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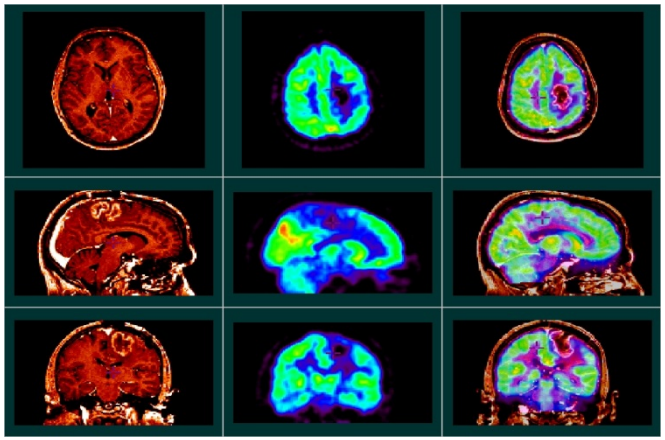
SRS/SBRT/SABR:
Safely and Accurately Delivering
High-Precision, Hypofractionated Treatments

Imaging & Fusion Fundamentals

Jinkoo Kim
Henry Ford Health System



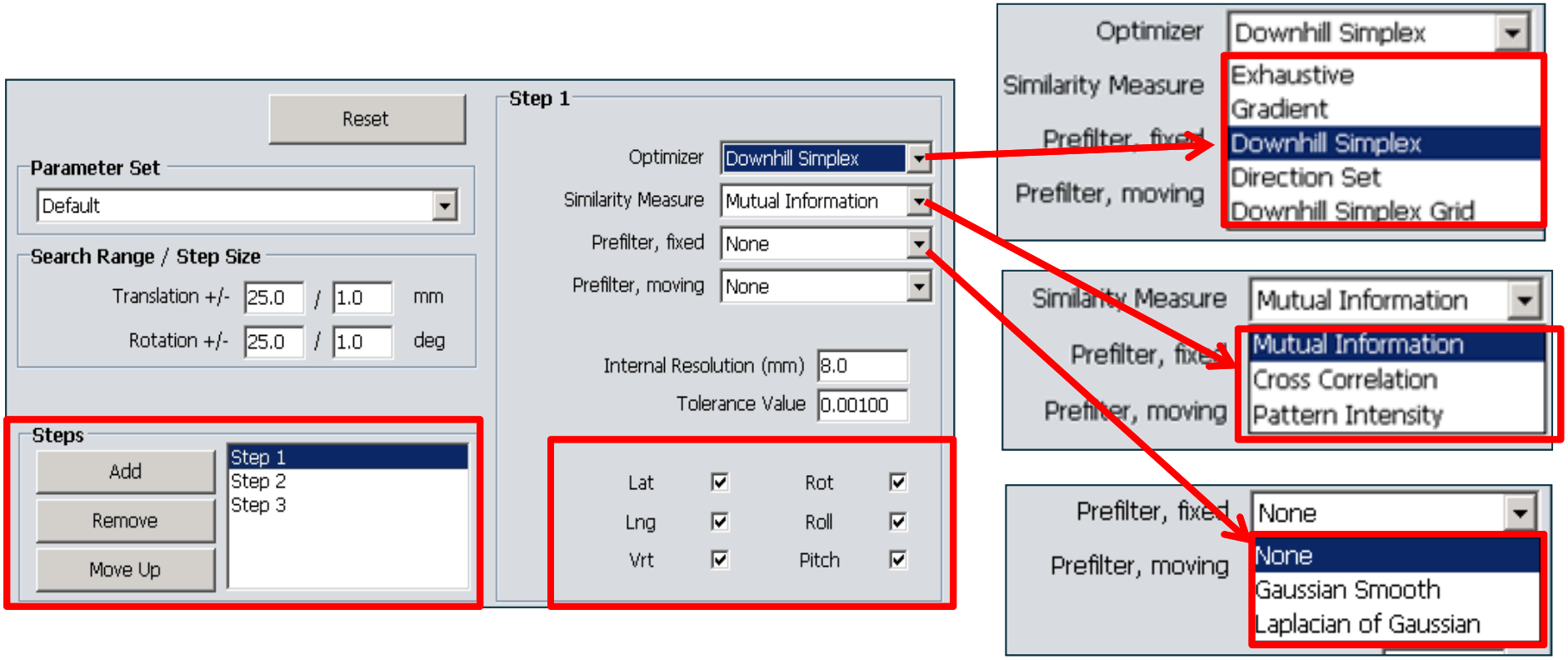
Disclosures

- I participate in research funded by Varian Medical Systems.

Learning Objectives

- Understand basic components of image registration algorithms.
- Understand 3D/3D and 3D/2D image registration algorithms.
- Understand basics of similarity metric, transformation, and optimization

Parameter Sets in Eclipse



Just a note about DIR… @ AAPM Virtual Library

- 2011 - Atlas Based Auto-Segmentation Based On Deformable Image Registration, Lei Dong, PhD, UT MD Anderson Cancer Center,
- 2012 - Effects of Different Parameters On Deformable Image Registration, Jinkoo Kim, PhD, Henry Ford Health System
- 2013 - Deformable Image Registration, Contour Propagation and Dose Mapping: 101 and 201, Marc Kessler, PhD, The University of Michigan,
- 2013 - Validation and QA of Deformable Image Registration Part II, Jean Pouliot, PhD, UC San Francisco

Outline of Presentation

- What is image registration.
- 3D/3D and 3D/2D image registration algorithms
- Basic components of image registration algorithms
- Discussions

What is Image Registration?

- "The process of determining the spatial transformation that maps points from one image to homologous points on a object in the second image." - ITK[1]

- "The task of finding a spatial one-to-one mapping from voxels in one image to voxels in the other image." – elastix[2]

1. Luis Ibanez et al., "The ITK Software Guide, 2nd Ed", www.itk.org. (2005)
2. Stefan Klein and Marius Staring, "Elastix, the manual" , elastix.isi.uu.nl (2011)

What is Image Registration?

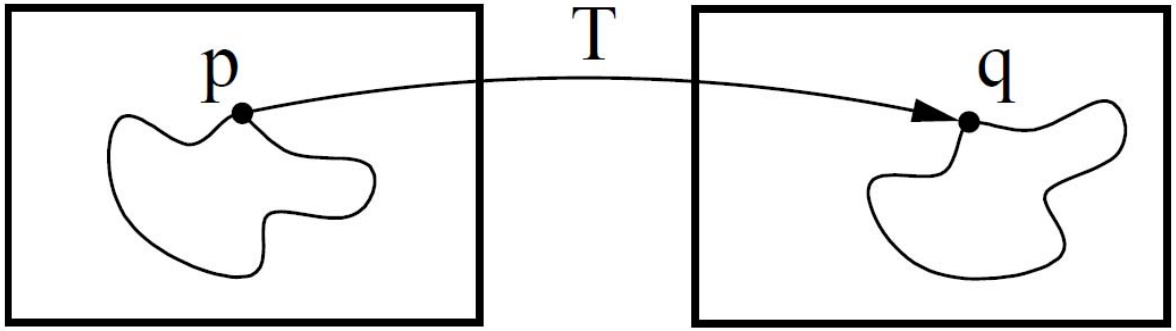


Figure 8.1: Image registration is the task of finding a spatial transform mapping on image into another.

elastix

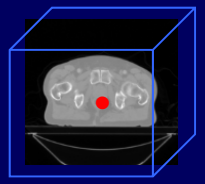
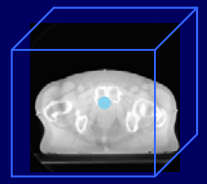
Why we need Image Registration?

