Statistical Atlases of Bone Anatomy and Applications

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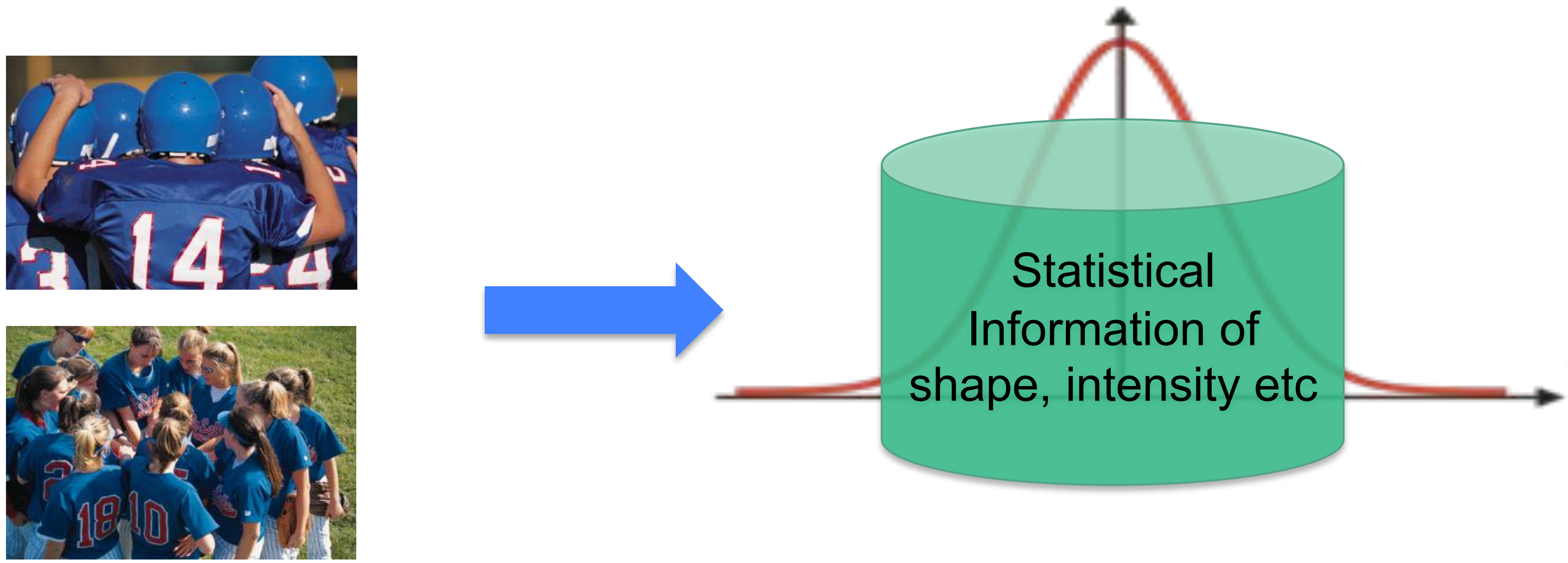
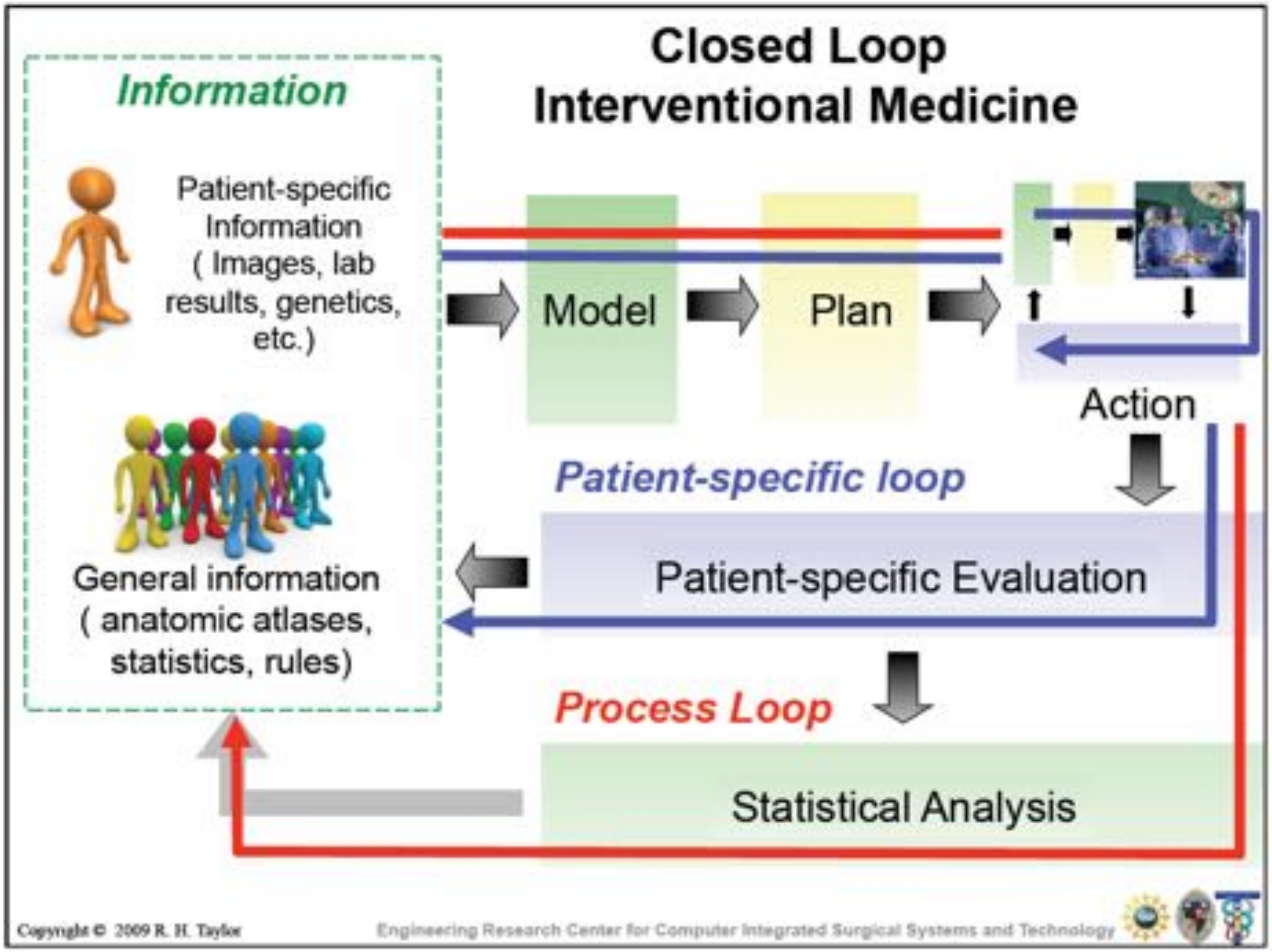
What is a "Statistical Atlas" ?

- An atlas that incorporates **<u>statistics of anatomical shape and intensity variations</u>** of a given population



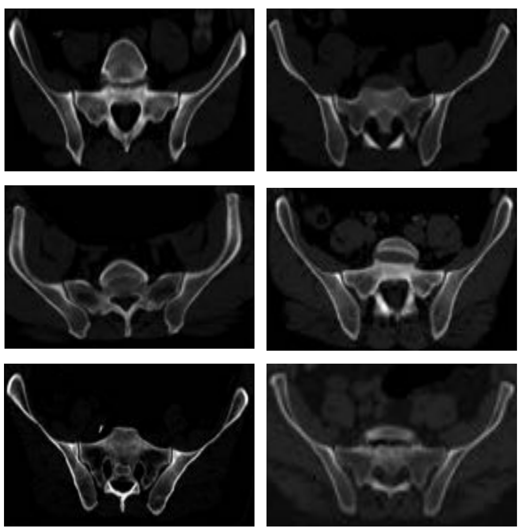
Atlases in Closed Loop Intervention



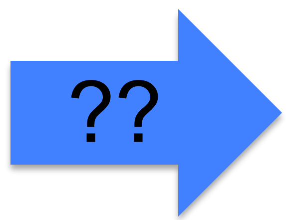
Outline

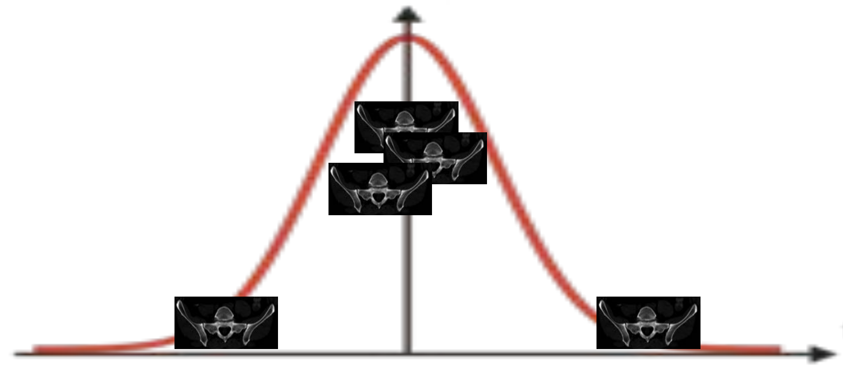
- Statistical Atlases
  - Construction
  - Iterative Improvement
  - Validation
- Applications of atlases
  - Segmentation
  - Registration
  - Hip Osteotomy
  - C-arm Distortion Correction
- Conclusion

Statistical Atlases

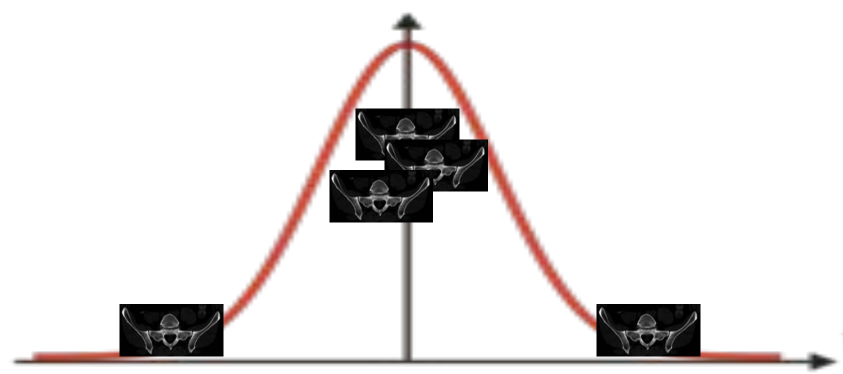


CT scans from a population



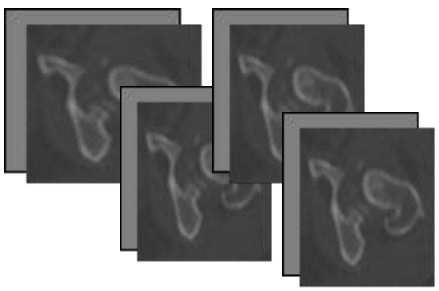


Shape distribution



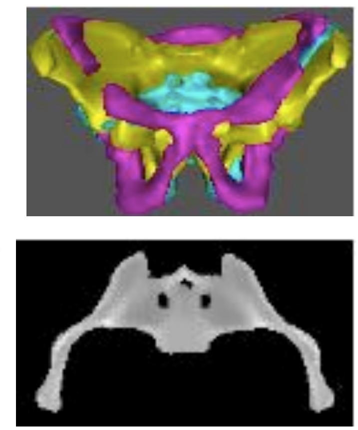
Intensity distribution

Atlas Construction



Training CT data sets

1. Model Representation
2. Model Correspondence
3. Statistical Analysis



Statistical atlas

References: Cootes *et al*. CVIU ’95; Yao *et al.* IJPRAI ‘03;

Model Representation

- Tetrahedral mesh represents shape

- Bernstein polynomials approximate CT density within each tetrahedron[1,2]

