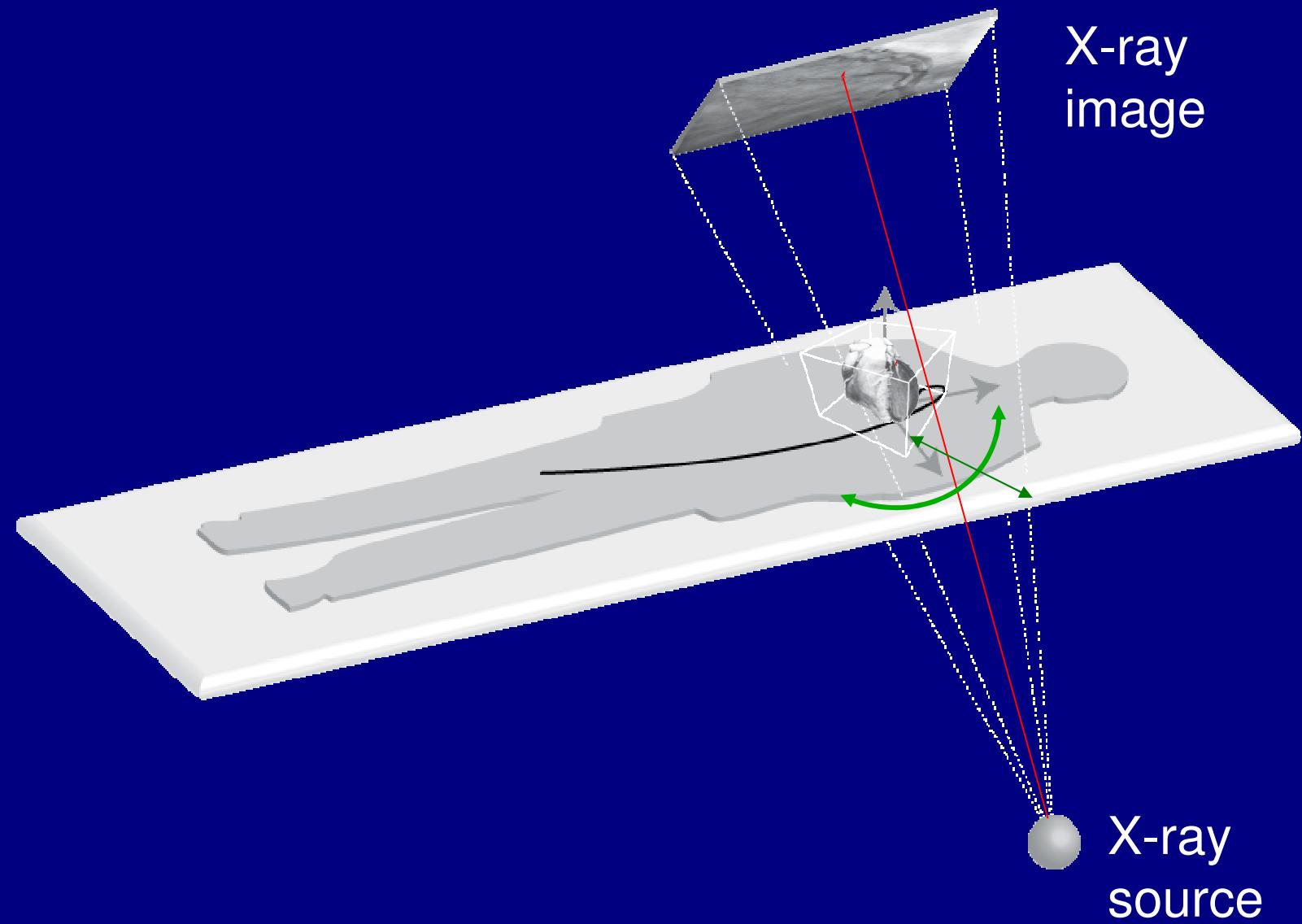
## Registration in IGI: fuse information!



# Registration in IGI: fuse information!



# Registration in IGI: fuse information!



## Registration in IGI: examples

2D – 3D : X-ray with CT

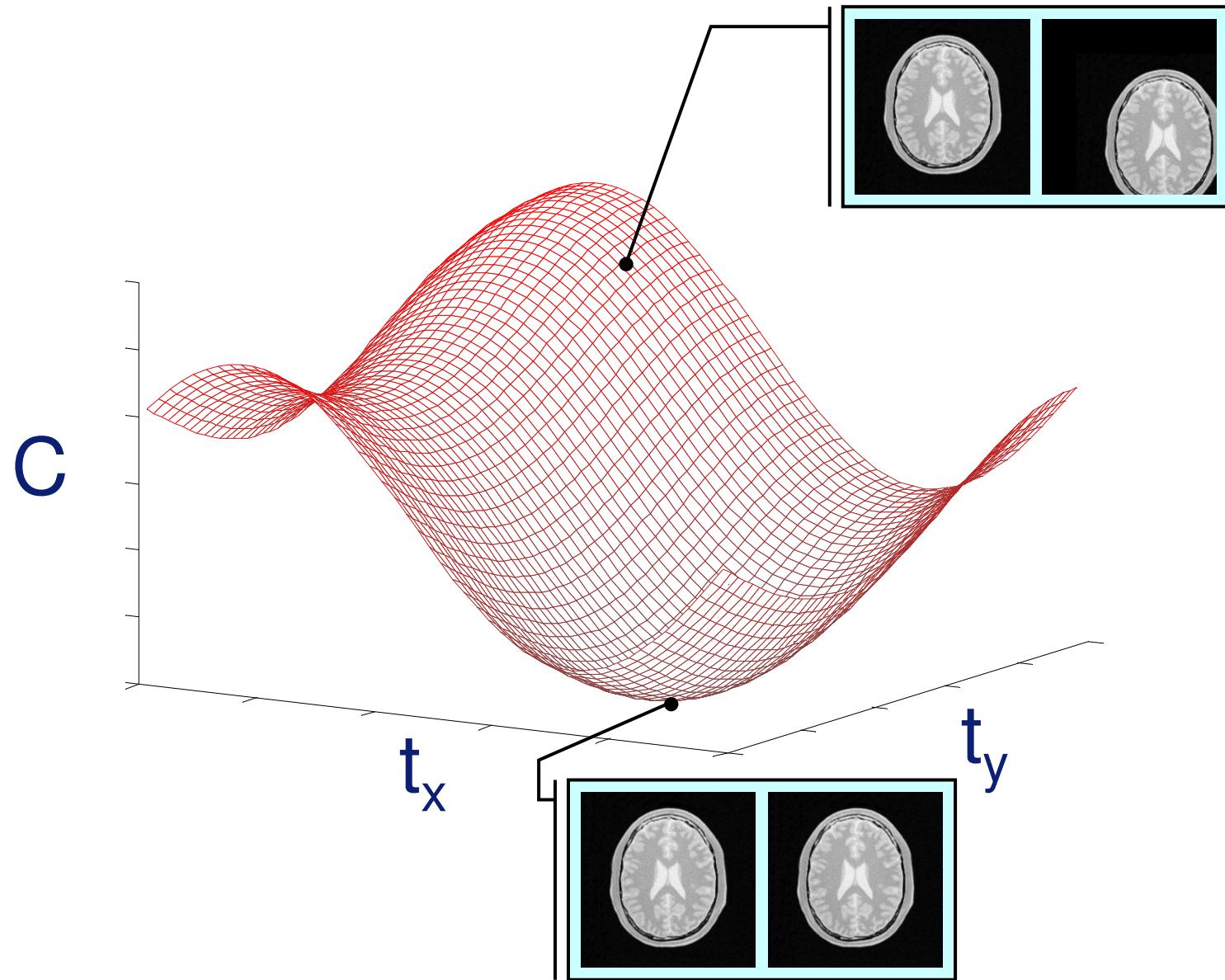
3D – 3D : intraoperative MRI with preoperative MRI