- IGRT – daily patient setup in treatment rooms.
  - CBCT/CT, OBI 2D/2D, ExacTrac 3D/2D, Cyberknife, etc.
- Treatment Planning - complementary information fusion
  - PET/CT, MR/CT, Angiogram/CT, etc
- Adaptive radiotherapy (ART)
  - Contour propagation: ex) CT→ CBCT
  - Dose accumulation: ex) CBCT→ CT.
- Atlas-based segmentation
  - Model-Image registration for automatic organs segmentation.

How it works?

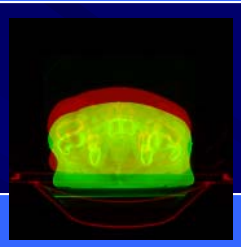
Q: What happens under the hood…?

3D/3D Registration (CT / CBCT)

Simulation	Treatment
	
3D Sim CT + Plan Isocenter	3D CBCT + Machine Isocenter
Planned Setup	Current Setup

3D/3D Registration

Measure Similarity



Repeat

Similar?

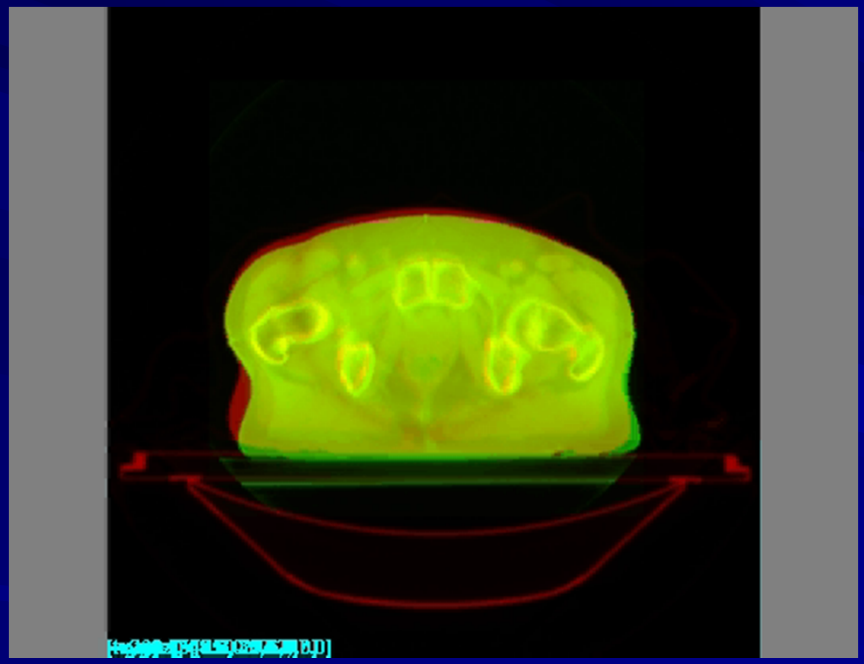
No

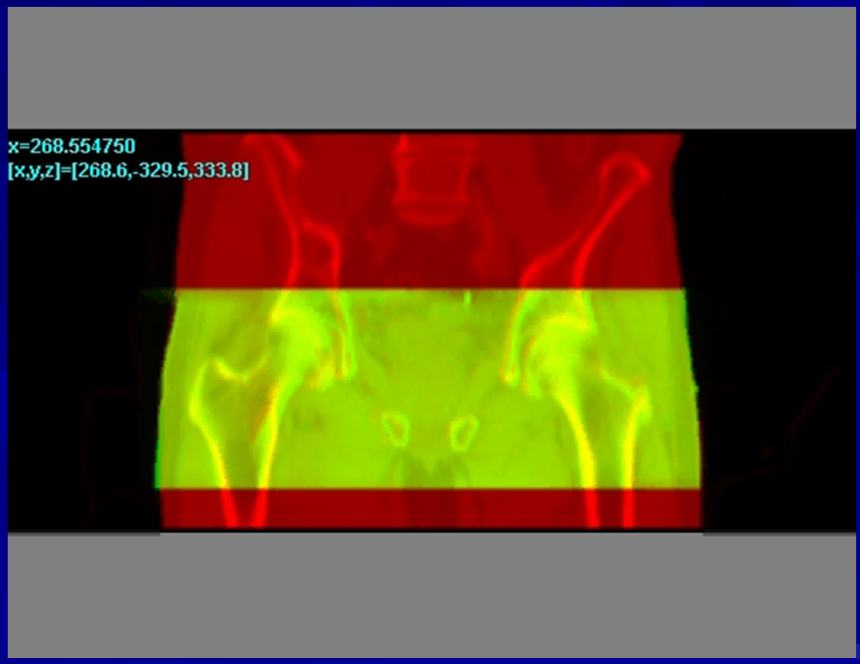
Transform CBCT

Align CBCT isocenter to the machine isocenter

until the two images are similar/matched.

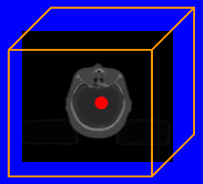
3D/3D Registration Example (Animation)





3D/2D Registration (CT/Dual X-ray)