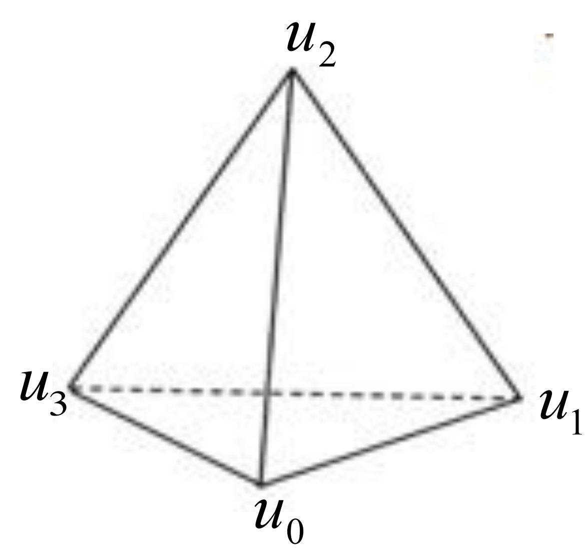
$$P^d(\mathbf{u}) = \sum_{|\mathbf{k}|=d} C_{\mathbf{k}} B^d_{\mathbf{k}}(\mathbf{u})$$

where

$$\mathbf{k} = (k_0, k_1, k_2, k_3) \quad \mathbf{u} = (u_0, u_1, u_2, u_3)$$

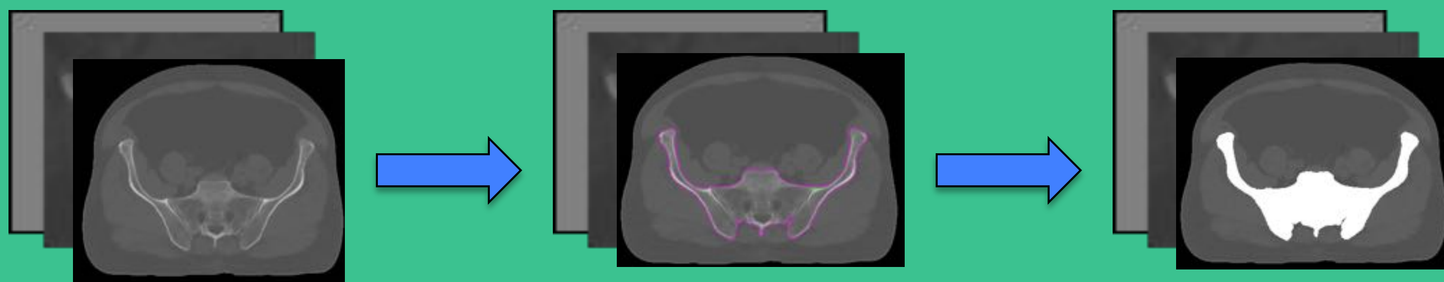
$$|\mathbf{k}| = k_0 + k_1 + k_2 + k_3 \qquad |\mathbf{u}| = 1$$

$$B^d_{\mathbf{k}}(\mathbf{u}) = \frac{d!}{k_0!k_1!k_2!k_3!} u_0^{k_0} u_1^{k_1} u_2^{k_2} u_3^{k_3}$$



[1] Yao, PhD Thesis, 2002; [2] Sadowsky, PhD Thesis, 2008

Model Creation

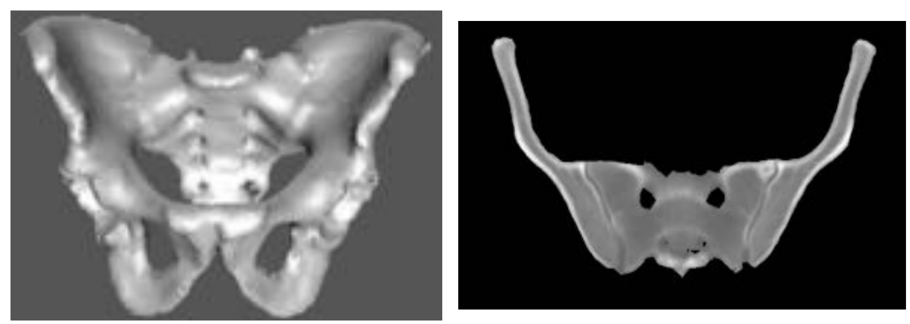


CT dataset

Labelled CT

Segmentation of pelvis anatomy using Analyze[1]

Mesher

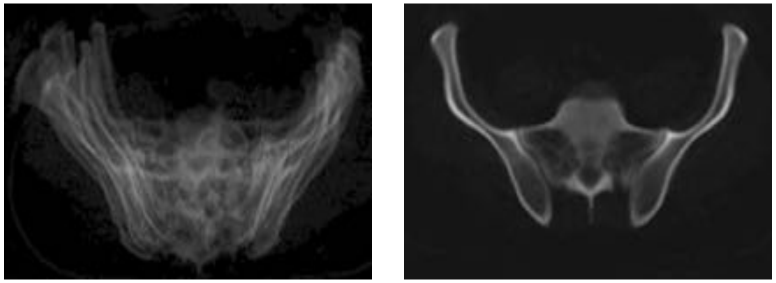


Surface rendering of pelvis tetrahedral model; Cross-section of tetrahedral model showing CT densities

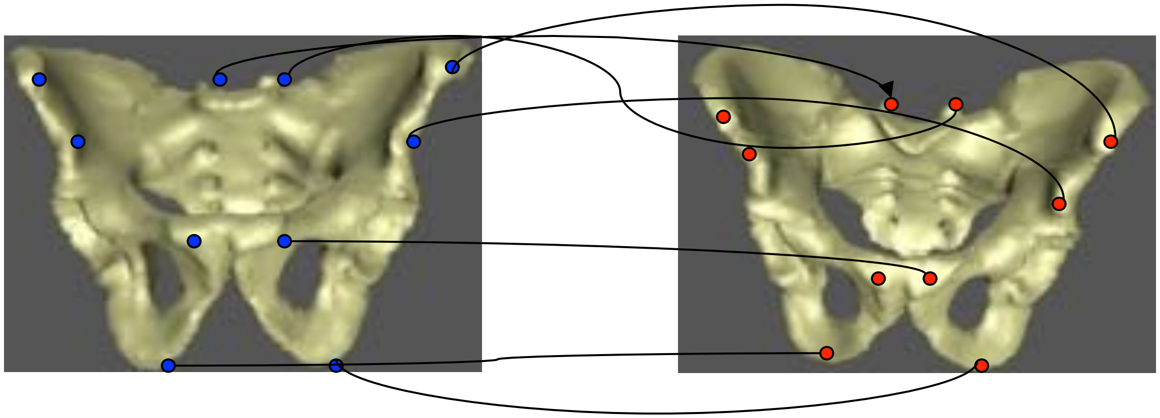
[1]Analyze, www.mayoclinic.org

Model Correspondence

- Need to establish a common coordinate frame for the training database

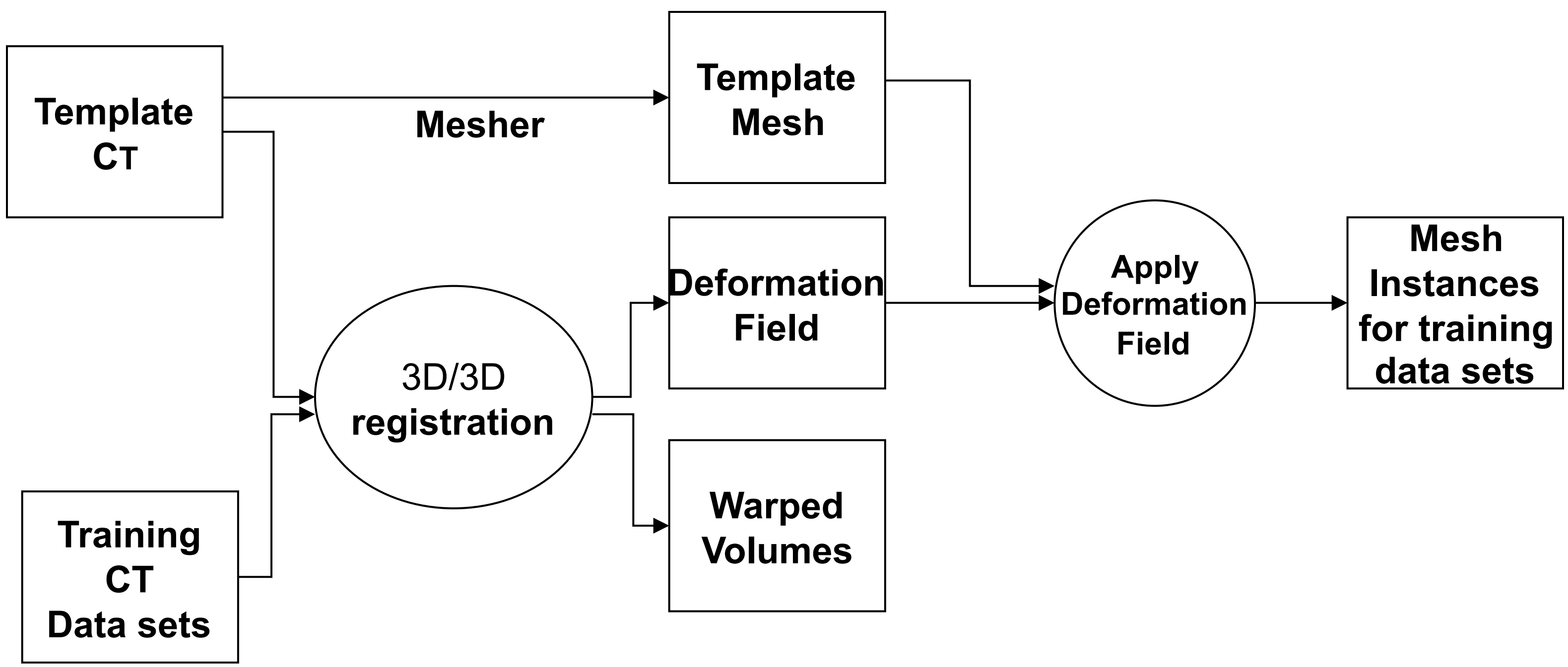


- Need to establish point correspondence between the training datasets



Model Shape Correspondences

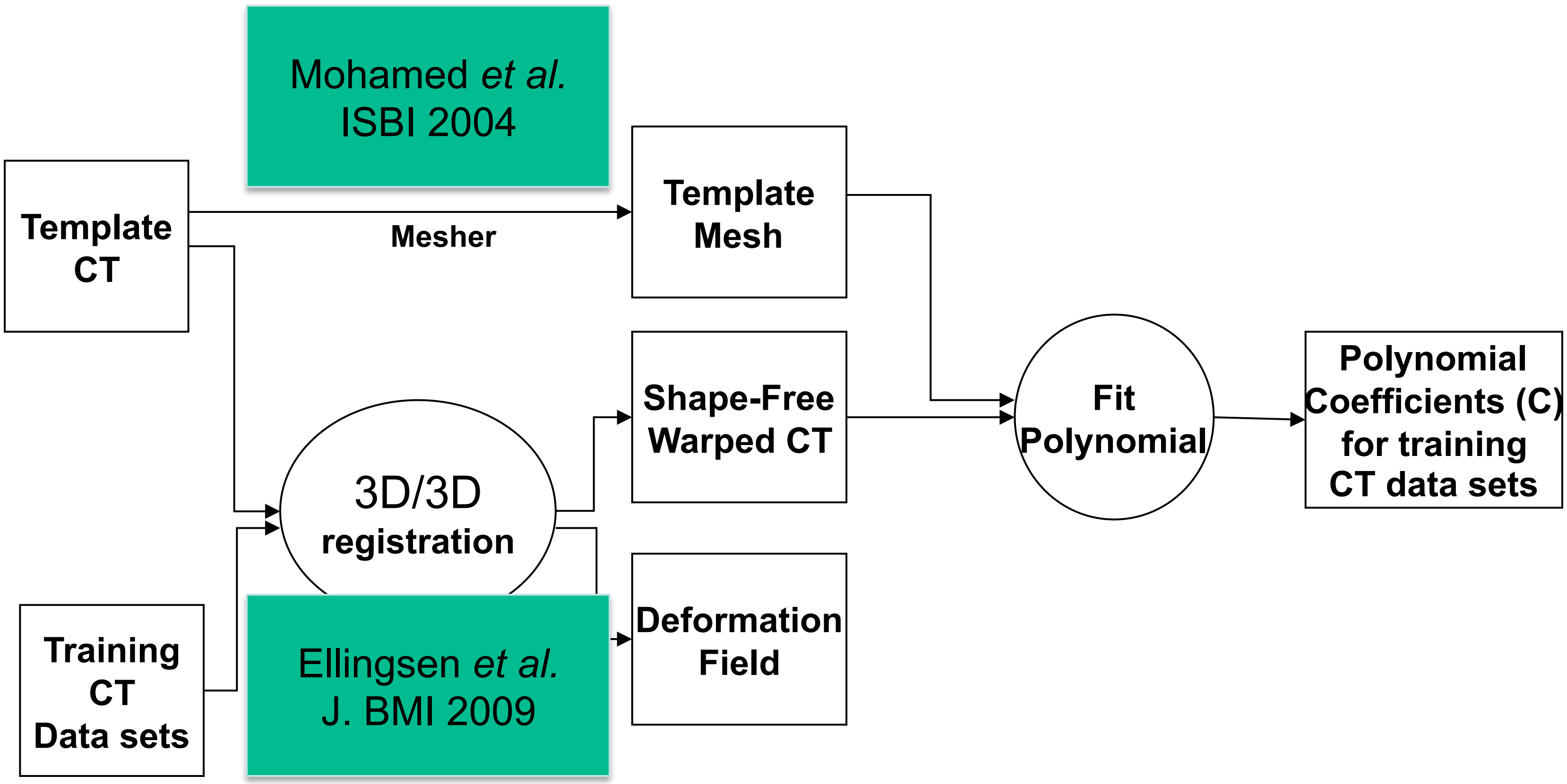
- Automatic deformable registration based shape correspondences