2D+t – 3D : US with MRI/CT

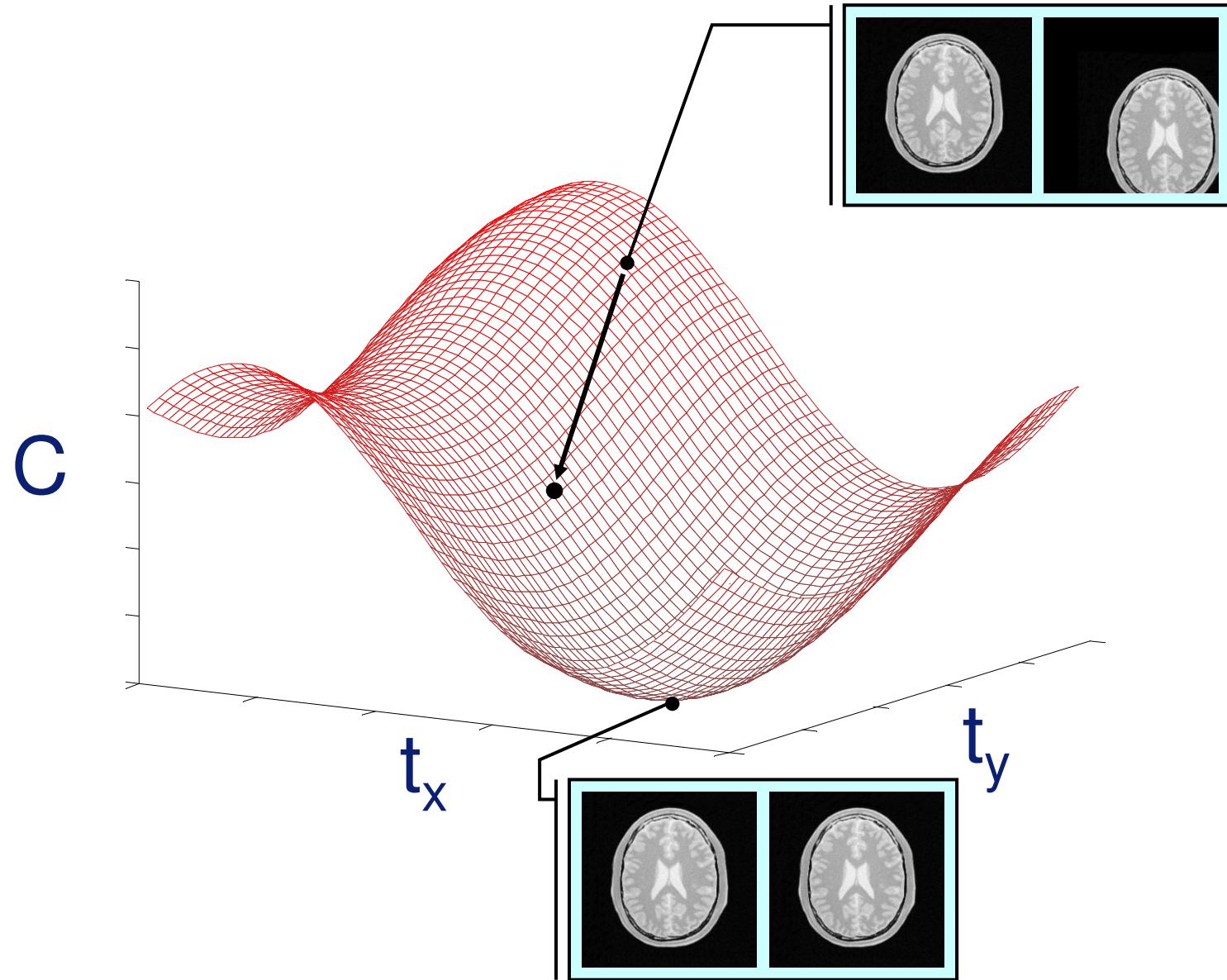
2D+t – 3D+t : X-ray sequence with dynamic CT