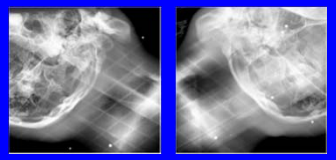
Simulation



3D CT
+
Isocenter

Planned Setup

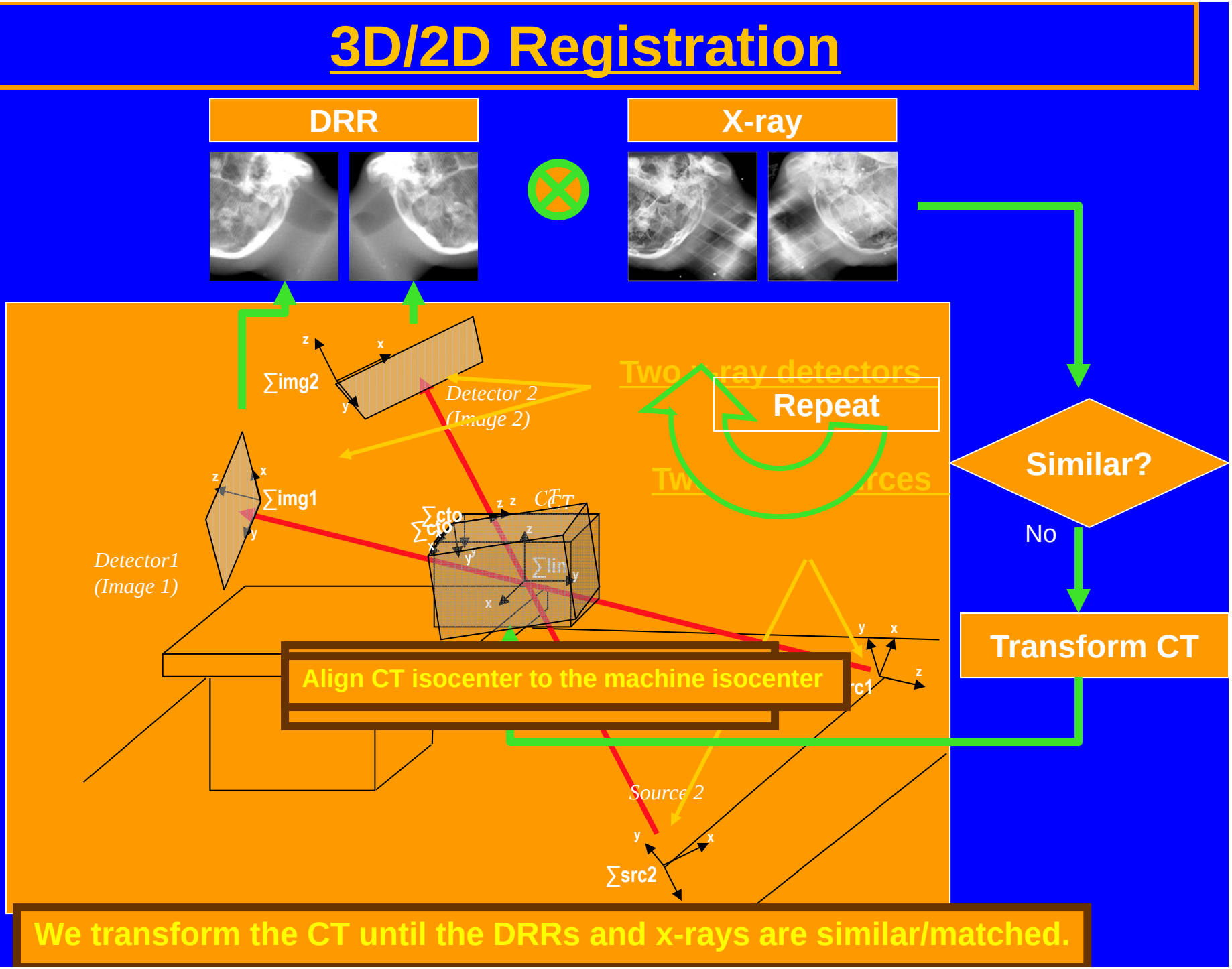
Treatment



2D X-ray images
+
Imaging Geometry

Current Setup

3D/2D Registration

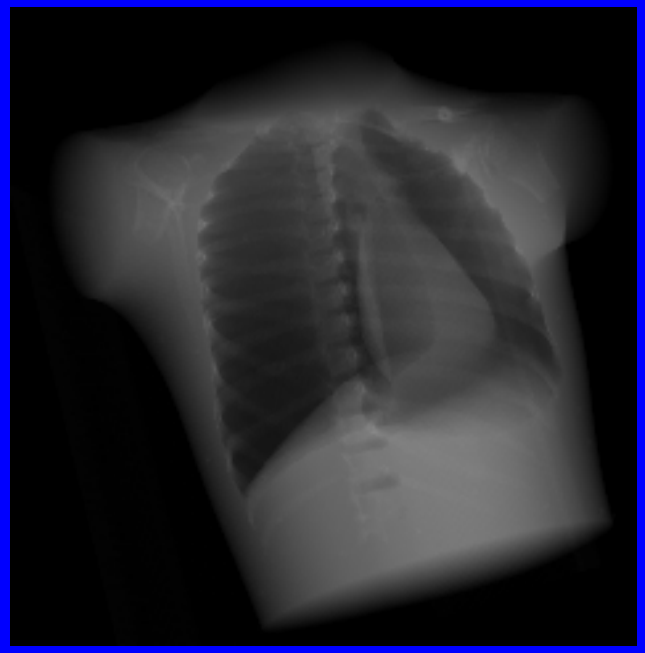


3D/2D Registration
DRR (Digitally Reconstructed Radiograph)

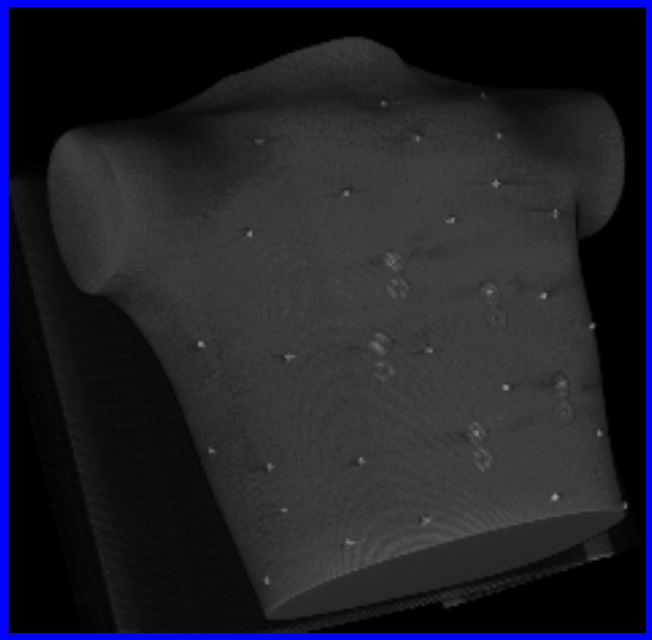
- 3D/2D registration needs DRR generation.
- DRR generation is one of the direct volume rendering techniques (DVR) in computer graphics.
- Volume rendering techniques utilize graphics processing units (GPU) for rapid rendering [1,2].
- DRR generation depends on the imaging geometry (source and detector pose and pixel geometry, which are determined thought imaging system calibration.
  - Accurate system calibration & verification is essential for IGRT application.

1. C. Rezk-Salama, “Volume rendering techniques for general purpose graphics hardware,” PhD Thesis, Computer Science Department, Universität Erlangen-Nürnberg, (2002).
2. R. Fernando, “GPU Gems, Programming Techniques, Tips, and Tricks for Real-Time Graphics”, Addison-Wesley, 2004- chap 39 “Volume Rendering Techniques”.

3D/2D Registration
DRR (Digitally Reconstructed Radiograph)



DVR with Attenuate operator



DVR with Over operator

3D/2D Registration Example (Animation)