Flowchart for establishing shape correspondences for the training sample

Model Intensity Correspondences

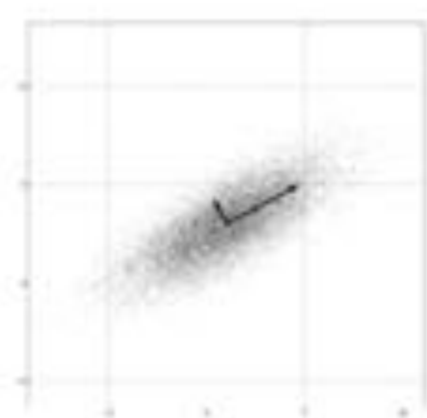
- Automatic deformable registration based correspondences



Flowchart for establishing intensity correspondences for the training sample

Principal Component Analysis

- Given the mesh instances of training sample



$$S = \begin{bmatrix} \hat{s}_1 & \hat{s}_2 & . & . & \hat{s}_N \end{bmatrix}_{3nXN} = \begin{bmatrix} x_{11} & x_{12} & . & . & x_{1N} \\ y_{11} & y_{12} & . & . & y_{1N} \\ z_{11} & z_{12} & . & . & z_{1N} \\ . & . & . & . & . \\ y_{n1} & y_{n2} & . & . & z_{nN} \\ z_{n1} & z_{n2} & . & . & z_{nN} \end{bmatrix}$$

- Compute mean and subtract the mean from the sample

$$\cancel{S} = S - \bar{s} = S - \frac{1}{N}\sum_{i=1}^{N} \hat{s}_i$$

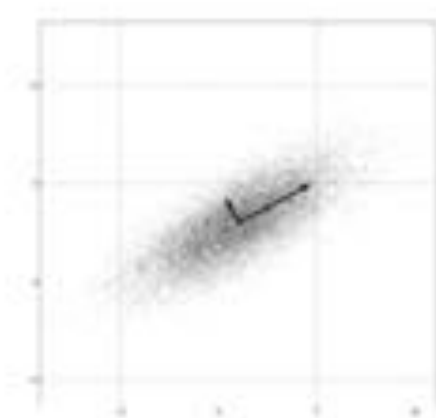
- Compute $SVD(\cancel{S}) = UDV^T$

With principal components in U and eigen values $\lambda = \frac{1}{N-1} DD^T$

Principal Component Analysis

- Given the PCA model, any data instance can be expressed as a linear combination of the principal components

$$\bar{s} + \sum_{k=1}^{N-1} U_k \lambda_k$$



- Compact model → fewer components
- Select first ‘d’ components represented by the ‘d’ eigen values

Statistical Shape and Intensity Models

- Shape statistical model: Mesh vertices become data matrix

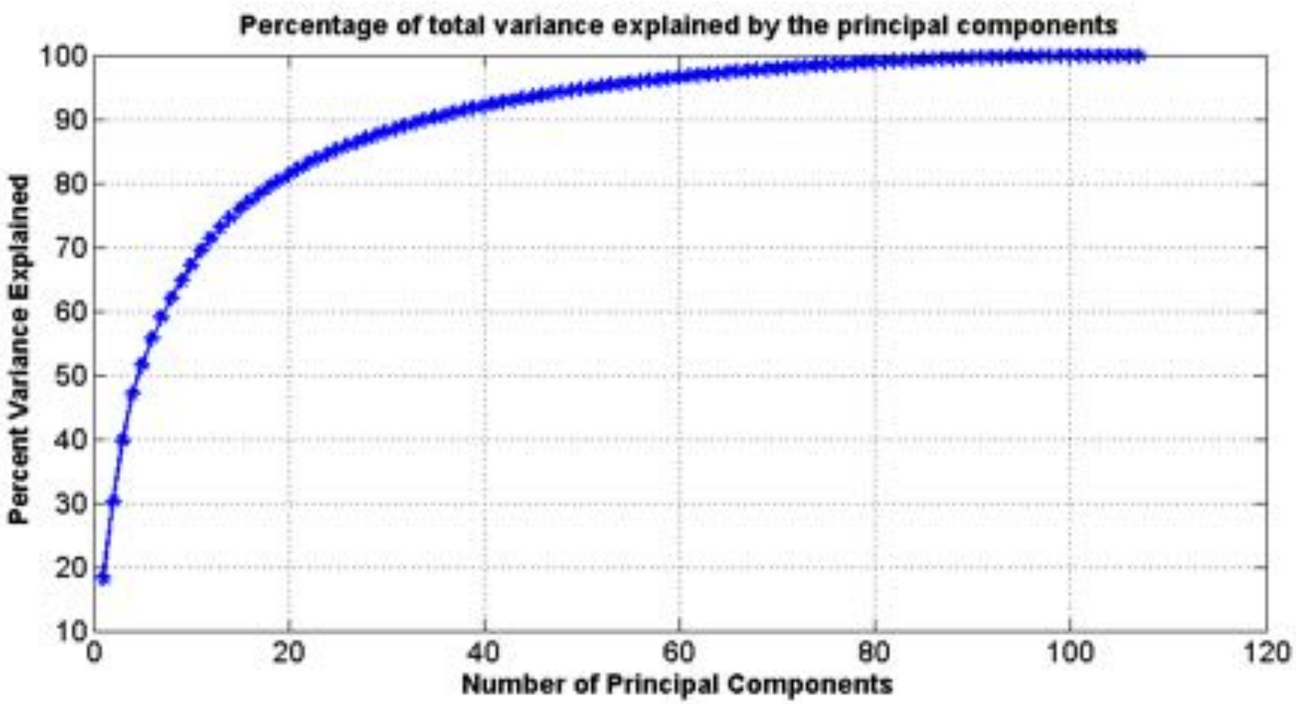
$$\bar{s} + \sum_{k=1}^{d} U_k \lambda_k = \bar{s} + U^T \lambda$$

- Intensity statistical model: Polynomial coefficients become data matrix

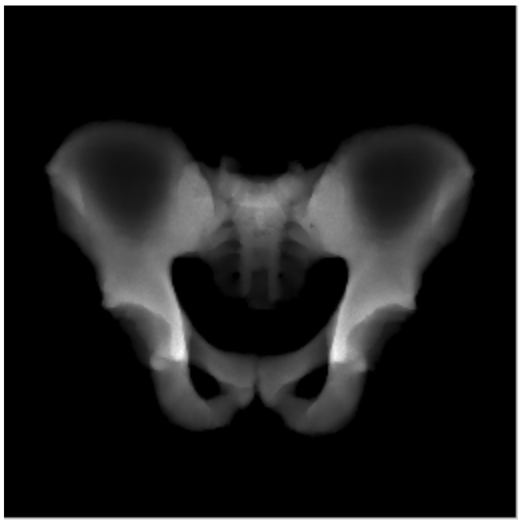
$$\bar{c} + \sum_{k=1}^{p} Y_k \mu_k = \bar{c} + \mathrm{Y}^T \mu$$

Statistical Atlas of Pelvis

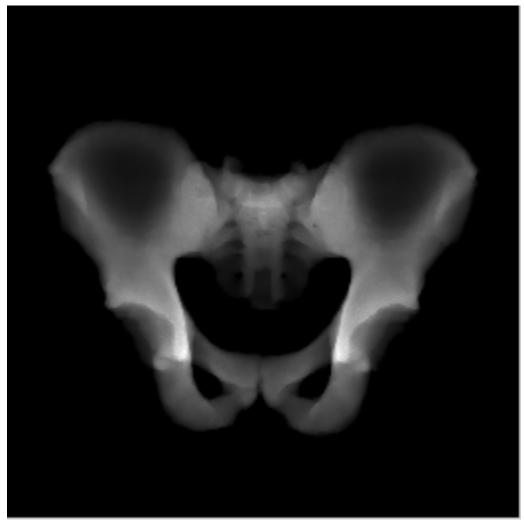
- # of CT data sets in the training sample: 150
- # of data sets used for atlas building: 110
- # of shape modes retained: 18
- # of intensity modes retained: 12