***registration = optimisation***

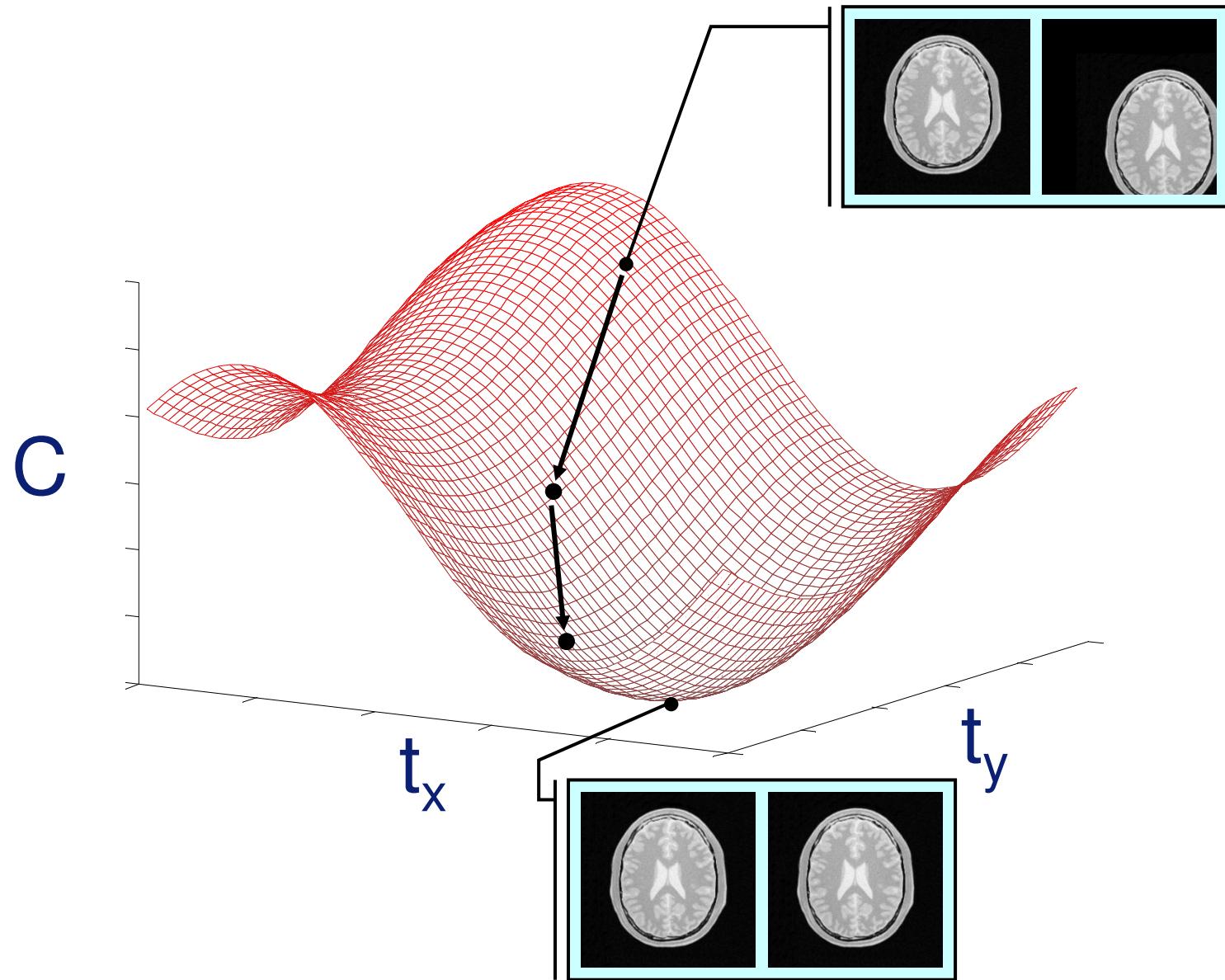
# Registration = optimisation



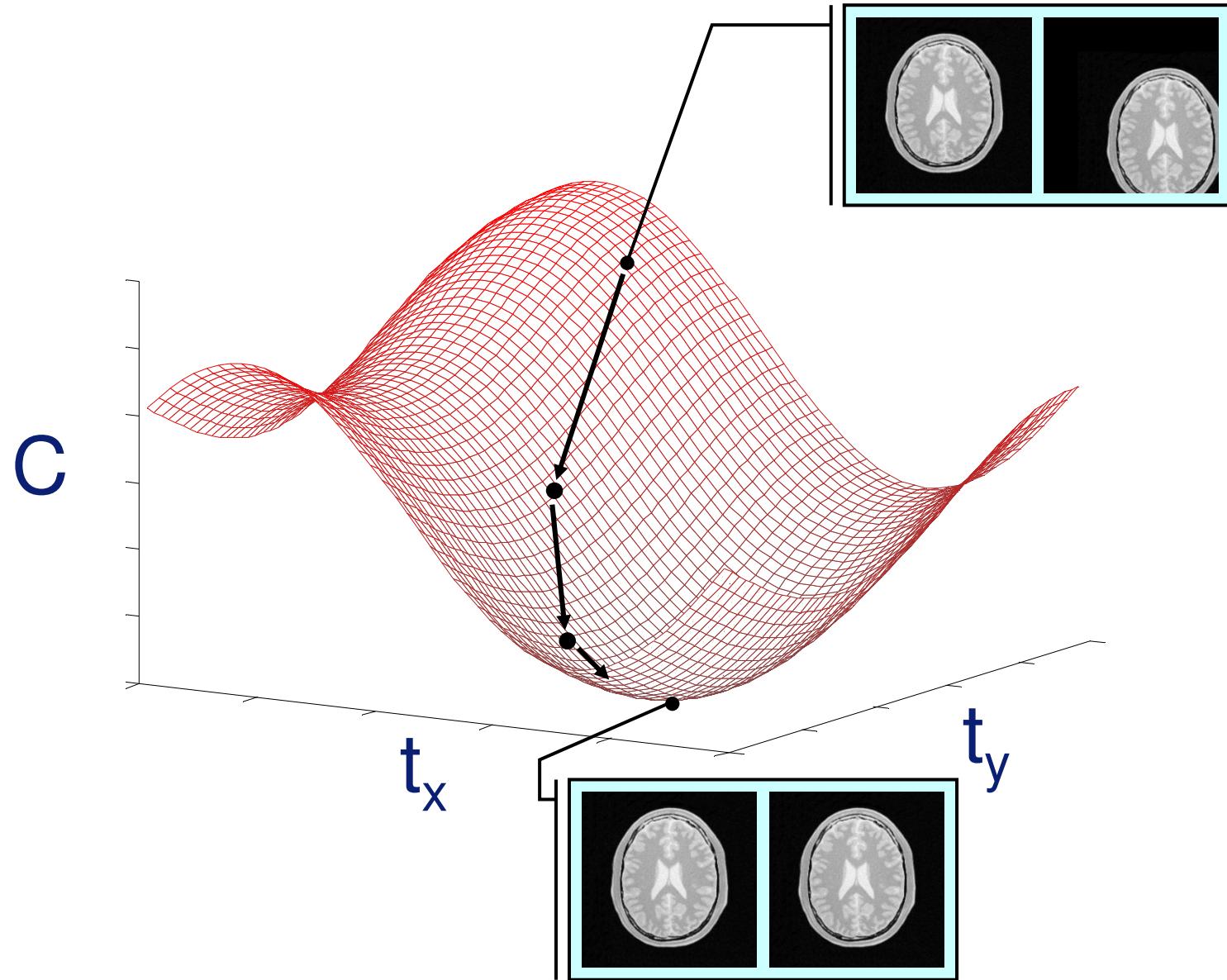
# Registration = optimisation



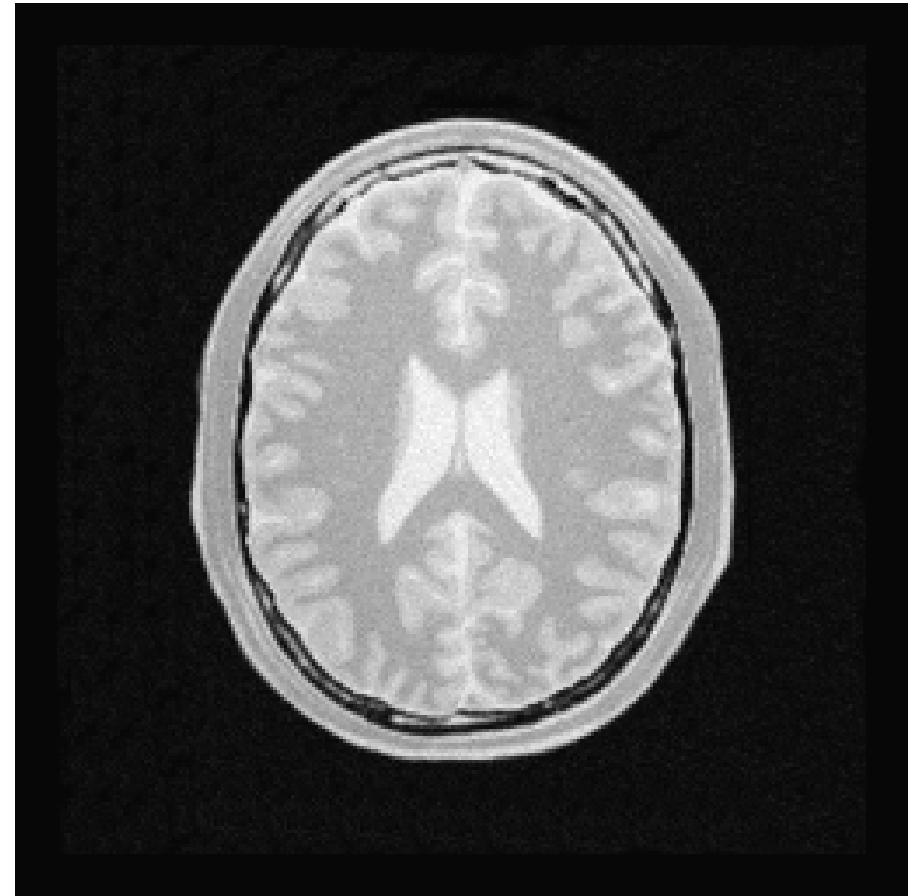
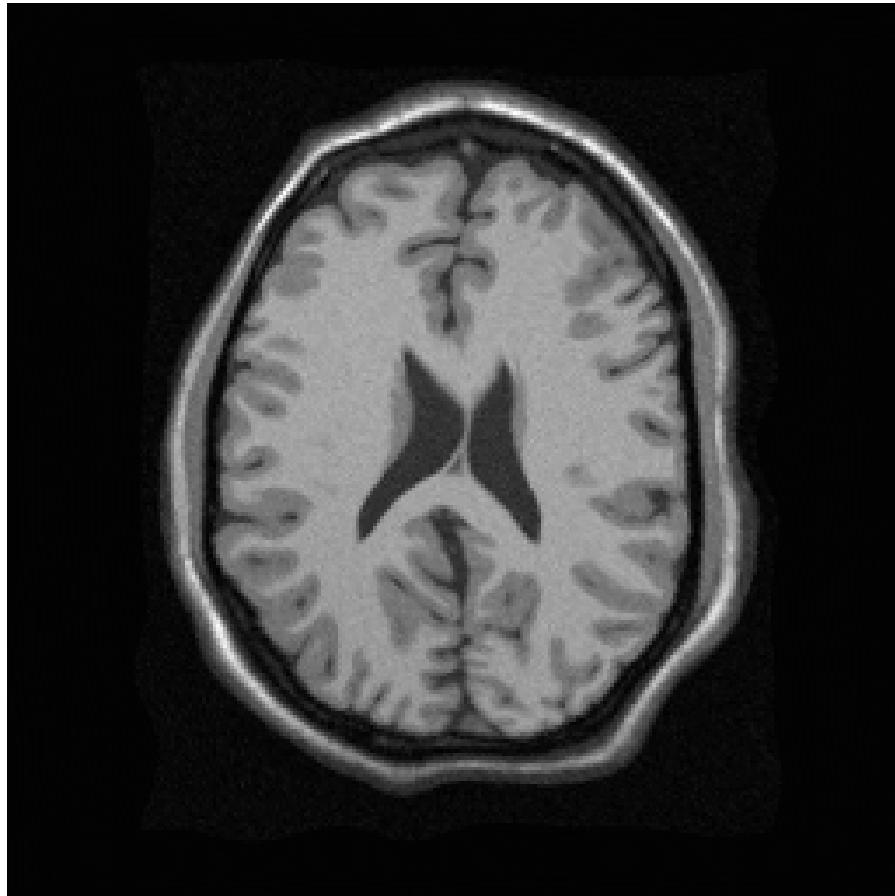
# Registration = optimisation