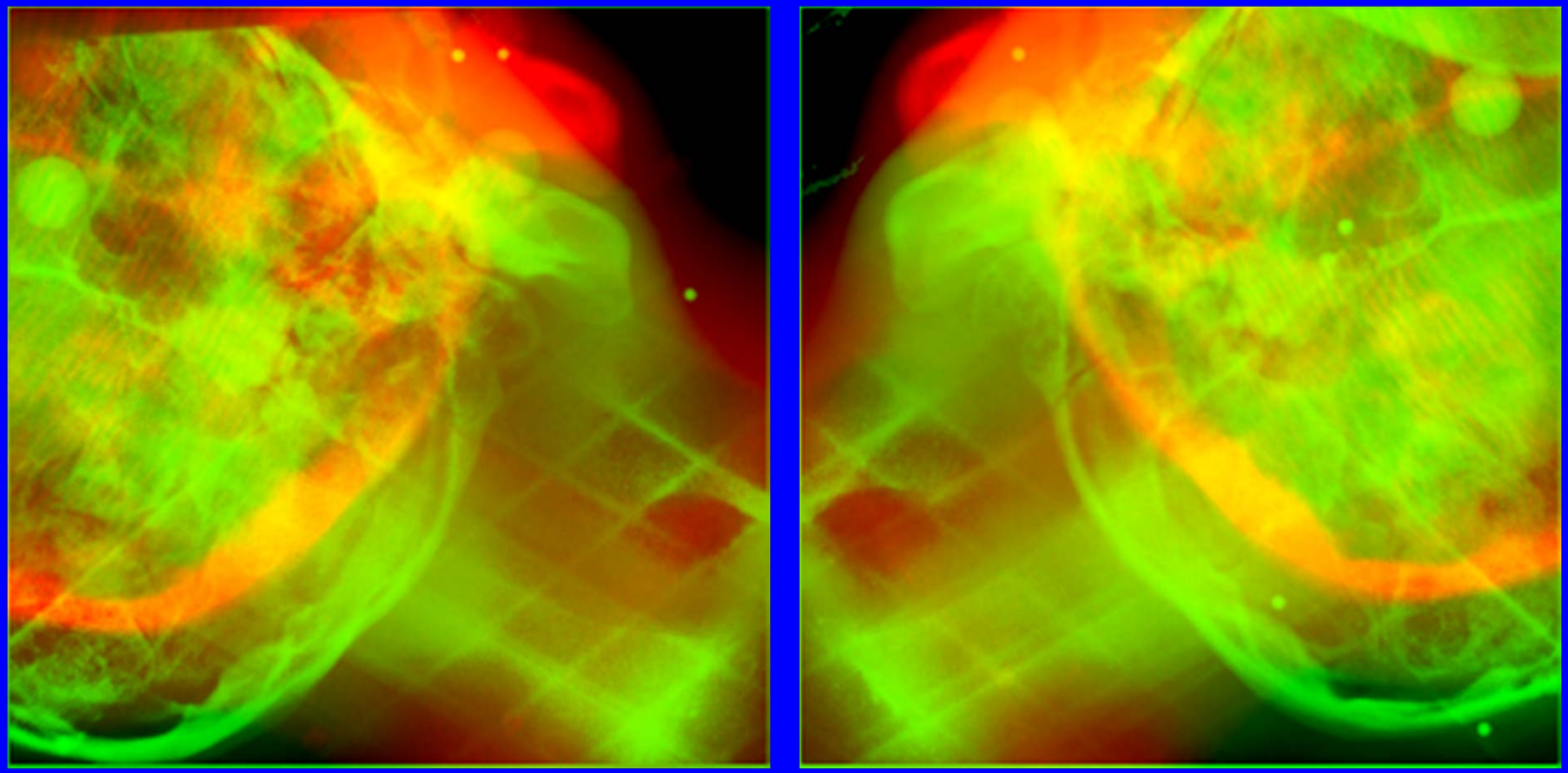


Image Registration is …

- To iteratively find the shifts of one image such that the two images look overlapped.

→ To iteratively find the transformation of one image that maximizes the similarity between the two images.

Basic Components of Image Registration

- Image registration consists of three components.
  - **Similarity Metric**
  - **Transformation**
  - **Optimization**

- **Optimization** updates the **Transformation** parameters until the **Similarity Metric** reaches maximum between two input images.

Basic Components of Image Registration

- Mathematically put:

$$\hat{T} = \arg\max_{T} S(T; I_F, I_M)$$

$$\Rightarrow \hat{T} = \arg\min_{T}\left[-S(T; I_F, I_M)\right]$$

$$\Rightarrow \hat{T} = \arg\min_{T}\left[-S(T; I_F, I_M) + \gamma P(T)\right]$$

Penalty term on T
(smoothness, rigidity, …)

Basic Components of Image Registration

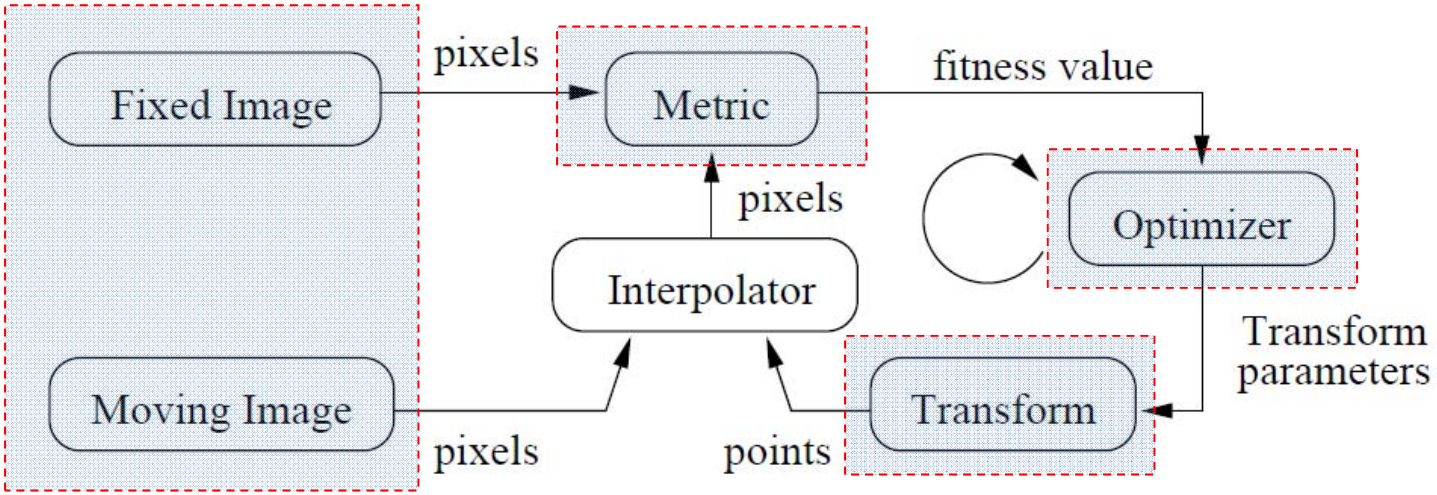


Figure 8.2: The basic components of the registration framework are two input images, a transform, a metric, an interpolator and an optimizer.

1) Luis Ibáñez et al , “The ITK software guide : updated for ITK version 2.4”, 2005

Q1.What is the primary aim of typical 3D/3D image registration?

1%	1.	To segment organs on input images automatically.
95%	2.	To find the spatial correlation between two input image spaces.
0%	3.	To optimize the quality of input images.
3%	4.	To convert pixel intensities of one image to another.
1%	5.	To correct imaging artifacts.

Q1.What is the primary aim of typical 3D/3D image registration?

- **Answer: (2)**
- Ref: "The ITK Software Guide Second Edition", Luis Ib´a˜nez et al, 2005. Chap 8. P.315

Basic Components of Image Registration

- **Similarity Metric (Measure)**
- Optimization
- Transformation

Similarity Metric

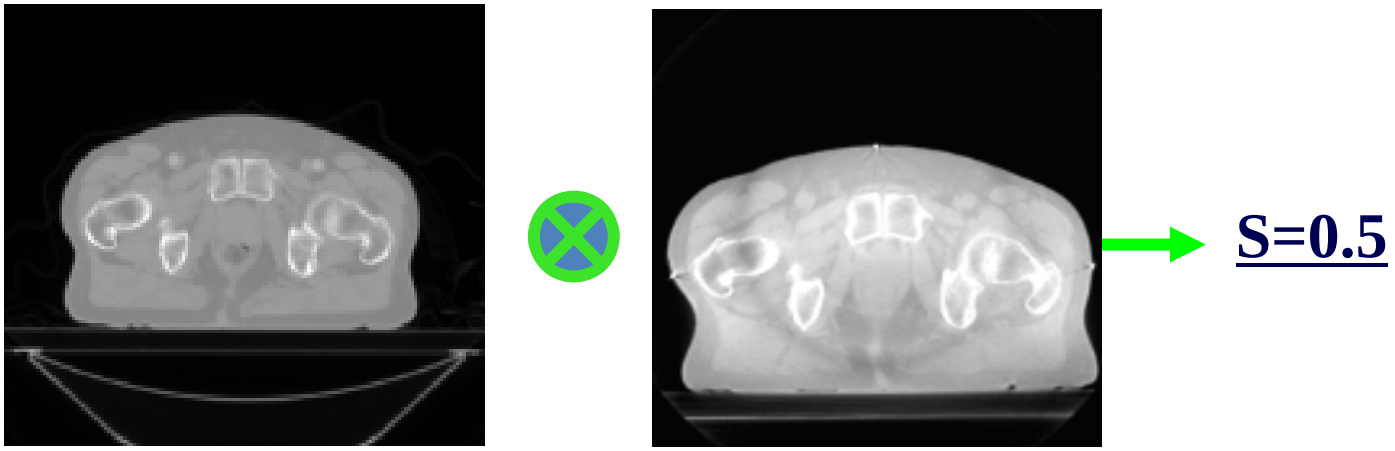
Q: Which one is overlapped better?