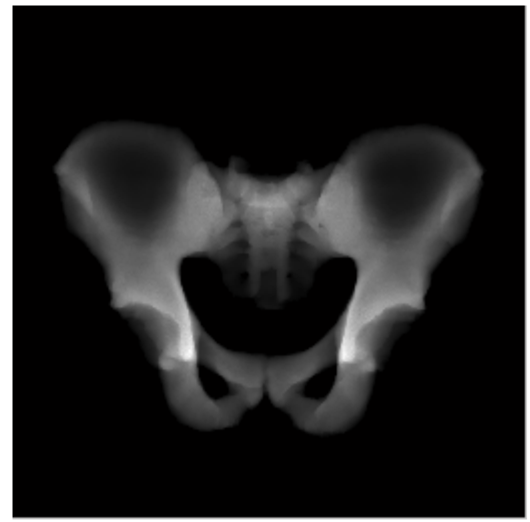
Pelvis Shape Modes



PC1



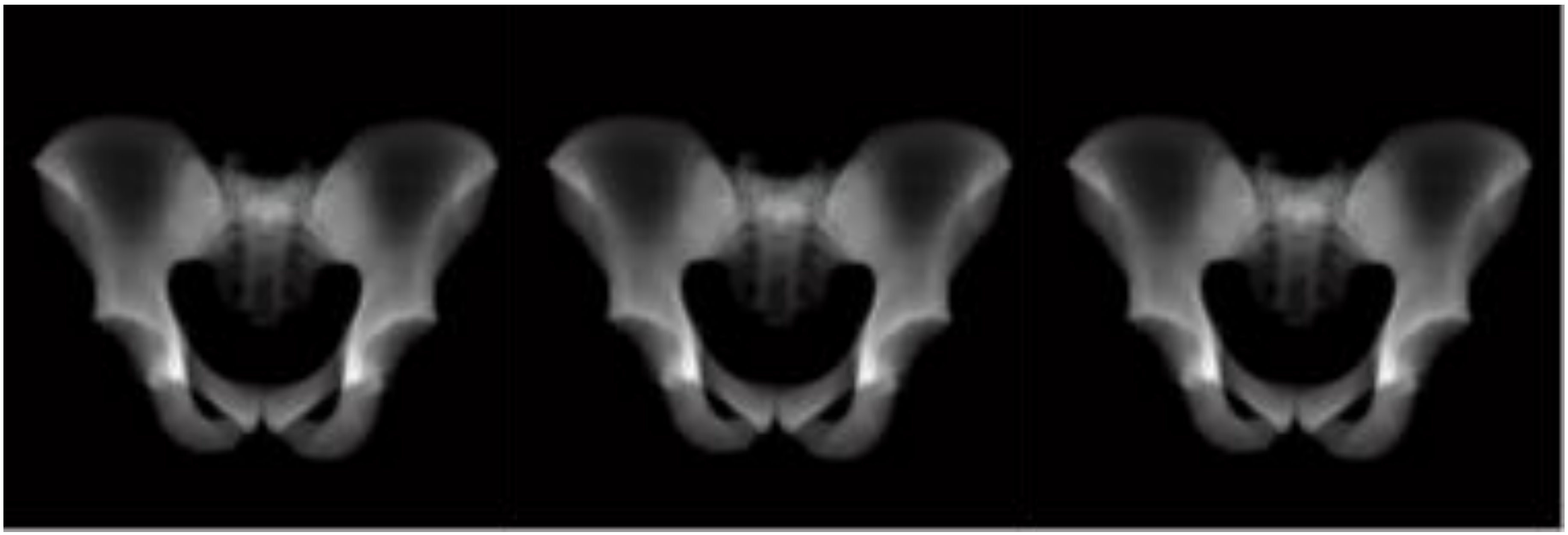
PC2



PC3

Shape variational modes from a male healthy pelvis atlas of 110 CT datasets

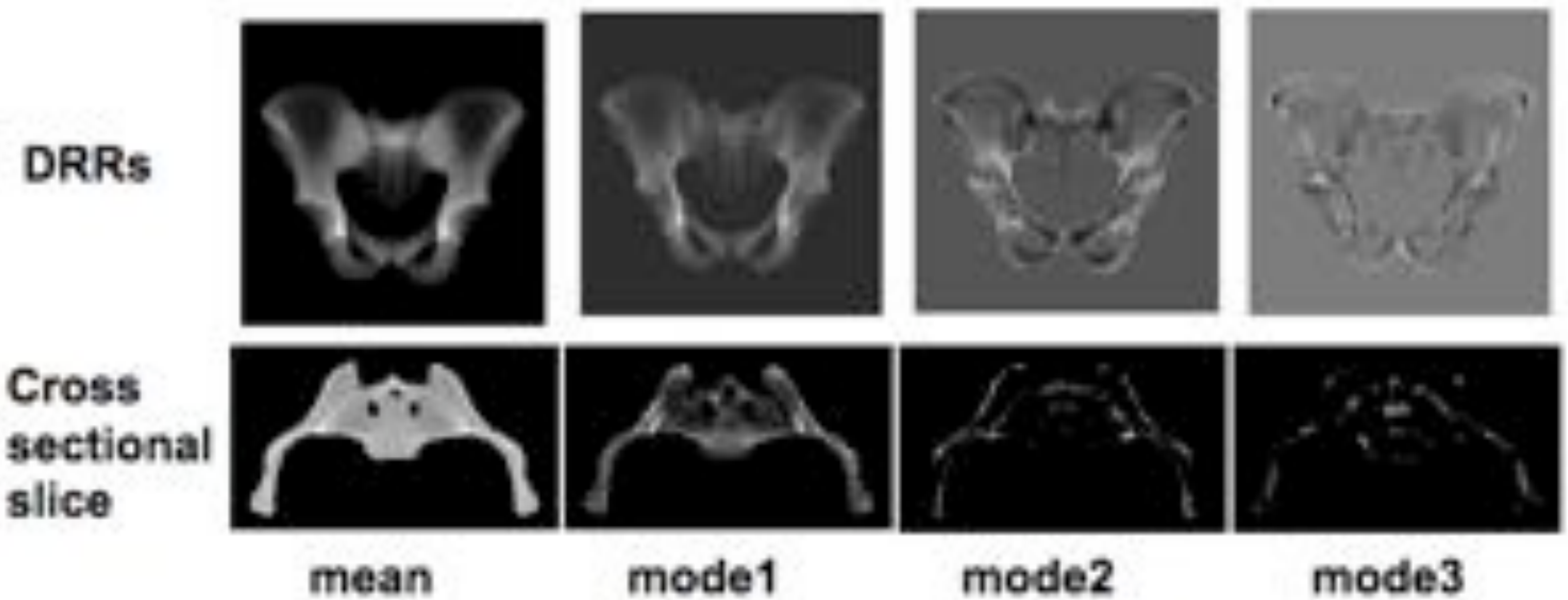
Pelvis Intensity Modes



PC1 PC2 PC3

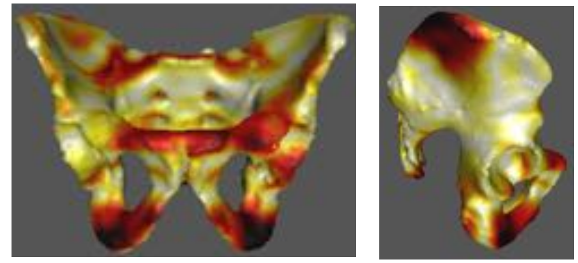
Intensity variational modes from a male healthy pelvis atlas of 110 CT datasets

Pelvis Intensity Modes

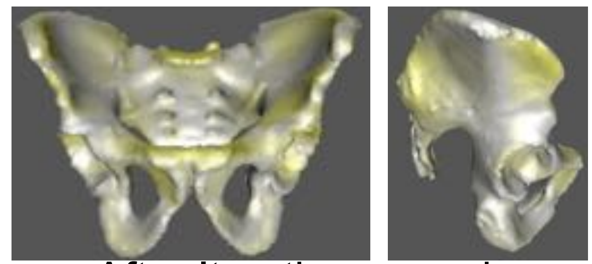


Statistical Atlas Construction

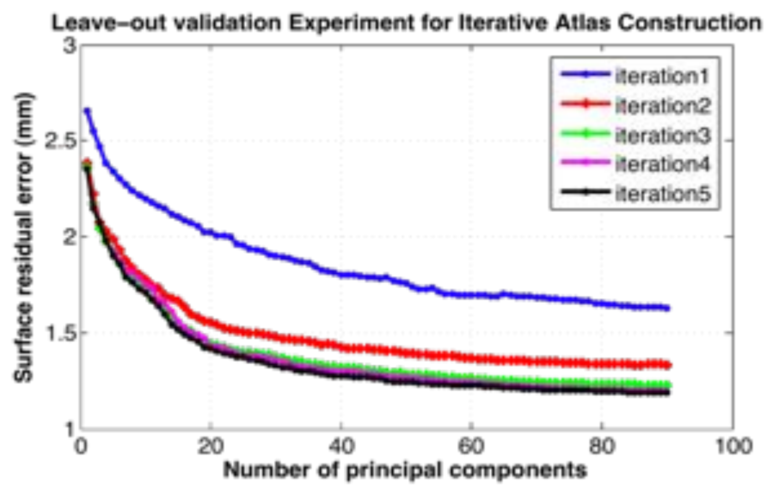
- **Problem**: Stability of the Atlas
  - Choice of deformable registration method
  - Choice of initial template
  - Size of training database
- **My approach**: Iterative Bootstrapping
  - Modified deformable registration
  - Validation to assess convergence
- **Results**
  - Significantly improved stability
  - Reduced residual error in deformable registration