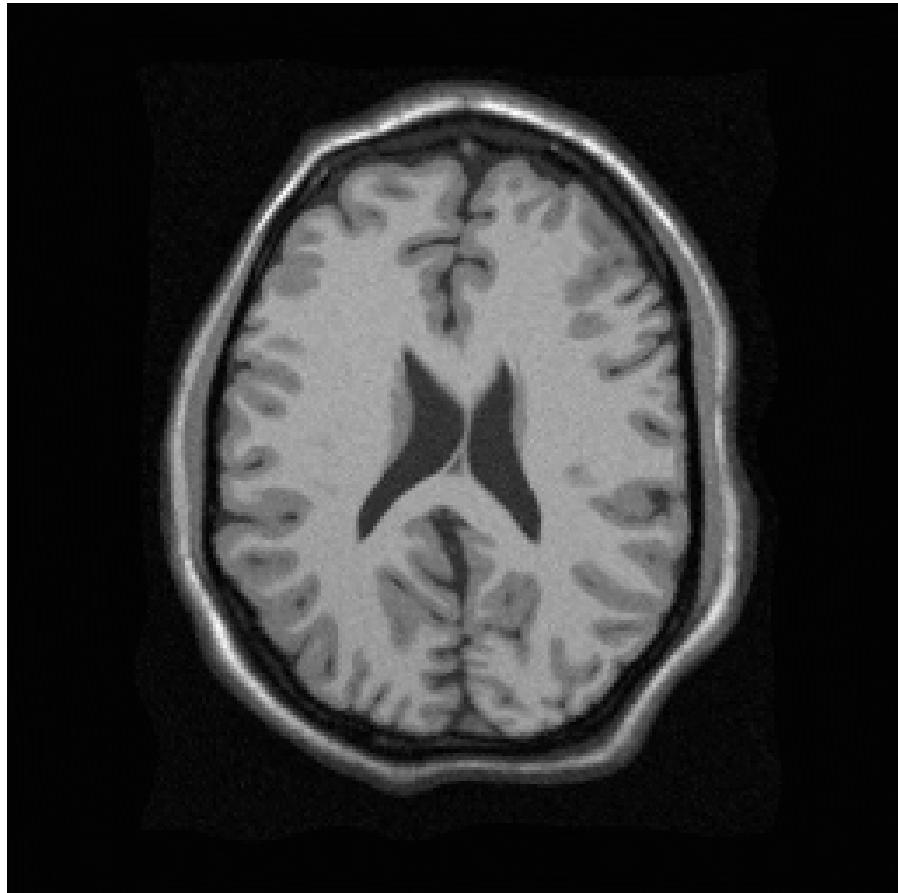
# Registration = optimisation



## Example



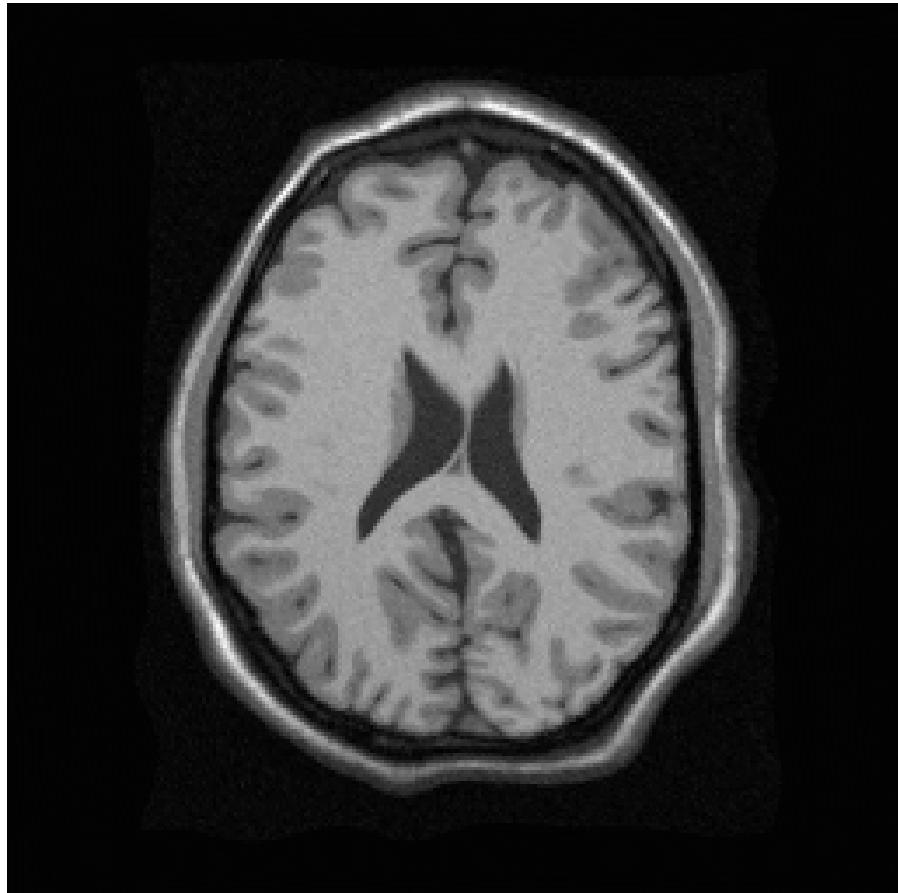
## Example



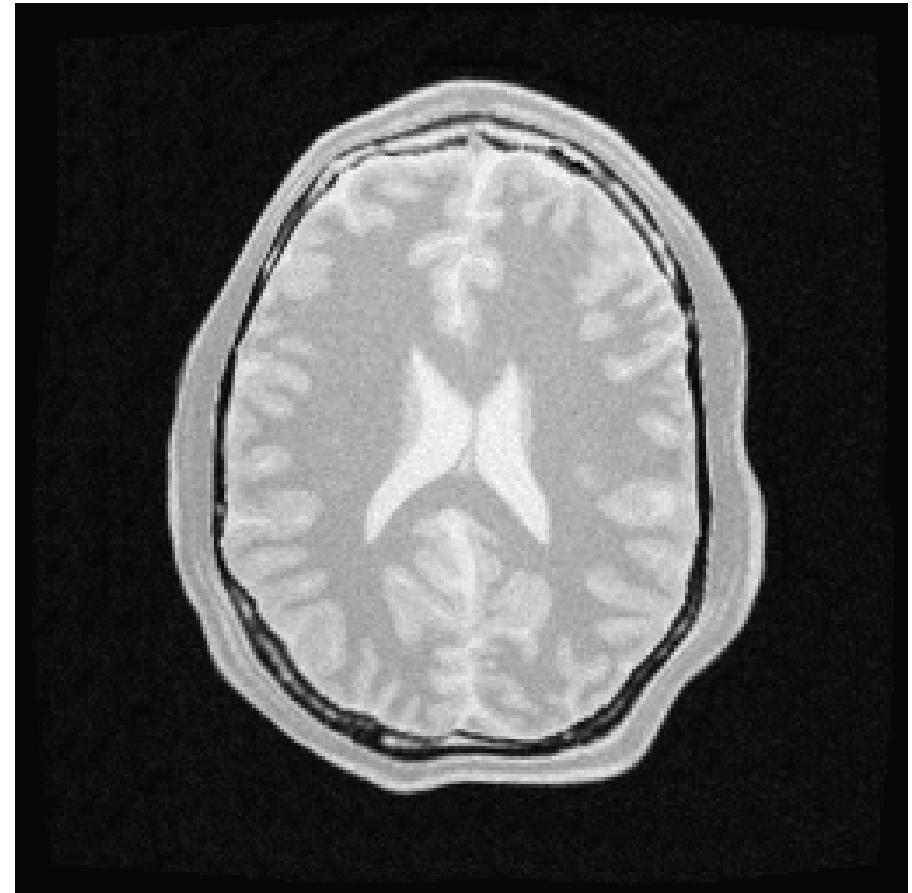
fixed image

moving image

## Example

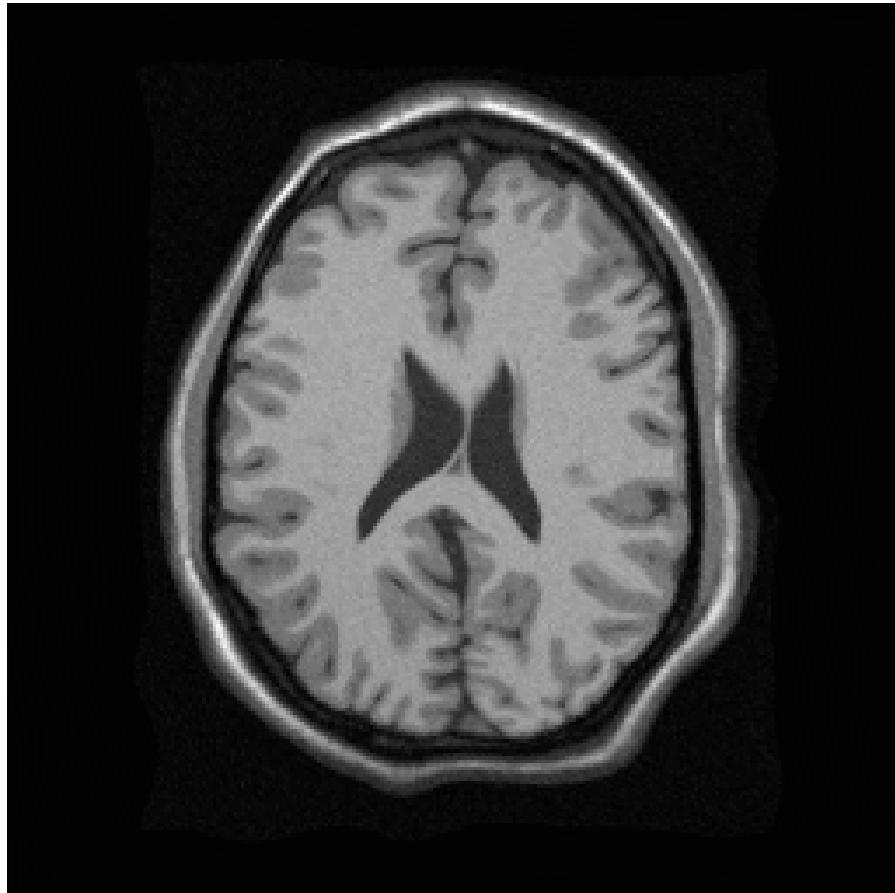


fixed image

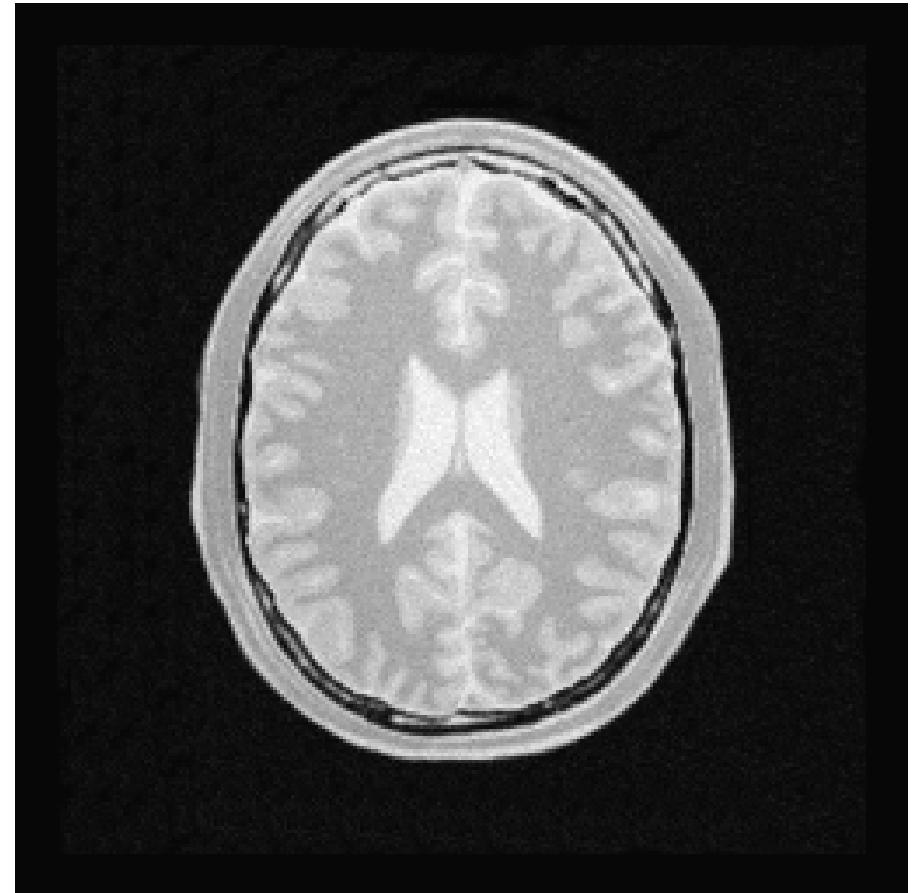


moving image

## Example



fixed image



moving image

- $F(\mathbf{x})$  = fixed image,  $M(\mathbf{x})$  = moving image  
 $\mathbf{x}$  = voxel coordinate
- Transformation function:  $T(\mathbf{x} ; \mathbf{p})$   
 $\mathbf{p}$  = vector of transformation parameters
- Cost function:  $C( \mathbf{p} )$   
measures similarity of fixed image  $F(\mathbf{x})$  and  
deformed moving image  $M( T(\mathbf{x}; \mathbf{p}) )$
- Find  $\mathbf{p}$  that minimises  $C$