(a)

(b)

Similarity Metric

- Q: How do you measure the **similarity** between two images?
- Similarity metric is supposed to give **a number** to a optimizer to indicate how similar the two images are.



Similarity Metrics

- Sum of Squared Difference (SSD)
- Normalized Cross Correlation (NCC)
- Entropy Of Difference (EOD)
- Gradient Correlation (GC)
- Gradient Difference (GD)
- Pattern Intensity (PI)

Mono-modal

- Mutual Information (MI)
- Normalized Mutual Information (NMI)

Multi-modal

- … and More!

(Ref)

- B. Zitova and J Flusser, “Image registration methods: a survey”, Image and Vision Computing 21 (2003)
- J. Maintz and M Viergever, “A survey of medical image registration”, Medical Image Analysis (1998)

Similarity Metrics

Sum of Squared Difference

$$S_{SSD}(I_1, I_2) = \frac{1}{N} \sum_{i,j} \left(I_1(i,j) - I_2(i,j) \right)^2$$

1. Subtract pixel values
2. Square
3. Sum

→ Requires same pixel intensity values btw two corresponding anatomical points.

Similarity Metrics

Normalized Cross Correlation

$$S_{NCC}(I_1, I_2) = \frac{\sum_{i,j}\left(I_1(i,j) - \bar{I}_1\right)\left(I_2(i,j) - \bar{I}_2\right)}{\sqrt{\sum_{i,j}\left(I_1(i,j) - \bar{I}_1\right)^2}\sqrt{\sum_{i,j}\left(I_2(i,j) - \bar{I}_2\right)^2}}$$

1. Subtract mean pixel values

2. Calculate vector inner product

→ NCC consider the image pixel array as a vector.

Similarity Metric

Mutual Information

$$S_{MI}(X,Y) = \sum_{x,y} p(X,Y) \log_l \frac{p(X,Y)}{p(X)\,p(Y)}$$

Joint prob. density function(PDF) of random variables X and Y

Marginal PDFs

→ PDF is a normalized form of image histogram.

→ MI can be used for different modality images (ex, CT/MR)

Pluim et al., "Mutual-Information-Based Registration of Medical Images: A Survey", IEEE TRANS MED IMAG, VOL. 22 (8), p986-1004, 2003

Q3. Which one of the following similarity metrics would you use for CT-MR registration?

76%	1.	Mutual Information
9%	2.	Normalized Cross Correlation
5%	3.	Sum of Squared Difference
2%	4.	Entropy of Difference
7%	5.	Histogram Equalization

Q3. Which one of the following similarity metrics would you use for CT-MR registration?

Answer: (1) Mutual Information.

- Pluim et al., “Mutual-Information-Based Registration of Medical Images: A Survey”, IEEE TRANS MED IMAG, VOL. 22 (8), p986-1004, 2003
- “The ITK Software Guide Second Edition”, Luis Ib´a˜nez et al, 2005. Chap 8. P.315

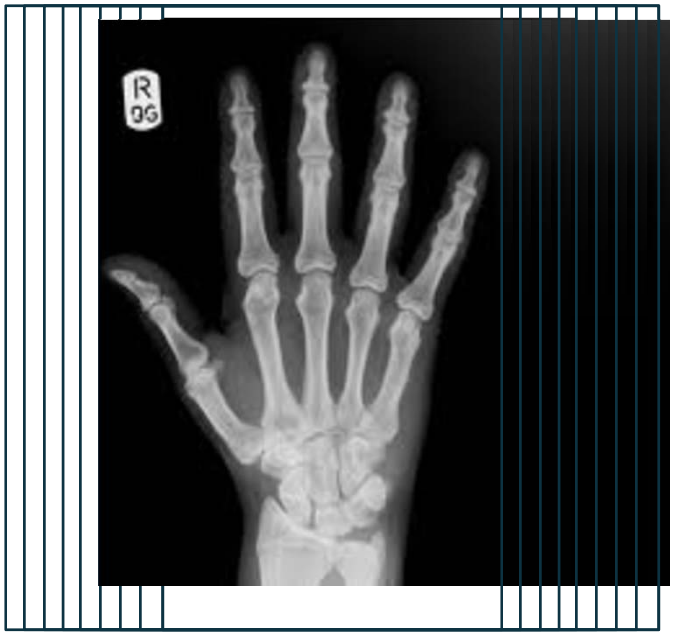
Basic Components of Image Registration

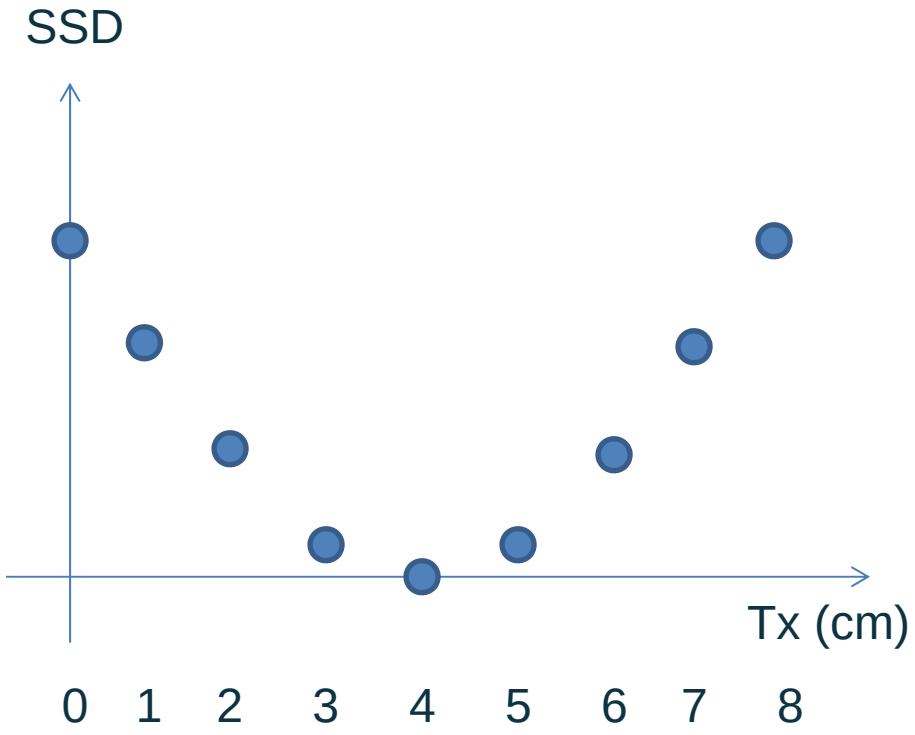
- Similarity Metric/Measure
- **Optimization**
- Transformation

Optimization

- Optimization algorithms
  - Local optimization
    - Gradient descent, Downhill simplex, etc.
  - Global optimization
    - Simulated annealing
    - Genetic algorithm
    - Exhaustive search
- Registration algorithms mostly uses local optimization for faster conversance.