Before Iterative procedure



After Iterative procedure

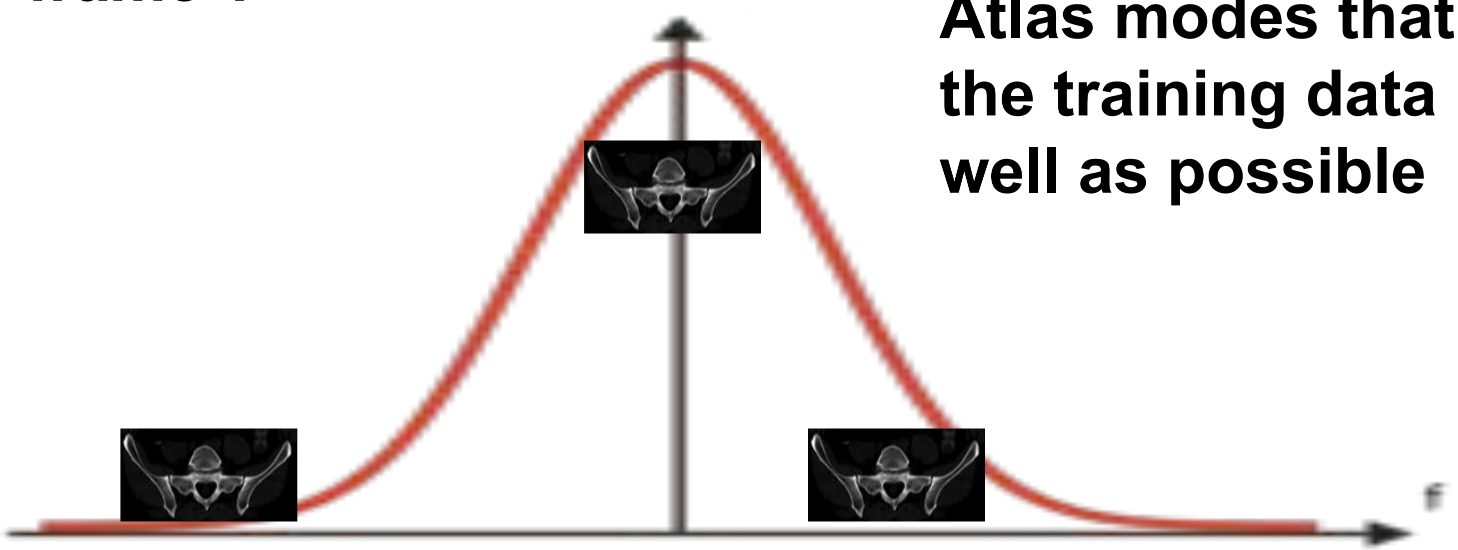


Chintalapani *et al.* MICCAI 2007

Iterative Technique - Motivation

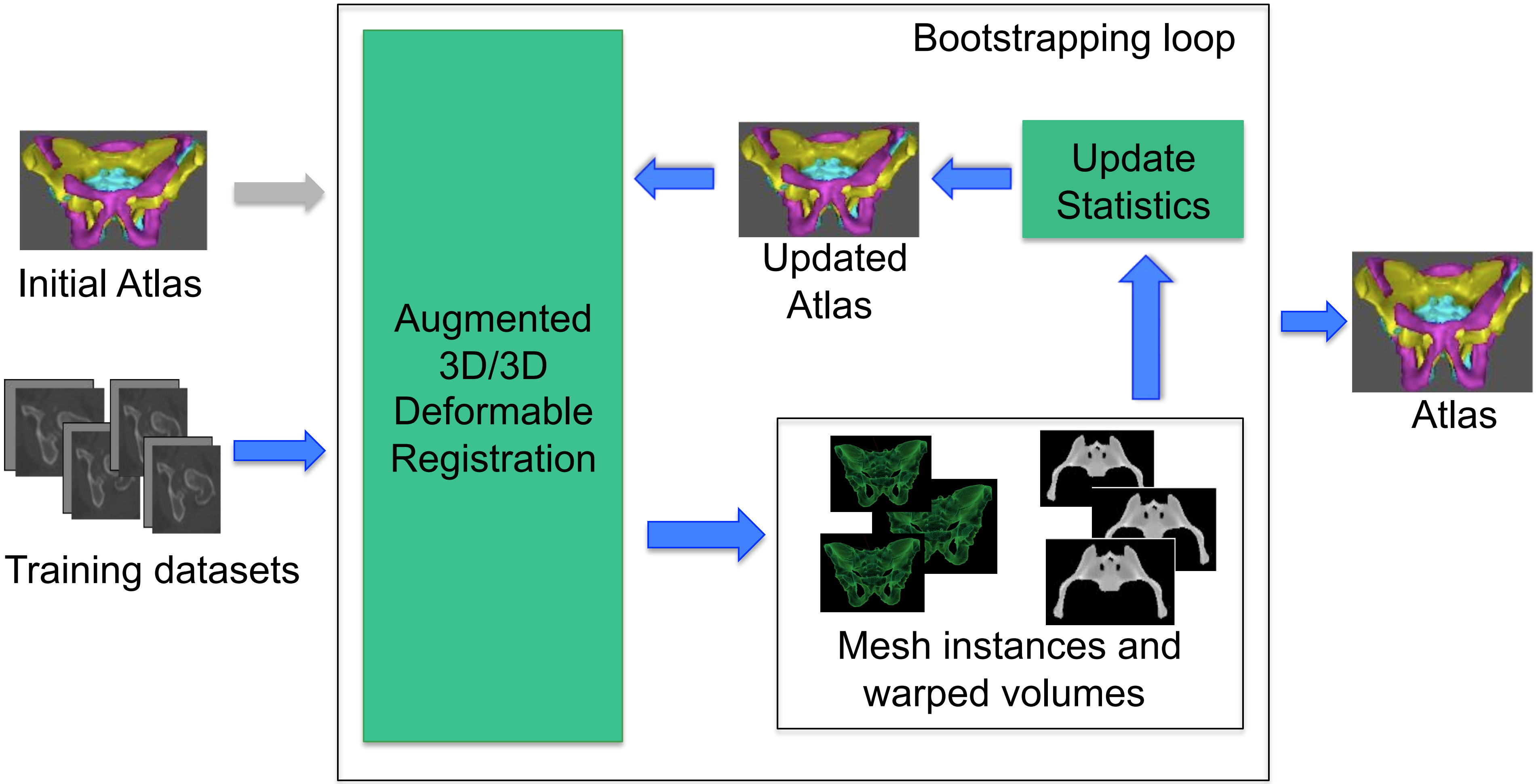
Mean shape as a common reference frame ?

Atlas modes that explain the training data base as well as possible



Chintalapani *et al.* MICCAI 2007

Iterative Technique



Chintalapani *et al.* MICCAI 2007

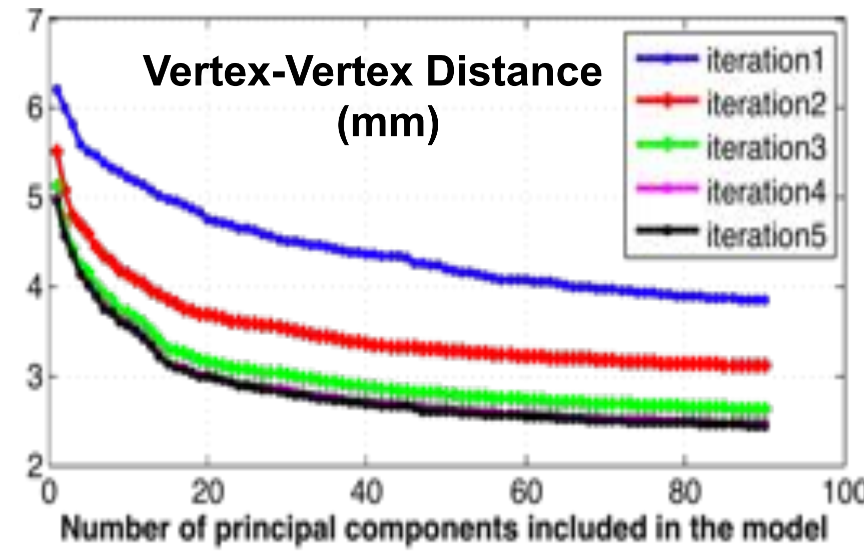
Leave-Out Validation Experiments

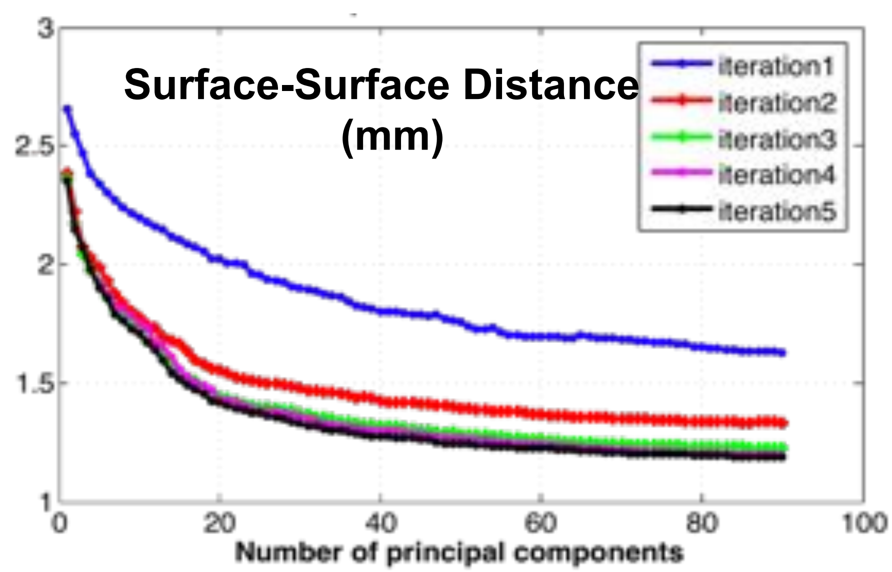
- # of iterations: 5
- # of data sets: 110
- # of data sets in atlas: 90
- # of data sets left out: 20
- Given a left-out dataset, s_j

compute the estimated shape from atlas using

$$\lambda = U'^{*}(s_j - \bar{S})$$

$$s_j^{est} = \bar{S} + U\lambda$$



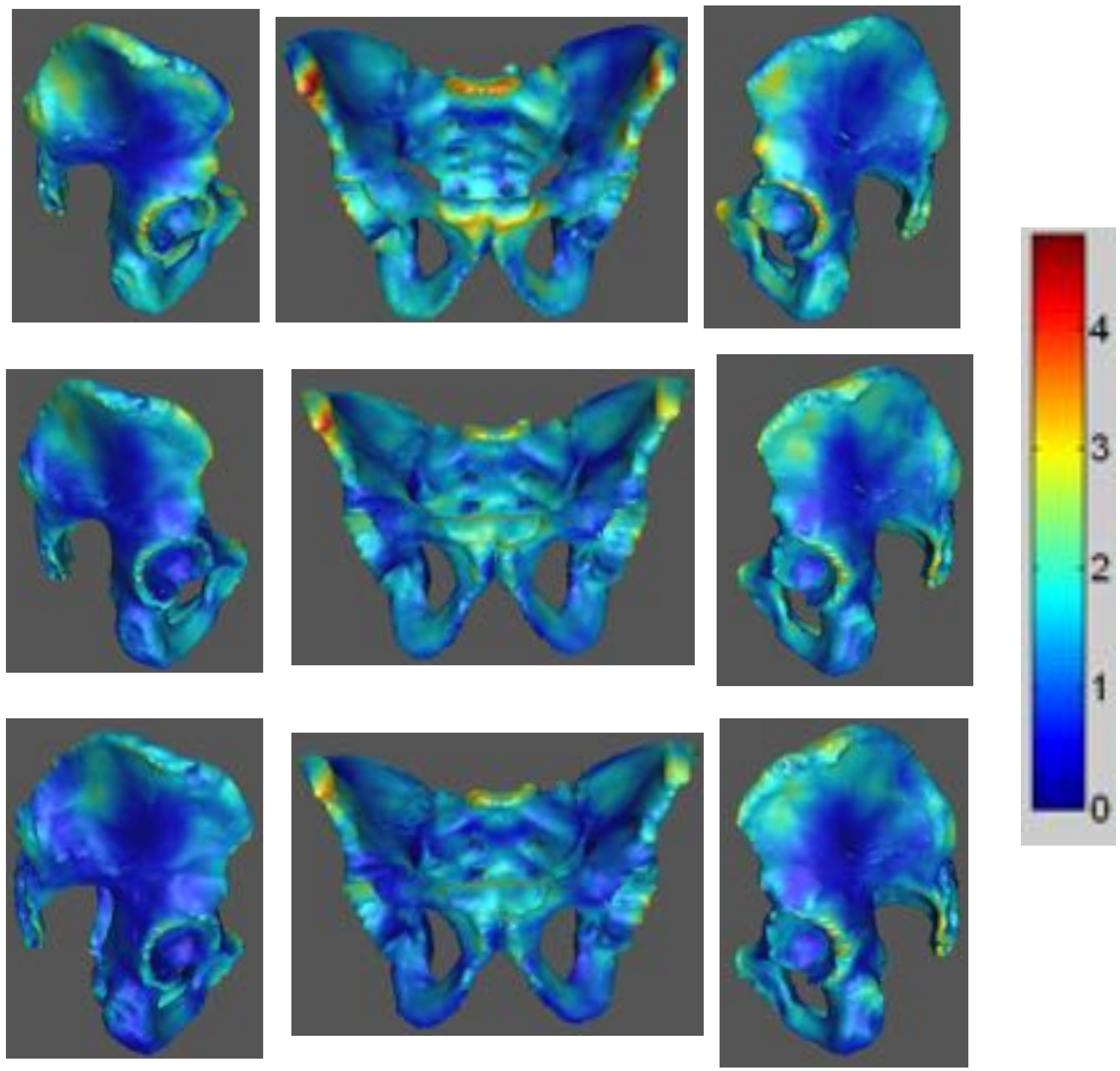


Distribution of Surface Registration Errors

Iteration 1

Iteration 3

Iteration 5



Choice of Initial Template

- Claim:
  - iterative method does not depend on the choice of template
- Criteria:
  - Mean shape converges
  - Modes exhibit similar deformation patterns
- Experimental setup:
  - Three random templates
  - Atlases with and without bootstrapping compared
- Result
  - All three atlases exhibit similar deformation patterns after bootstrapping

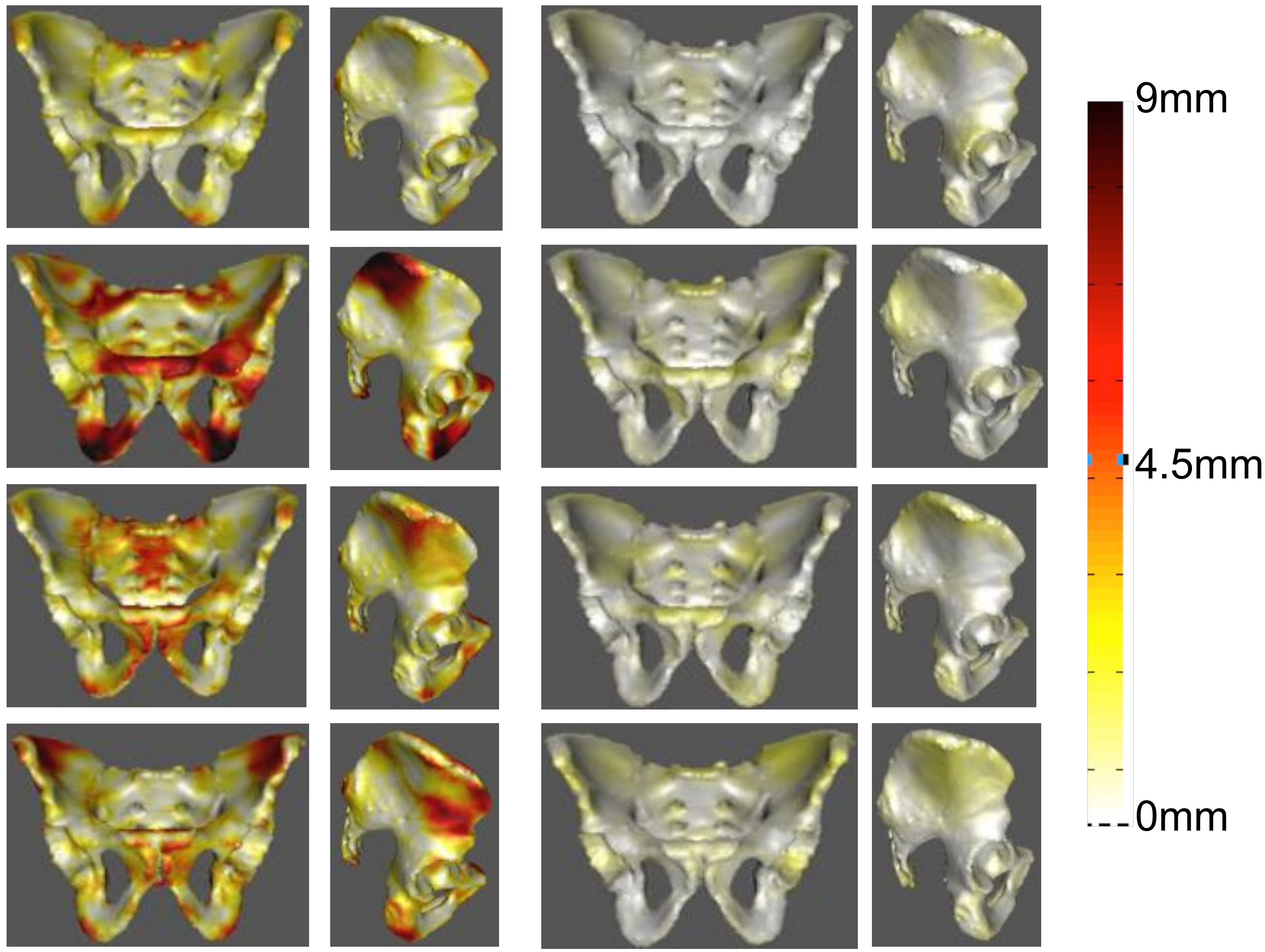
Average Difference between Atlases 1,2 and 3