# Iterative optimisation

$$\mathbf{p}_{k+1} = \mathbf{p}_k + a_k \cdot \mathbf{d}_k$$

$\mathbf{d}_k$  = search direction

$a_k$  = step size

gradient descent:  $\mathbf{d}_k = -\frac{\partial C}{\partial \mathbf{p}}(\mathbf{p}_k) \equiv -\mathbf{g}_k$

# Cost function derivative

Example for mean of squared differences:

$$C(\mathbf{p}) = \frac{1}{N} \sum_{\mathbf{x}} (F(\mathbf{x}) - M(\mathbf{T}(\mathbf{x}; \mathbf{p})))^2$$

$$\frac{\partial C}{\partial \mathbf{p}} = -\frac{2}{N} \sum_{\mathbf{x}} (F(\mathbf{x}) - M(\mathbf{T}(\mathbf{x}; \mathbf{p}))) \frac{\partial M}{\partial \mathbf{p}}$$

$$= -\frac{2}{N} \sum_{\mathbf{x}} (F(\mathbf{x}) - M(\mathbf{T}(\mathbf{x}; \mathbf{p}))) \left( \frac{\partial \mathbf{T}}{\partial \mathbf{p}} \right)^t \frac{\partial M}{\partial \mathbf{x}}$$

# Cost function derivative

Example for mean of squared differences, with projection step (2D-3D):

$$\begin{aligned}
 C(\mathbf{p}) &= \frac{1}{N} \sum_{\mathbf{x}} \left( F(\mathbf{x}) - \int_{\mathbf{r} \in RAY[\mathbf{x}]} M(\mathbf{T}(\mathbf{r}; \mathbf{p})) d\mathbf{r} \right)^2 \\
 \frac{\partial C}{\partial \mathbf{p}} &= -\frac{2}{N} \sum_{\mathbf{x}} \left( F(\mathbf{x}) - \int_{\mathbf{r} \in RAY[\mathbf{x}]} M(\mathbf{T}(\mathbf{r}; \mathbf{p})) d\mathbf{r} \right) \int_{\mathbf{r} \in RAY[\mathbf{x}]} \frac{\partial M}{\partial \mathbf{p}} d\mathbf{r} \\
 &= -\frac{2}{N} \sum_{\mathbf{x}} \left( F(\mathbf{x}) - \int_{\mathbf{r} \in RAY[\mathbf{x}]} M(\mathbf{T}(\mathbf{r}; \mathbf{p})) d\mathbf{r} \right) \int_{\mathbf{r} \in RAY[\mathbf{x}]} \left( \frac{\partial \mathbf{T}}{\partial \mathbf{p}} \right)^t \frac{\partial M}{\partial \mathbf{x}} d\mathbf{r}
 \end{aligned}$$

## Choice of $d_k$

$$p_{k+1} = p_k + a_k \cdot d_k$$

gradient descent:  $d_k = -g_k$

Newton:  $d_k = -[H_k]^{-1} g_k$

quasi-Newton:  $d_k = -B_k g_k$

conjugate gradient:  $d_k = -g_k + \beta_k d_{k-1}$

stochastic gradient:  $d_k \approx -g_k$  → cheaper steps



smarter steps

## Choice of $a_k$

$$p_{k+1} = p_k + a_k \cdot d_k$$

constant:  $a_k = a$

slowly decaying:  $a_k = f(k) = a / (A + k)^\alpha$

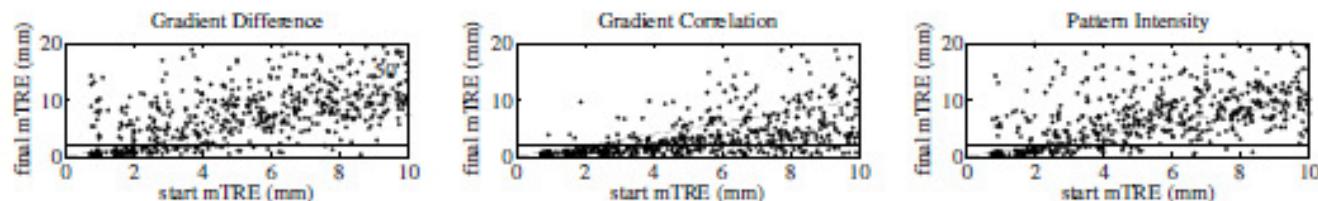
exact line search:  $a_k = \operatorname{argmin}_a C(p_k + a d_k)$

inexact line search:  $a_k \approx \operatorname{argmin}_a C(p_k + a d_k)$  [Wolfe conditions]

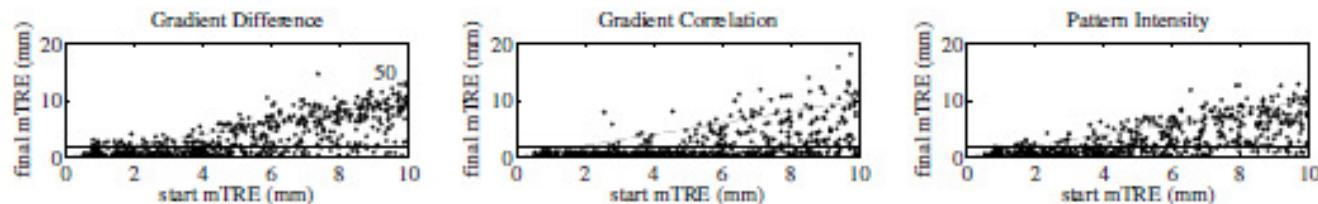
adaptive:  $a_k = F(\text{progress in previous iterations})$

## Literature

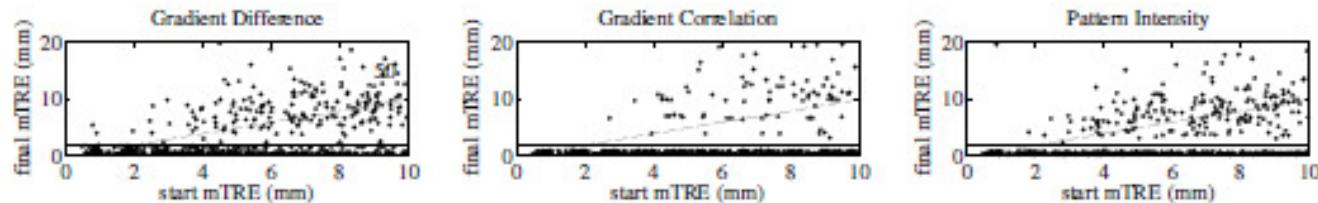
- Nocedal & Wright: Numerical Optimization
- IEEE Trans. Image Processing 2007 - Klein, Staring, Pluim  
*Evaluation of optimization methods for nonrigid medical image registration using mutual information and B-splines*
- IEEE Trans. Image Processing 2000 - Thevenaz, Unser  
*Optimization of mutual information for multiresolution image registration*
- SPIE2011 – van der Bom, Klein, Staring, Homan, Bartels Pluim  
*Evaluation of optimization methods for intensity-based 2-D-3D registration in X-ray guided interventions*



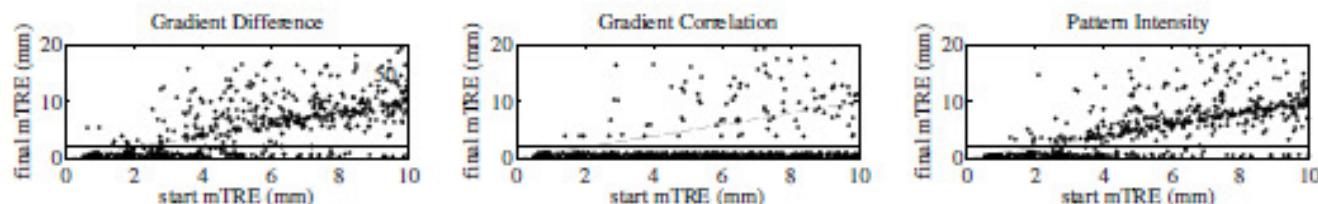
(a) Gradient descent ( $o_{GD} = 18, o_{GC} = 3, o_{PI} = 15$ )