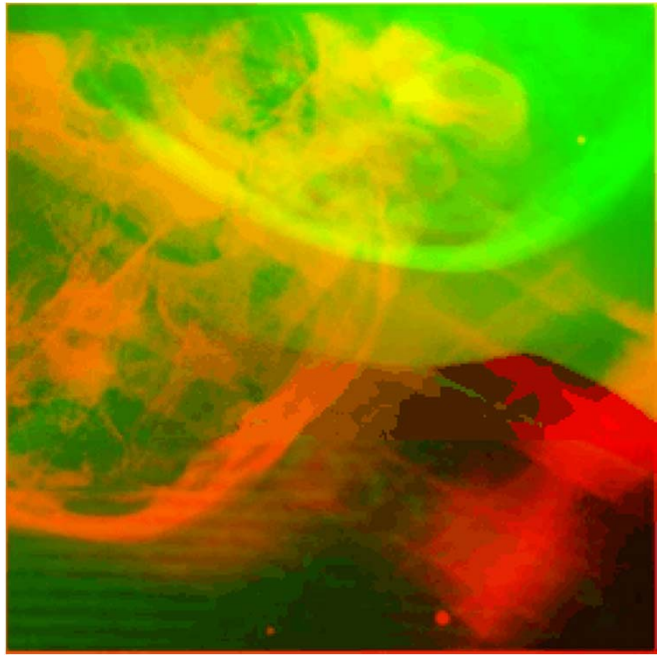
Optimization

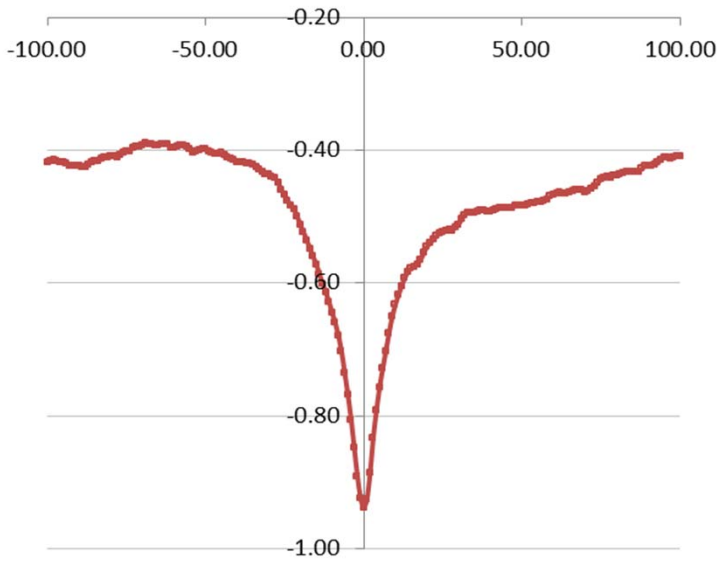




Exhaustive Search

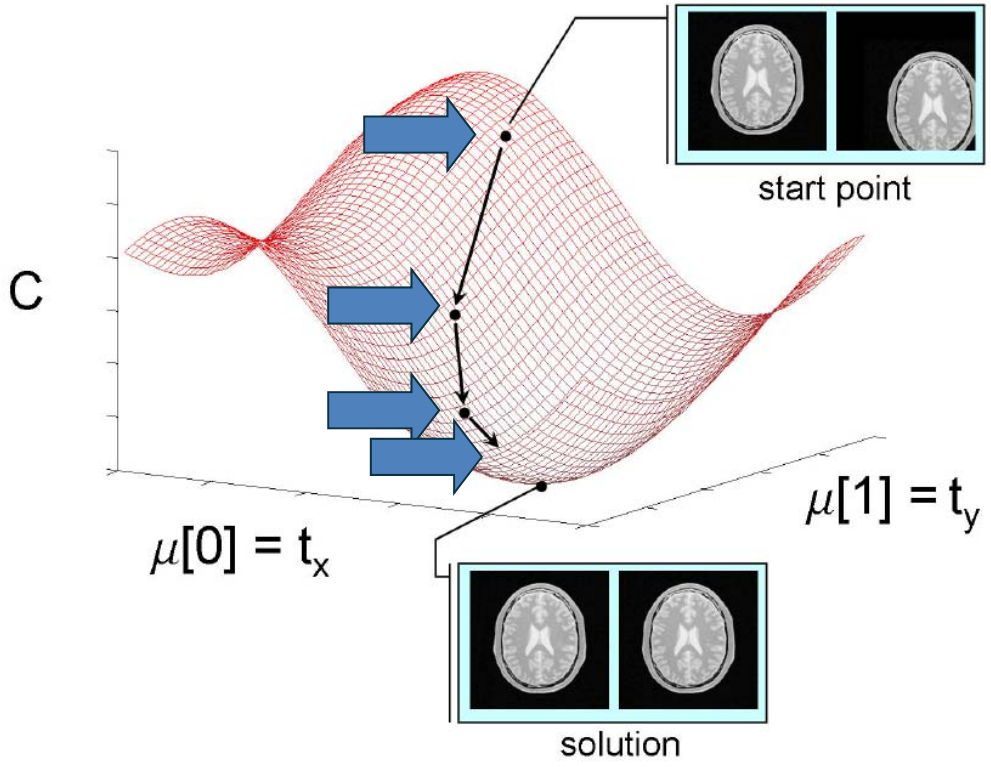
Optimization





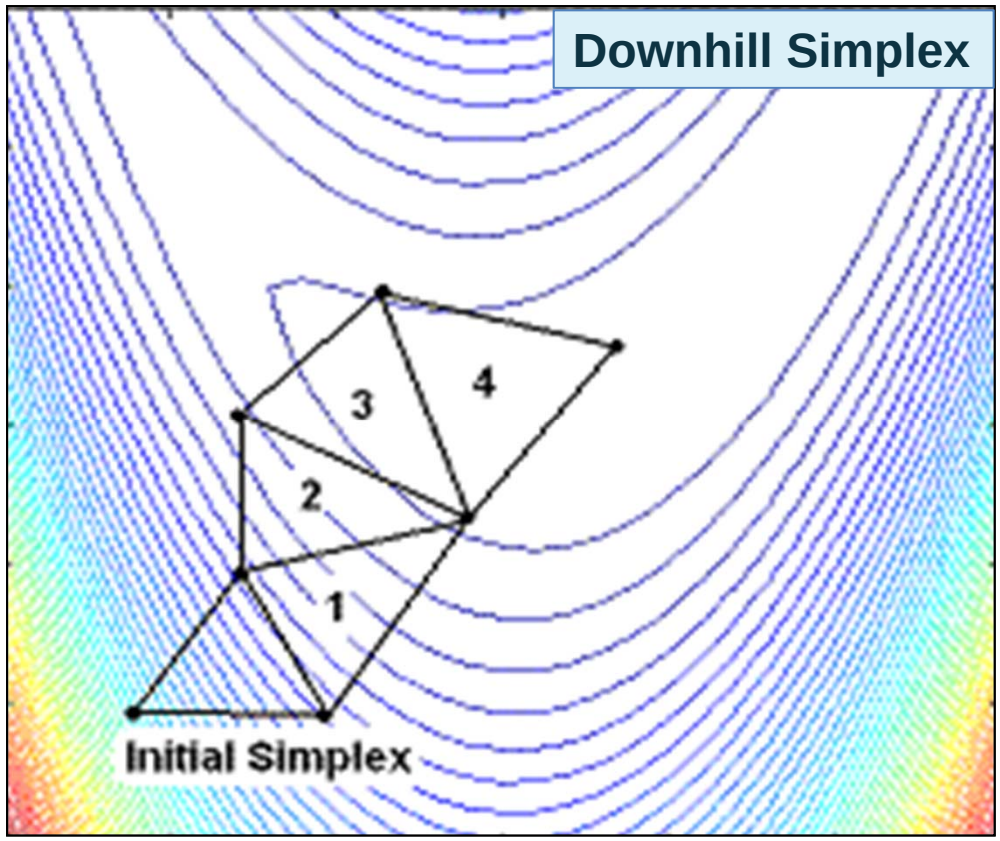
Exhaustive Search

Gradient Descent Search



1. Stefan Klein and Marius Staring, “Elastix, the manual” , elastix.isi.uu.nl (2011)
2. Press et al., “Numerical Recipes in C: The Art of Scientific Computing, Second Edition”, Cambridge University Press (1992).