Mean

Mean + Mode 1

Mean + Mode 2

Mean + Mode 3

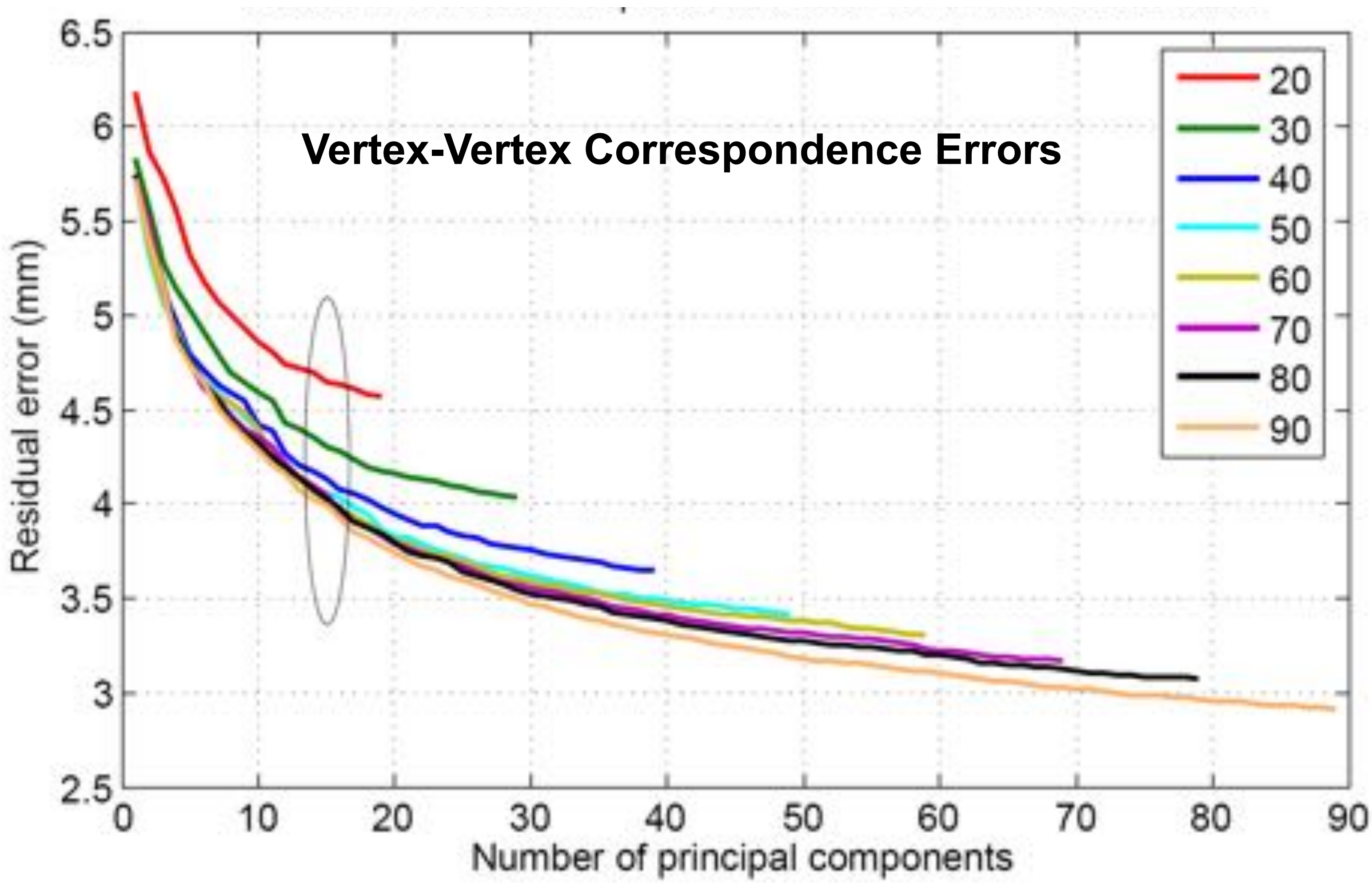


Before iteration **After iteration**

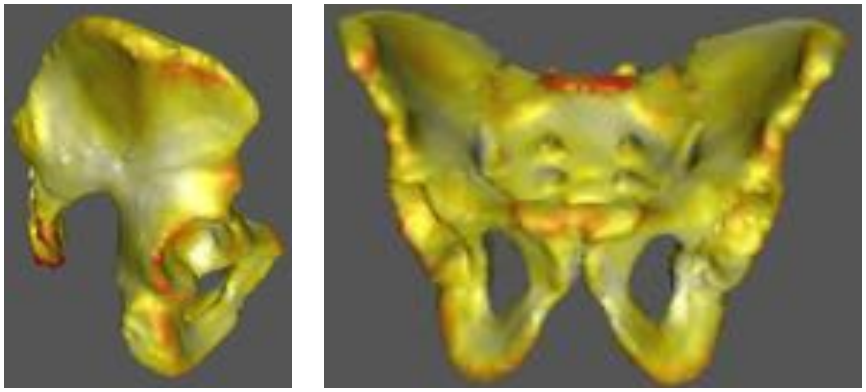
Training Sample Size

- Goal:
  - To determine the size of the training sample to build a stable statistical atlas
- Criteria:
  - Atlas is stable
  - No significant improvement in residual error
- Experimental setup:
  - Varying sample size 20, 40, 60, 80
  - Leave-20-out validation test
- Result:
  - Minimum of 50 data sets are required for pelvis atlas

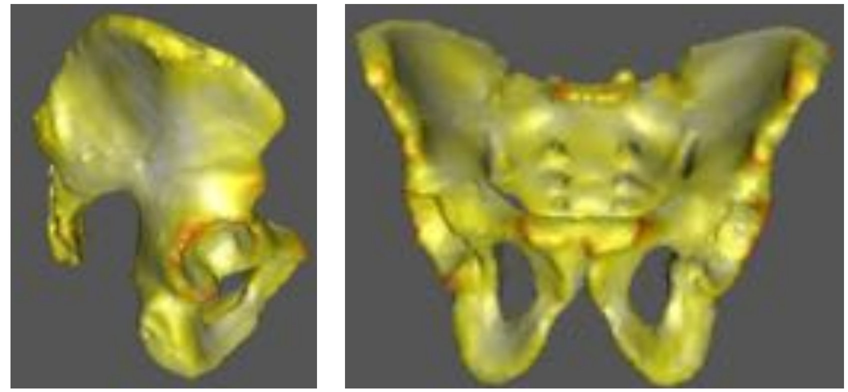
Training Sample Size



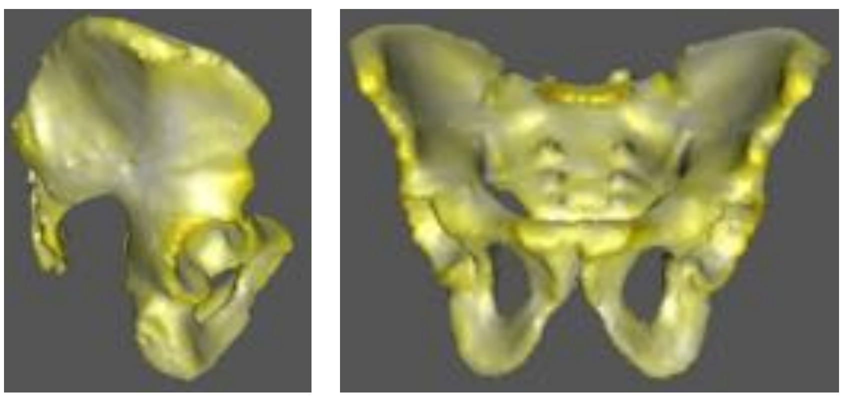
Surface residual error using 18 modes for different sample set sizes