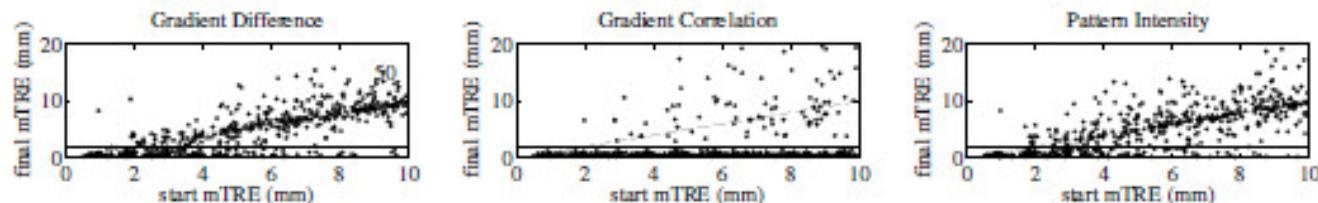
(b) Nelder-Mead ( $o_{GD} = 0, o_{GC} = 0, o_{PI} = 0$ )



(c) Powell-Brent ( $o_{GD} = 9, o_{GC} = 11, o_{PI} = 8$ )



(d) Quasi-Newton ( $o_{GD} = 9, o_{GC} = 18, o_{PI} = 4$ )



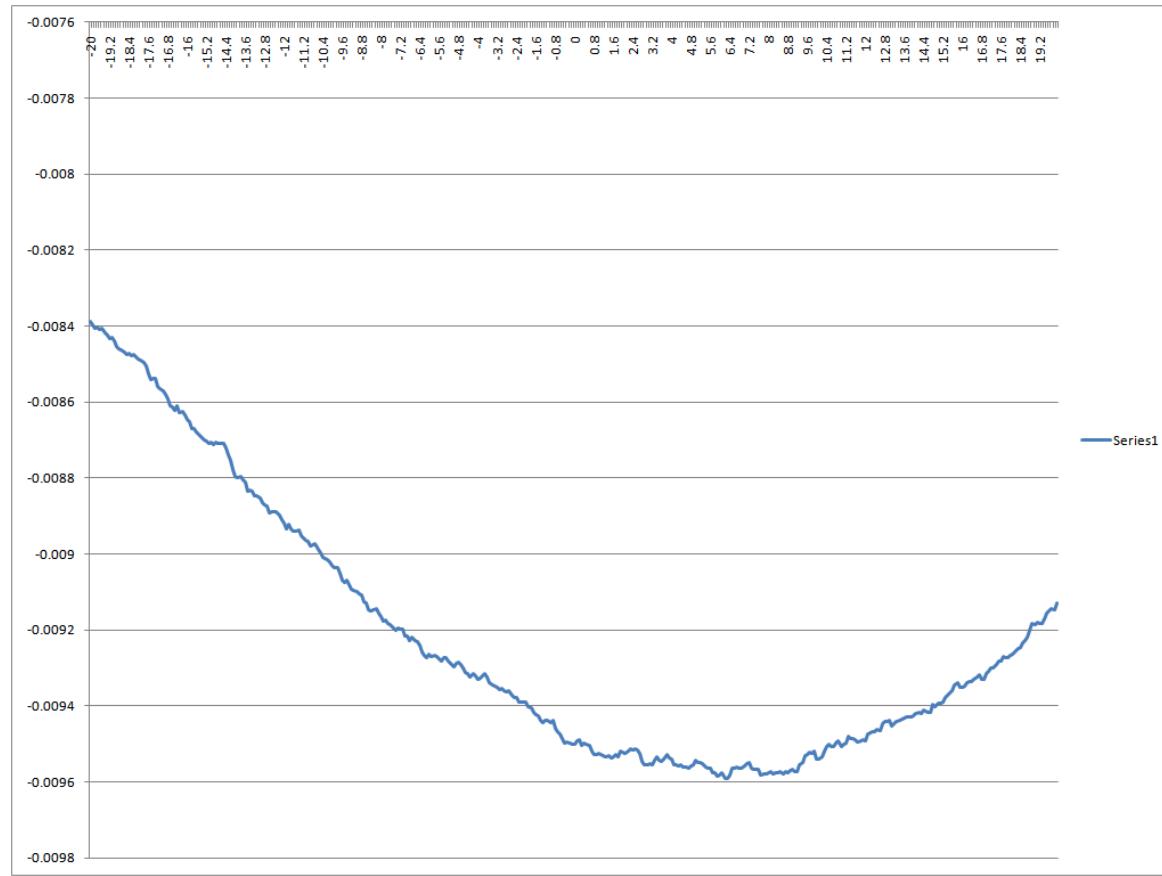
(e) Nonlinear conjugate gradient ( $o_{GD} = 11, o_{GC} = 31, o_{PI} = 9$ )

## Pitfalls

- Cost function is not smooth
- Cost function is badly scaled
- Capture range too small