Optimization



Press et al., “Numerical Recipes in C: The Art of Scientific Computing, Second Edition”, Cambridge University Press (1992).

Q2. Gradient descent search algorithm belongs to which of the following algorithm categories?

5% 1. Transformation

10% 2. Similarity Metric

3% 3. Interpolation

3% 4. Edge Detection

80% 5. Optimization

Q2. Gradient descent search algorithm belongs to which of the following algorithm categories?

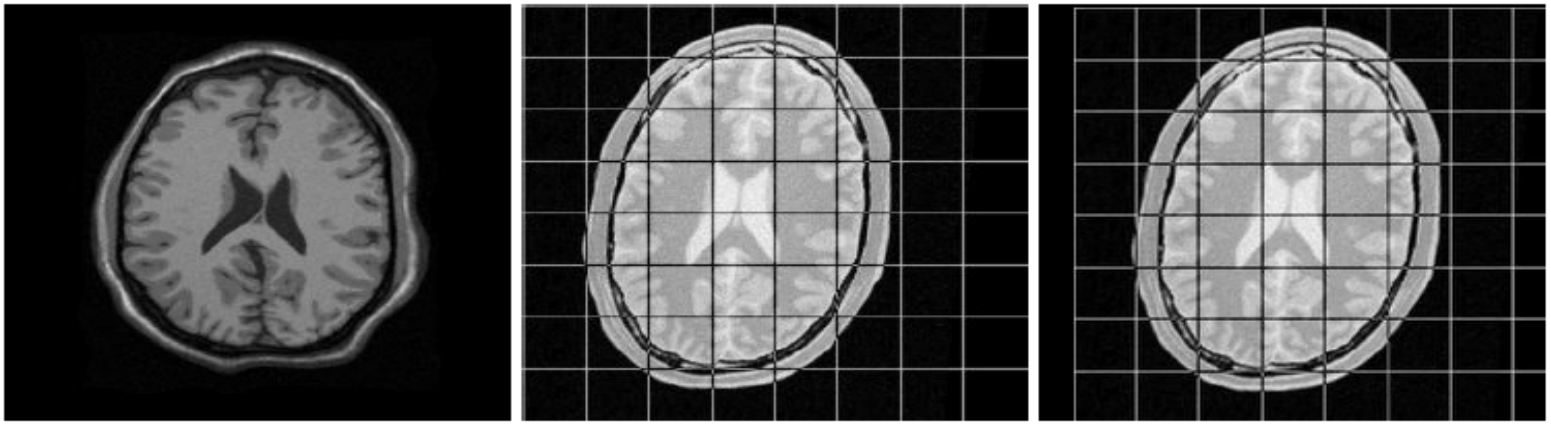
- **Answer: (5) Optimization.**

- 1. Stefan Klein and Marius Staring, “Elastix, the manual” , elastix.isi.uu.nl (2011)
- 2. Press et al., “Numerical Recipes in C: The Art of Scientific Computing, Second Edition”, Cambridge University Press (1992).

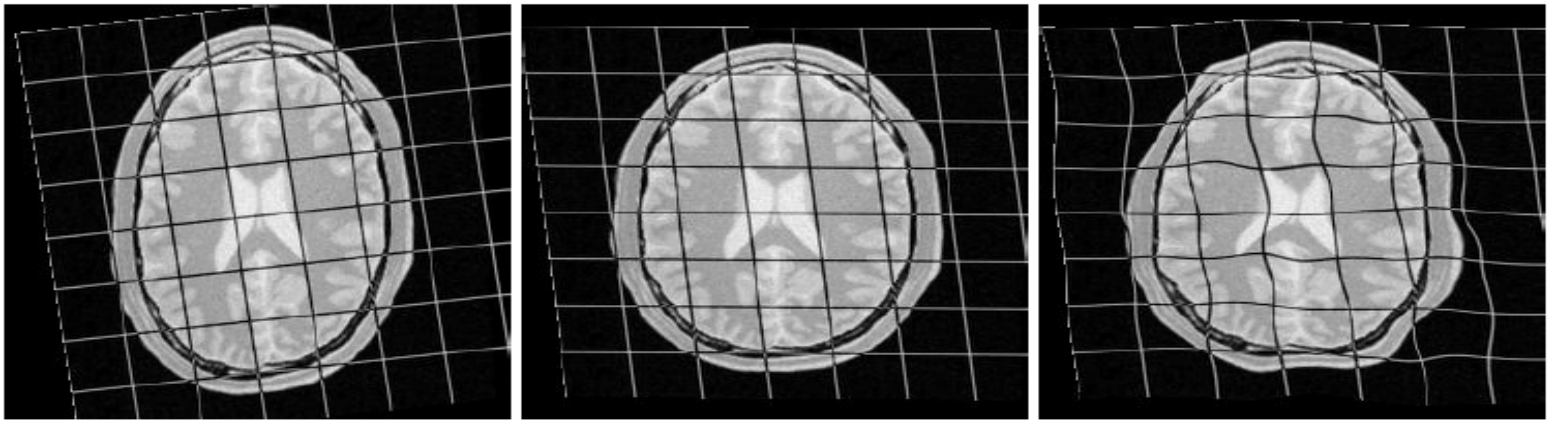
Basic Components of Image Registration

- Similarity Metric/Measure
- Optimization
- **Transformation**

Transformation



(a) fixed (b) moving (c) translation



(d) rigid (e) affine (f) B-spline

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Transformation

- **Rigid** (translation, rotation)
  - In 3D space, 3 translations & 3 rotations → 6 DOF
- **Affine** (translation, rotation, scale, shear)
  - In 3D space→ 12 DOF
- **Deformable**
  - Non-parametric
    - Spatial mapping is directly represented by a deformation vector field (DVF).
  - Parametric
    - A set of parameters represent underlying deformation
      - B-spline, thin plate spline, radial basis functions, etc.

Deformable Image Registration (DIR)

Non-parametric DIR algorithms:

1) J. Thirion, "Image matching as a diffusion process: an analogy with Maxwell's demons," Med. Image Anal 2(3), 243–260 (1998). → **Demons DIR**.
2) Lu. et al., "Fast free-form deformable registration via calculus of variations," Phys. Med. Biol. 49(14), 3067–3087 (2004).
3) …

Parametric DIR algorithms:

1) Rueckert et al., “Nonrigid registration using free-form deformations: application to breast MR images”, IEEE Trans. med. imag., vol 18 (8), 1999 → **Bspline DIR**.
2) F. L. Bookstein, "Principal warps: thin-plate splines and the decomposition of deformations," IEEE Trans. Pattern Anal. Mach. Intell. 11(6), 1989.
3) …

Q4. How many parameters are necessary in a 3D rigid transformation?

7%	1.	3
82%	2.	6
3%	3.	9
5%	4.	12
3%	5.	3 x number of control points

Q4. How many parameters are necessary in a 3D rigid transformation?

Answer: (2).