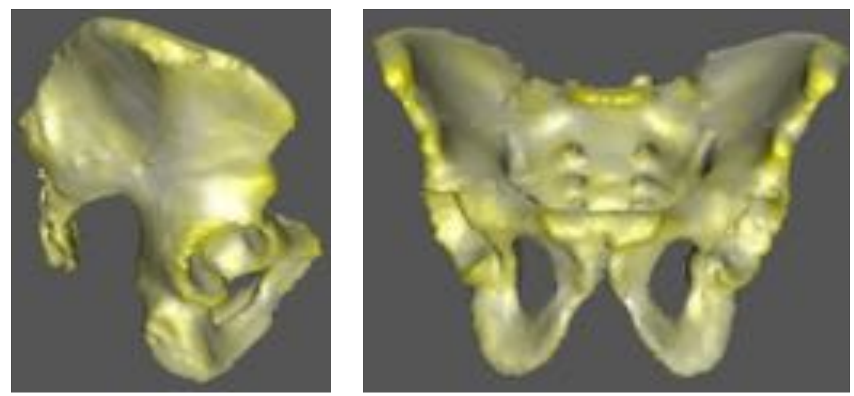
20 dataset atlas



40 dataset atlas

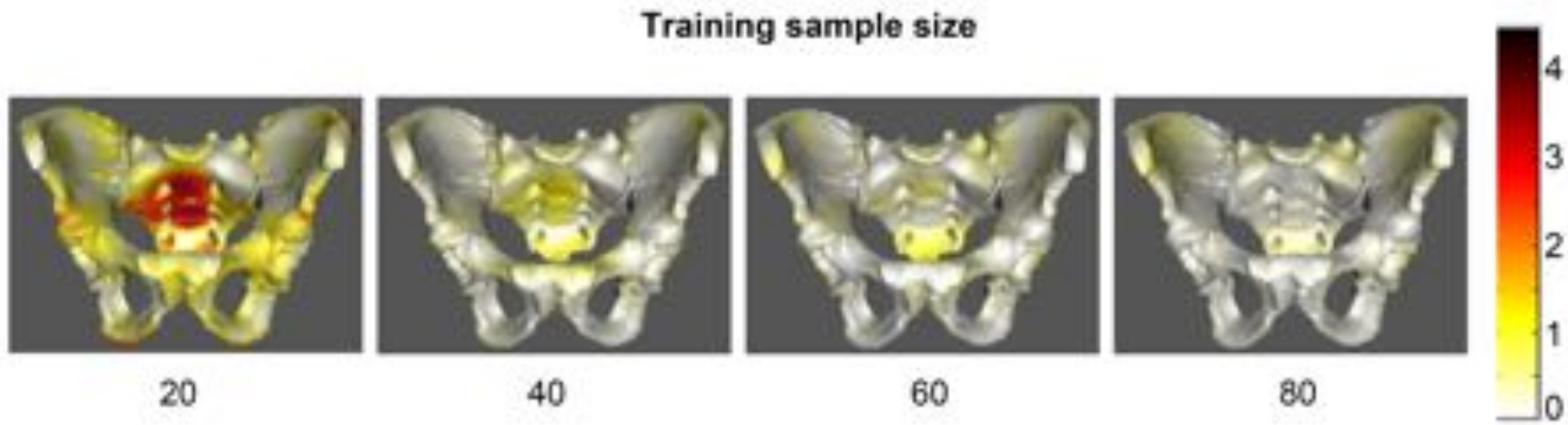


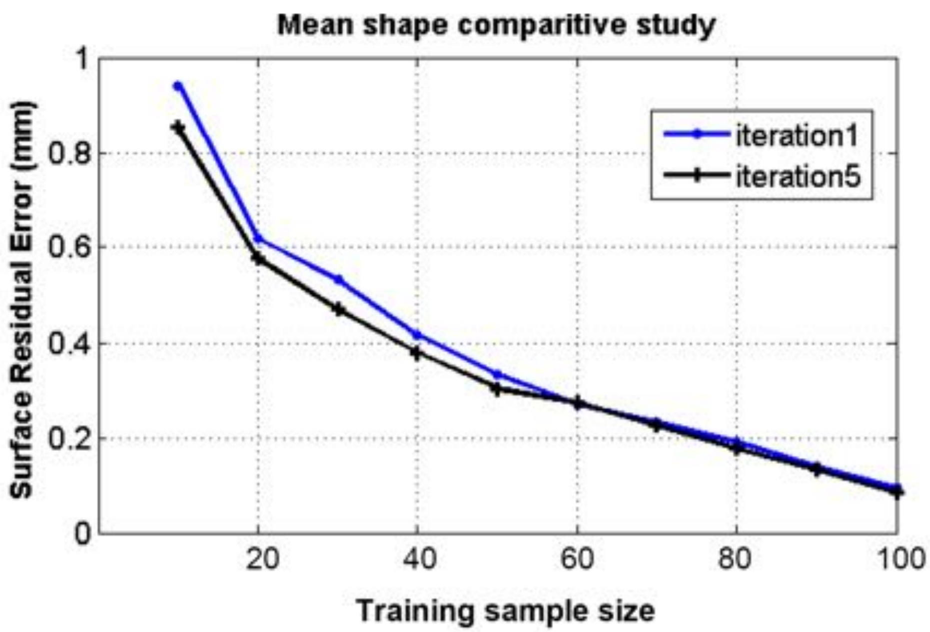
60 dataset atlas



80 dataset atlas

Stability Analysis – Mean Shape





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Applications of Atlases

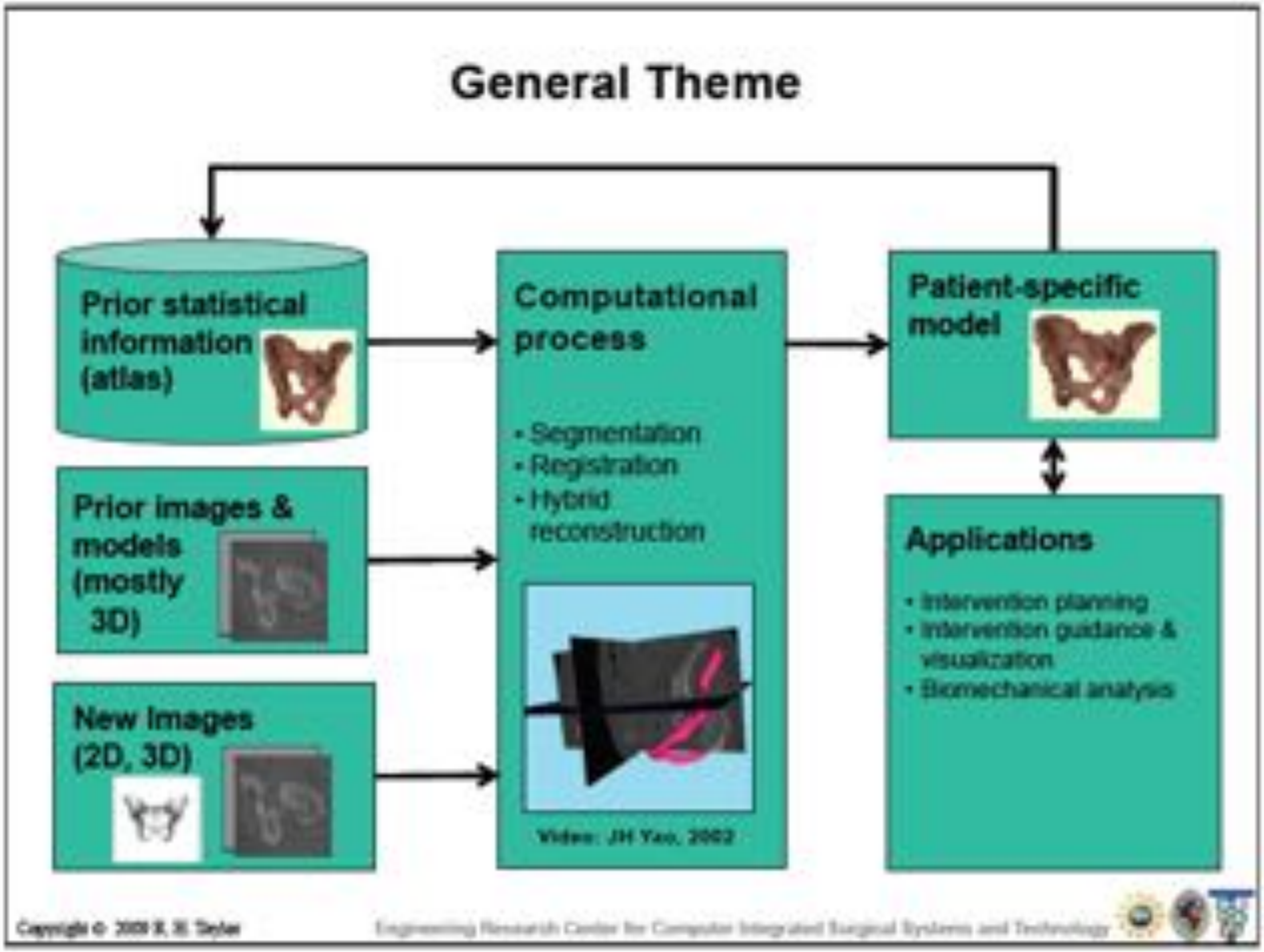

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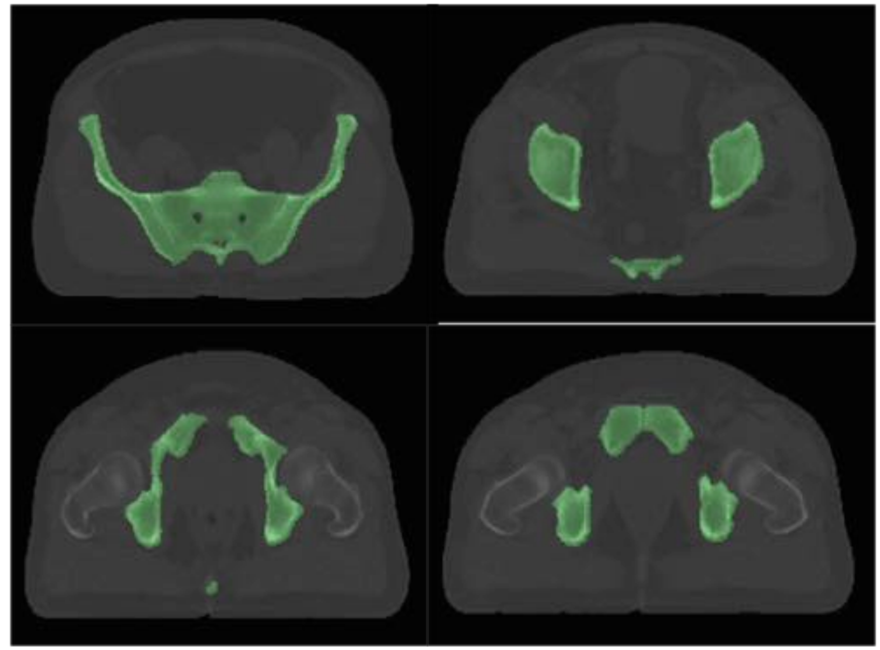
Image Segmentation

- Automatic segmentation through atlas deformations [1]



[1] Ellingsen L.M., Chintalapani G., Taylor, R.H., Prince J.L.. CMIG 2009

[1]

Outline

- Statistical Atlases
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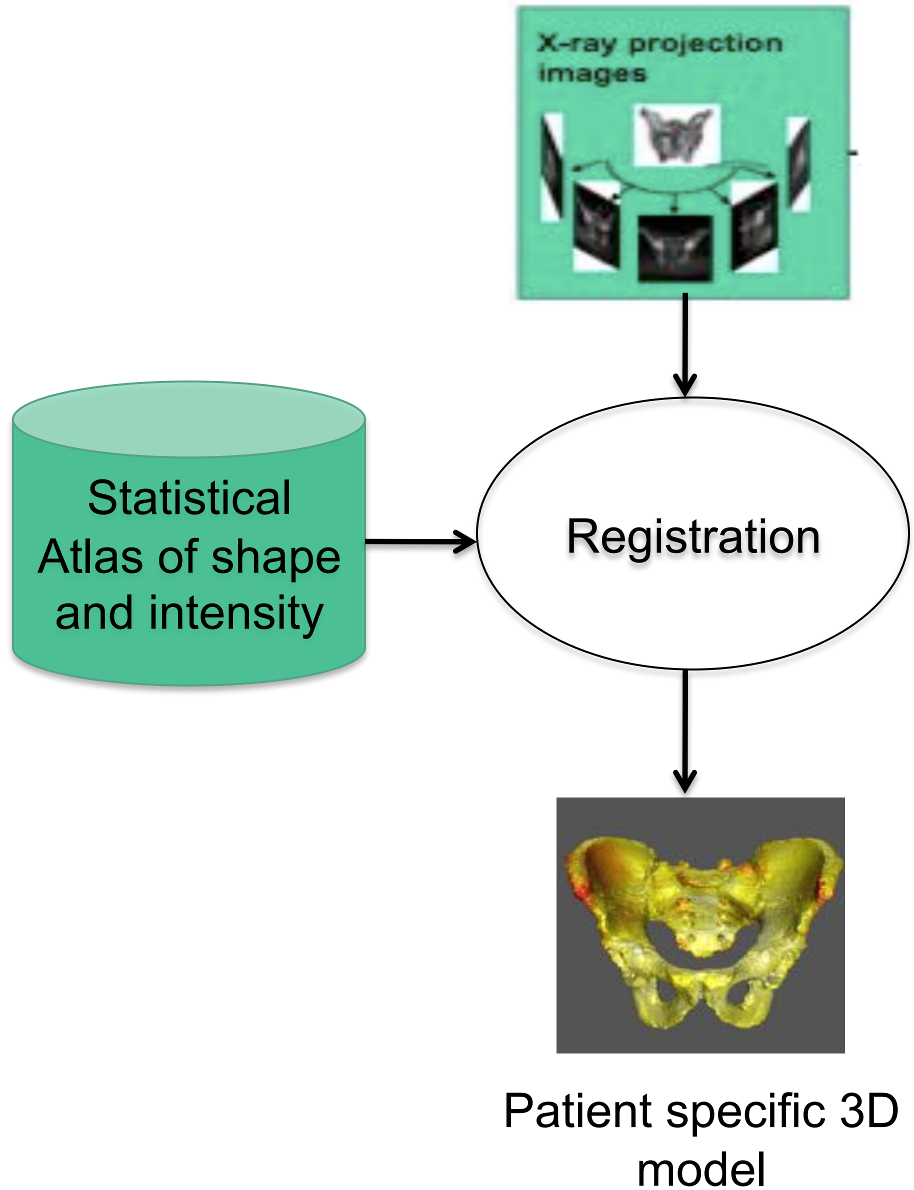
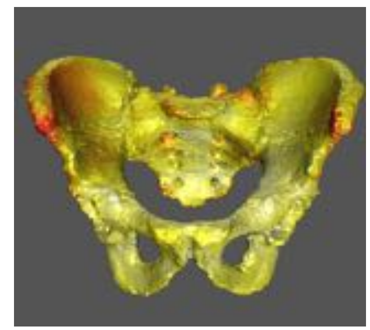