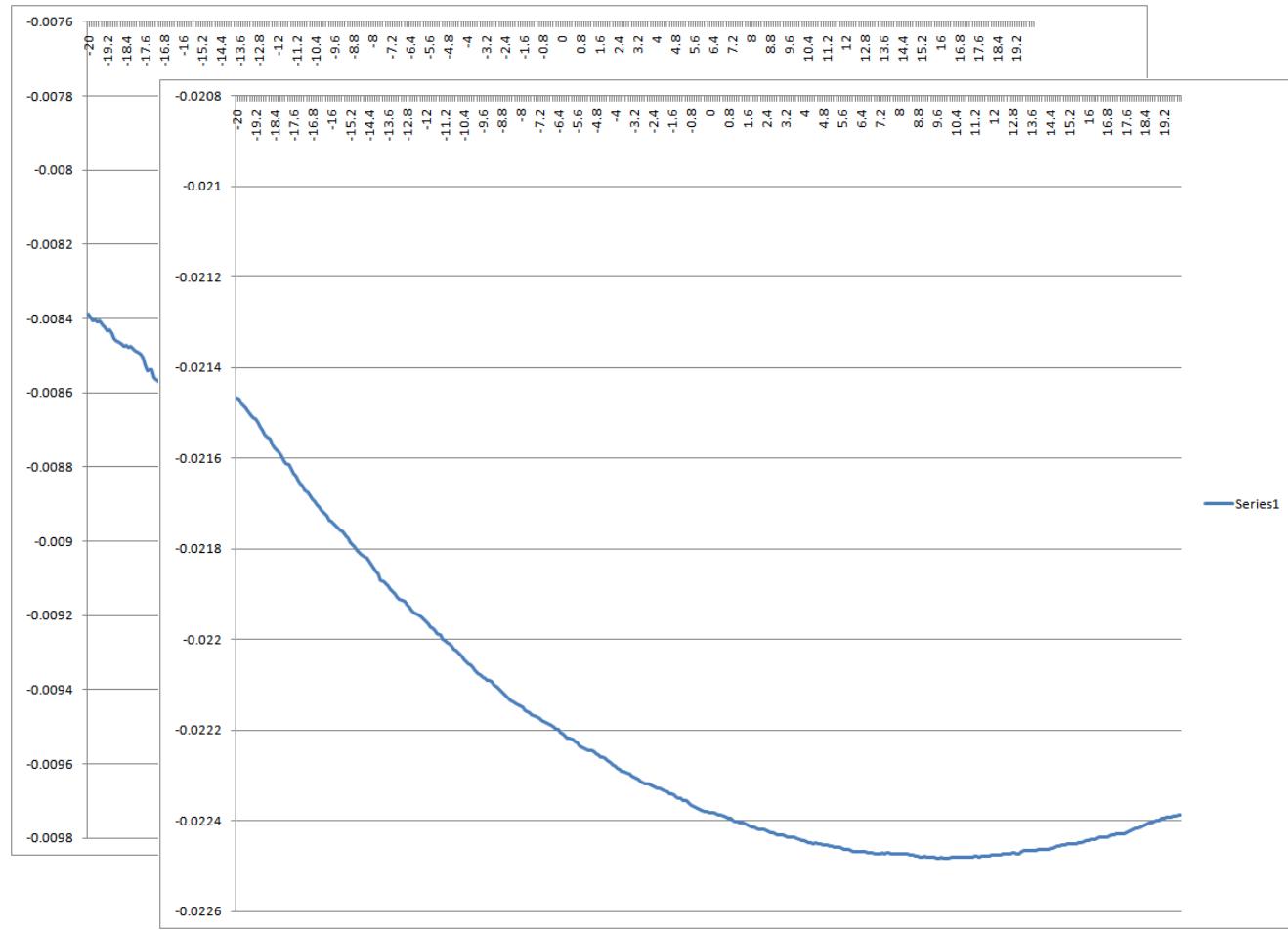
# Pitfalls

- Cost function is not smooth



# Pitfalls

- Cost function is not smooth



## Pitfalls

- Cost function is not smooth
- Cost function is badly scaled
- Capture range too small

## Pitfalls

- Cost function is not smooth
- Cost function is badly scaled
  - Use Hessian (Newton-like algorithm)
  - Scale parameters such that average  $\| \frac{dT}{dp_i} \|$  is equal for all i
- Capture range too small

## Pitfalls

- Cost function is not smooth
- Cost function is badly scaled
- Capture range too small

## Pitfalls

- Cost function is not smooth
- Cost function is badly scaled
- Capture range too small
  - Add information: prior motion model, additional images (bi-plane x-ray), landmarks, regularisation...
  - Multiresolution strategies
  - Global optimisation methods? (usually less time-efficient)

## Example

2D+t X-ray time sequence



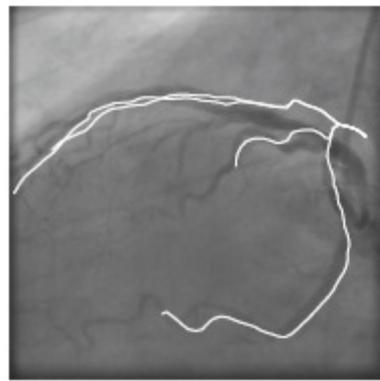
p0005x.avi

3D+t coronary motion model  
from dynamic CTA

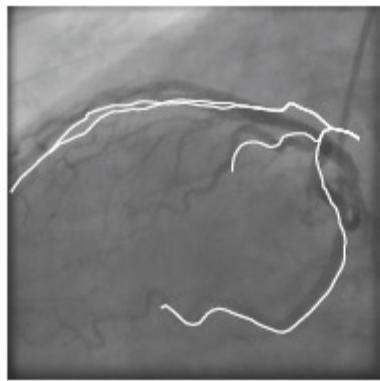


p0005.avi

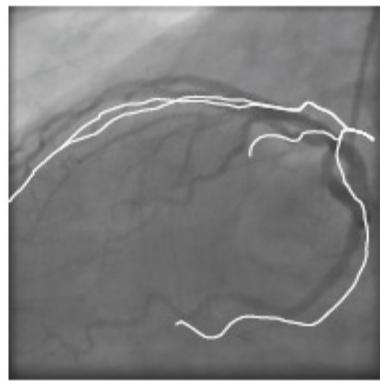
## Example



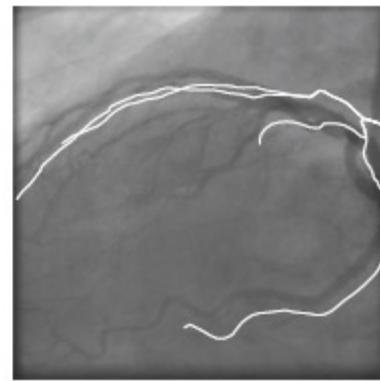
(a) 3-2 (L), 25%, before



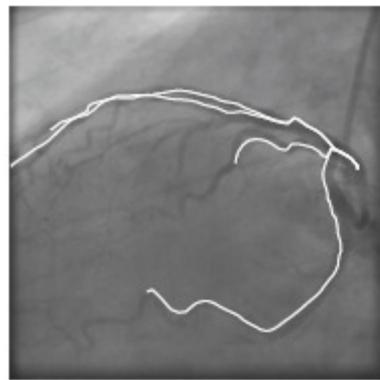
(b) 3-2 (L), 50%, before



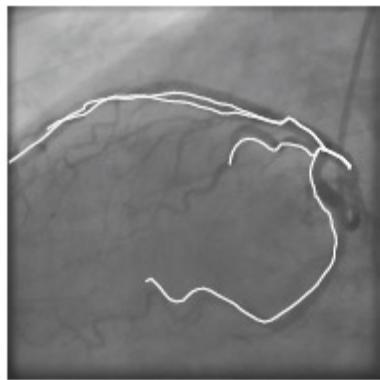
(c) 3-2 (L), 75%, before



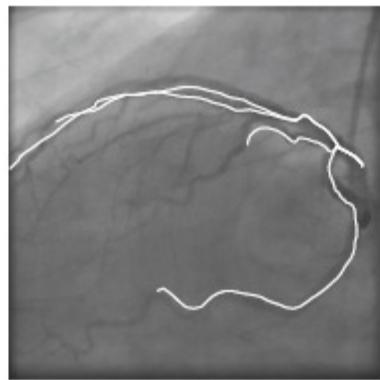
(d) 3-2 (L), 100%, before



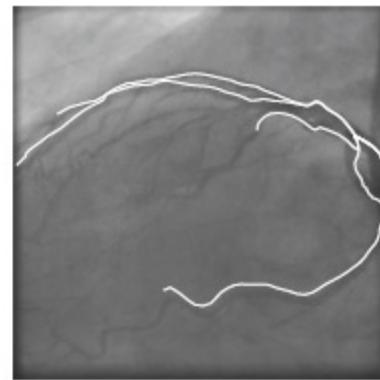
(e) 3-2 (L), 25%, after



(f) 3-2 (L), 50%, after



(g) 3-2 (L), 75%, after



(h) 3-2 (L), 100%, after

## For more details:

- Augmented Environments for Computer Assisted Interventions
- Oral presentation session III.
- September 22 2.45 - 3pm
- Alignment of 4D Coronary CTA with Monoplane X-Ray Angiography
- Coert Metz, Michiel Schaap, Stefan Klein, Peter Rijnbeek, Lisan Neefjes, Nico Mollet, Carl Schultz, Patrick Serruys, Wiro Niessen and Theo van Walsum



- Rigid and nonrigid registration
- Various cost functions, transformation models, multiresolution strategies etc.
- Many optimisation algorithms implemented
- Free: <http://elastix.isi.uu.nl>
- Based on Insight ToolKit (ITK): <http://www.itk.org>
- IEEE Trans. Medical Imaging 2010 - Klein, Staring, Murphy, Viergever, Pluim – elastix: a toolbox for intensity based medical image registration

## Experimental comparison