Ref: "Elastix, the manual", S. Klein and M. Staring, 2011. Chap 2. P.7

Multi-Resolution Image Registration

- Registration starts from lower resolution and increases the resolution progressively.
- The goal is
  - to properly handle large initial difference, and
  - to speed up the registration

elasti

Multi-Resolution Image Registration

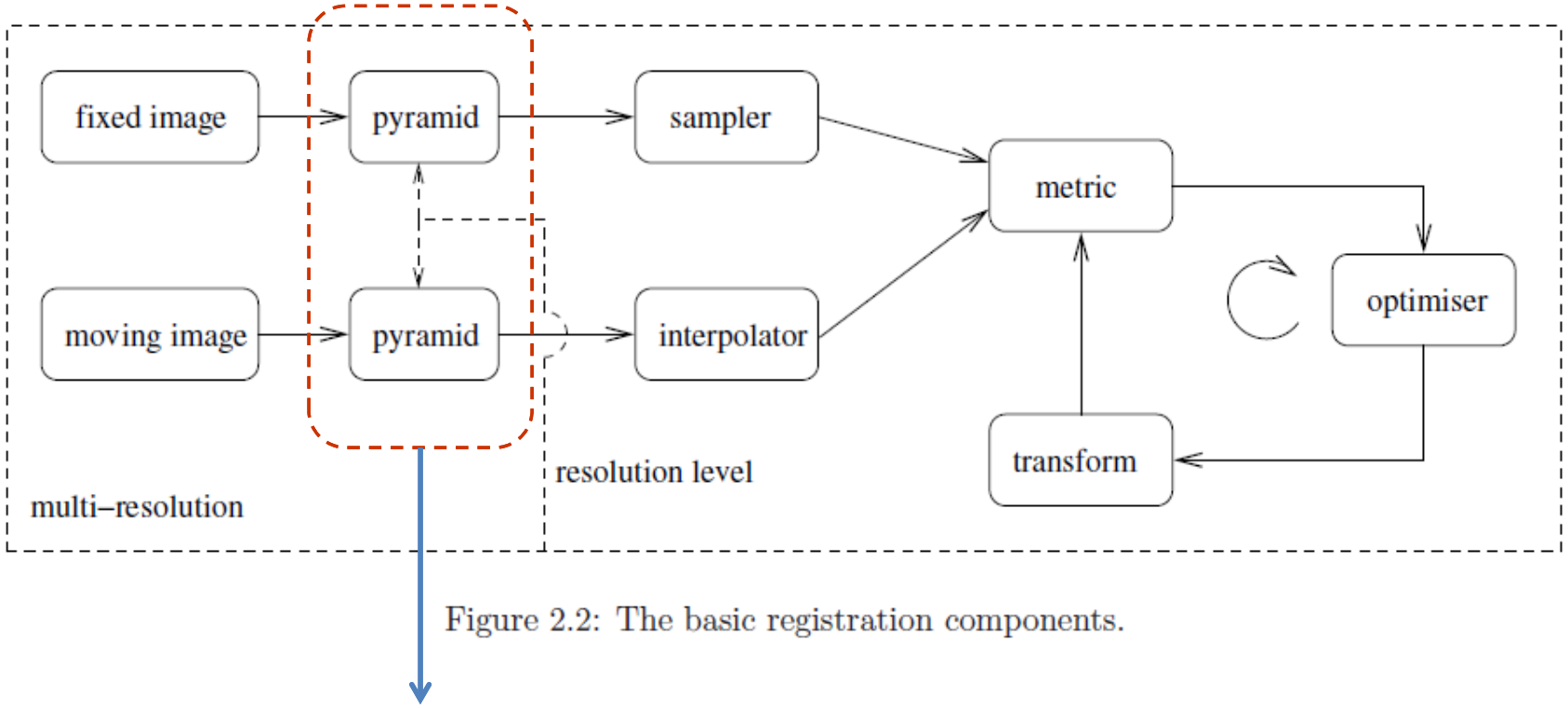

Figure 2.2: The basic registration components.

Image Pyramid creates multi resolution images from the input images.

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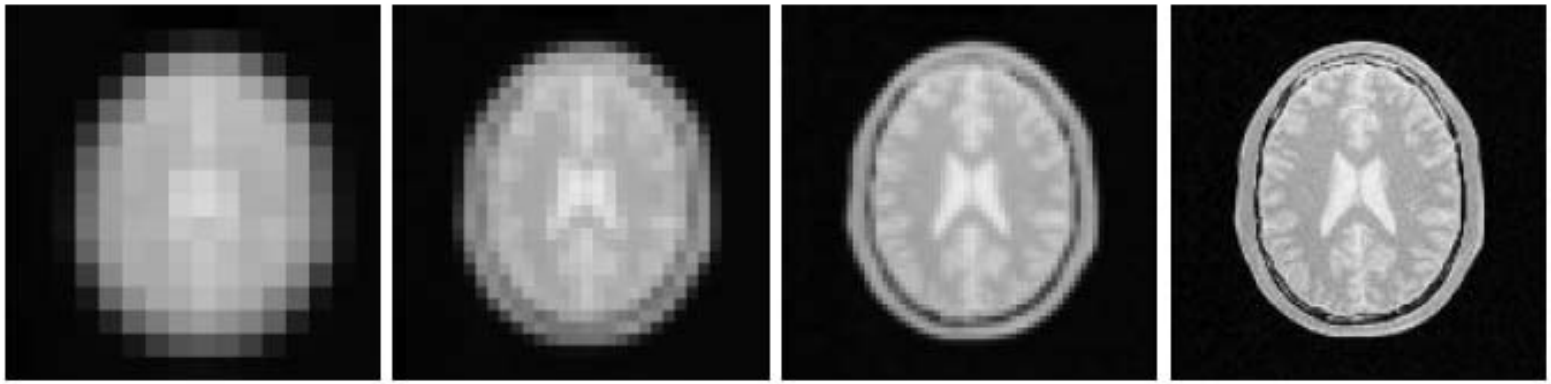
Multi-Resolution Image Registration



(a) resolution 0 (b) resolution 1 (c) resolution 2 (d) original

Down-sampling

References

1. Luis Ibanez et al., “The ITK Software Guide, 2nd Ed”, www.itk.org. (2005)
2. Stefan Klein and Marius Staring, “Elastix, the manual” , elastix.isi.uu.nl (2011)
3. S. Klein, M. Staring, K. Murphy, M.A. Viergever, J.P.W. Pluim, "elastix: a toolbox for intensity based medical image registration," IEEE Transactions on Medical Imaging, vol. 29, no. 1, pp. 196 - 205, January 2010
4. Press et al., “Numerical Recipes in C: The Art of Scientific Computing, Second Edition”, Cambridge University Press (1992).
5. Bissonnette et al.,” Quality assurance for image-guided radiation therapy utilizing CT-based technologies: A report of the AAPM TG-179”, Med. Phys. 39 (4), April 2012.
6. R. Fernando, “GPU Gems, Programming Techniques, Tips, and Tricks for Real-Time Graphics”, Addison-Wesley, 2004.
7. Markelj et al., “A review of 3D/2D registration methods for image-guided interventions”, Medical Image Analysis 16 (2012) 642–661
8. P Vilola and W Wells, “Alignment by maximization of mutual information”, Int. J. of computer vision, 1997.
9. Maes et al., “Multimodality image registration by maximization of mutual information” IEEE medical imaging, 1997.

References

10. J. Maintz and M Viergever, “A survey of medical image registration”, Medical Image Analysis (1998)
11. H Lester and S Arridge, “A survey of hierarchical non-linear medical image registration”, Pattern Recognition 32 (1999) 129-149
12. Fluck et al., “A survey of medical image registration on graphics hardware”, Computer Methods and Programs in Biomedicine, vol 104 (3), 2011
13. Pluim et al., “Mutual-Information-Based Registration of Medical Images: A Survey”, IEEE TRANS MED IMAG, VOL. 22 (8), p986-1004, 2003
14. Ref: C. Rezk-Salama, “Volume rendering techniques for general purpose graphics hardware,” PhD Thesis, Computer Science Department, Universität Erlangen-Nürnberg, (2002).

Summary

- Reviewed 3D/3D and 3D/2D image registration methods
- Reviewed fundamental building blocks of image registration algorithms
  - ❖Similarity Metric
  - ❖Transformation
  - ❖Optimization