Applications – 2D/3D Registration

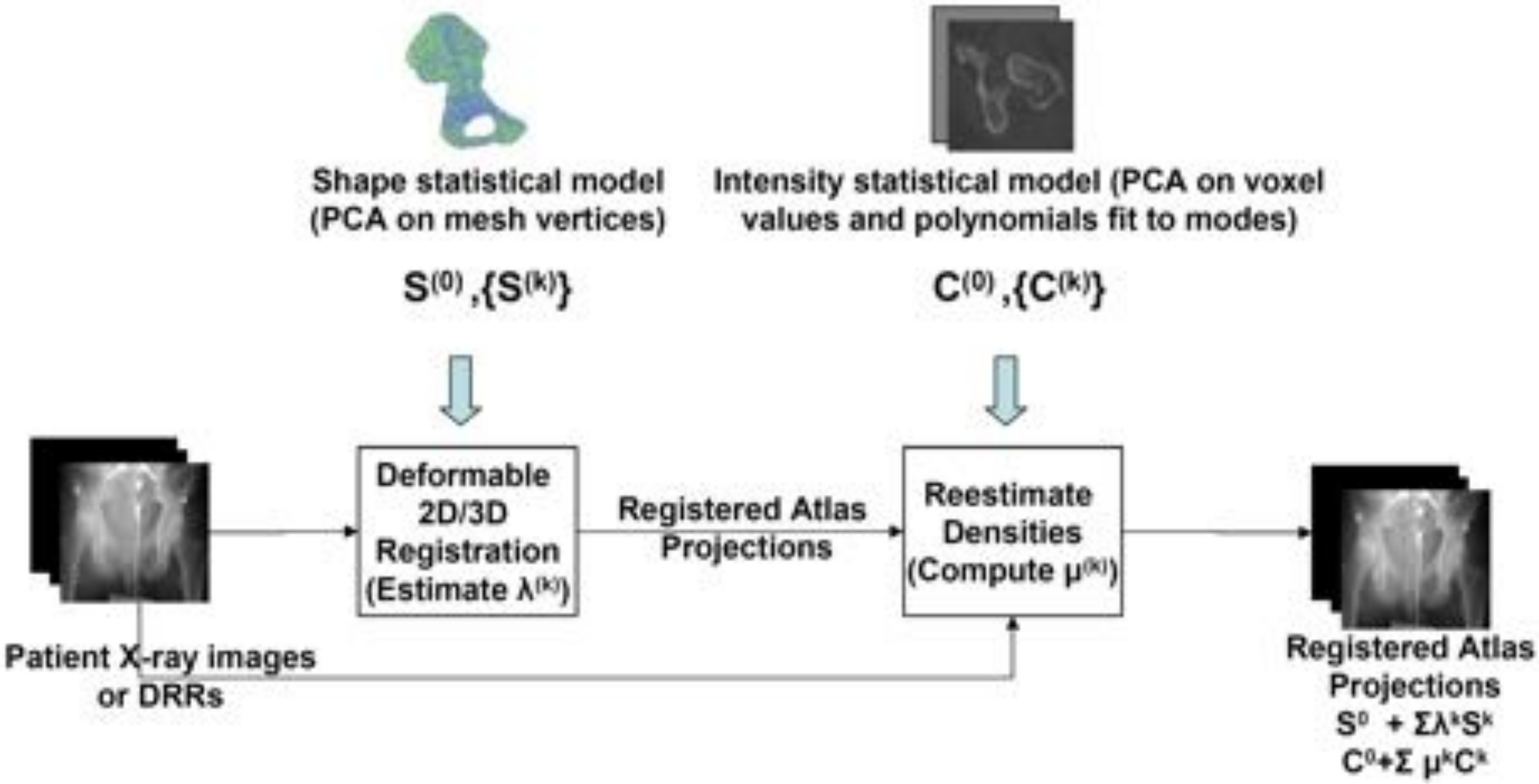
Statistical Atlas of shape and intensity

Patient 2D X-ray Images



Patient specific 3D Model

2D/3D Registration – Shape and Intensity Models



[1] Sadowsky, O., Chintalapani, G., Taylor, R.H., MICCAI 2007;
[2] Chintalapani *et al.* PMMIA/MICCAI 2009

2D/3D Registration – Shape and Intensity

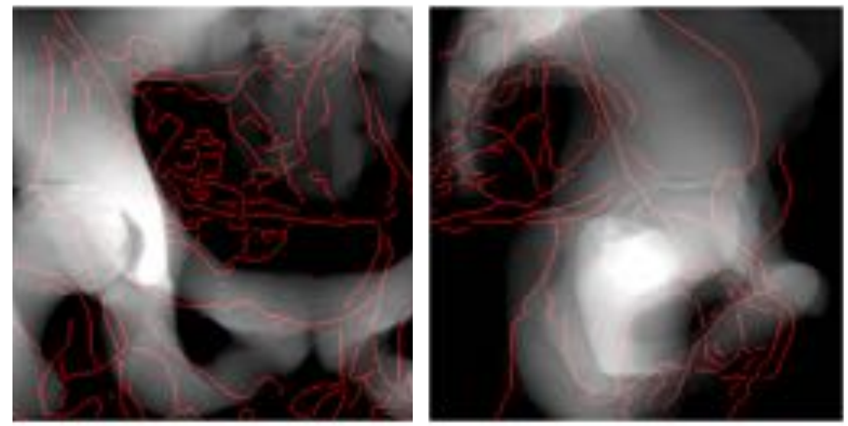
(1) #	(2) $S^{true} - S^{est}$ (mm)	(3) RMS (V^{true} , V^{est}_{mean}) (HU)	(4) RMS(V^{true} , V^{est}_{modes}) (HU)	(5) Δ ((3)-(4))/(3) %
1	1.94	109.92	58.88	**46.43**
2	1.62	128.32	96.0	**25.19**
3	1.90	98.4	77.12	**21.63**
4	2.60	51.68	41.6	**19.50**
5	2.48	109.44	84.8	**22.51**
6	1.95	73.44	50.56	**31.15**
7	2.30	72.96	47.52	**34.84**
8	2.93	101.28	85.76	**15.32**
avg	**2.21**	**93.18**	**67.78**	**27.07**

Table 1: Residual errors from leave-out-validation tests of the augmented registration algorithm. Column 2 shows the surface distance after 2D/3D shape registration. Columns 3 shows residual errors when using mean density only and column 4 shows residual errors with mean density and density modes. The % reduction in RMS error between columns 3 and 4 is given in Column 5

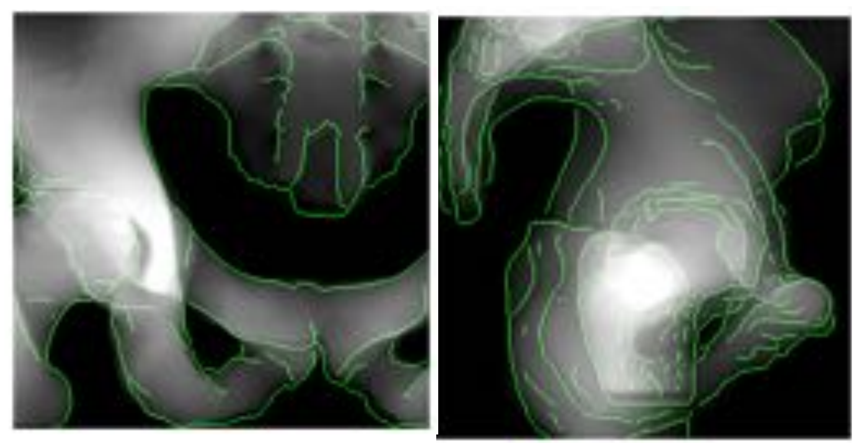
Avg surface registration accuracy: 2.21mm
Avg. reduction in RMS errors intensity: 27%

2D/3D Registration – Hip Model

- **Problem**: To create patient specific models using atlas
  - single organ atlases are insufficient
- **My approach**: Develop a multi-component atlas
  - Use hip atlas instead of a pelvis or femur atlas
  - Extend atlas building framework to incorporate hip joint
  - Extend the registration framework to incorporate articulated hip joint
- **Results**
  - Multi-component atlas registration is accurate compared to individual organ atlas



Pelvis atlas registered to hip projection images

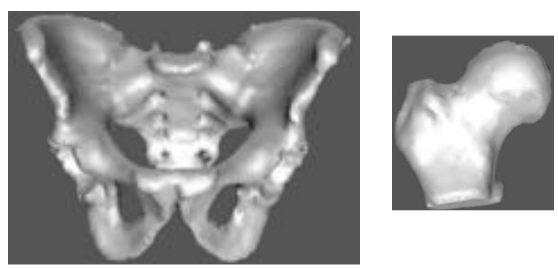


Hip atlas registered to hip projection images

Multi-Component Atlas

1. Two components – pelvis and femur
2. Create mesh instances of pelvis and femur separately
3. Align pelvis and femur meshes together
4. Align pelvis meshes
5. Align femur meshes
6. Concatenate pelvis and femur meshes
7. PCA on the concatenated mesh

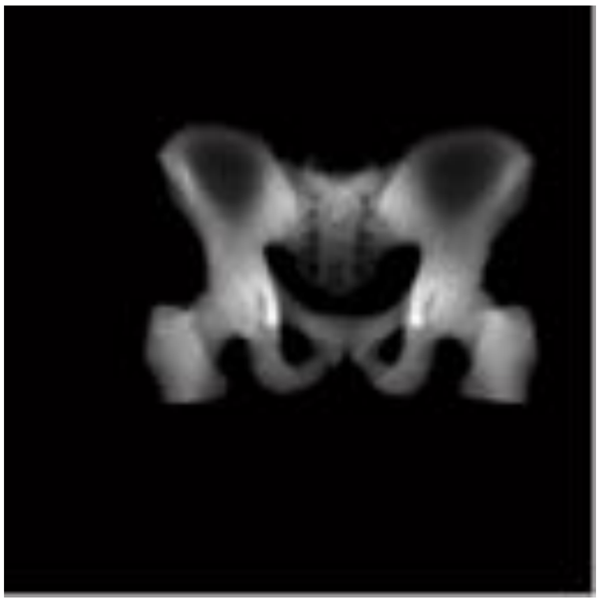
Combined Rigid+Scale

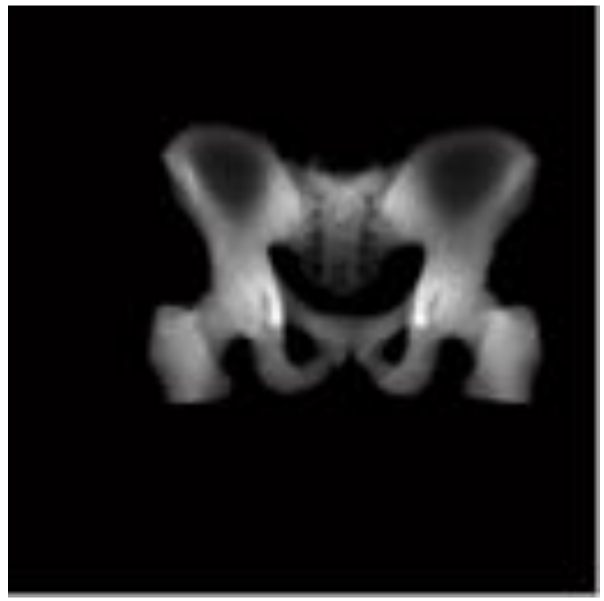


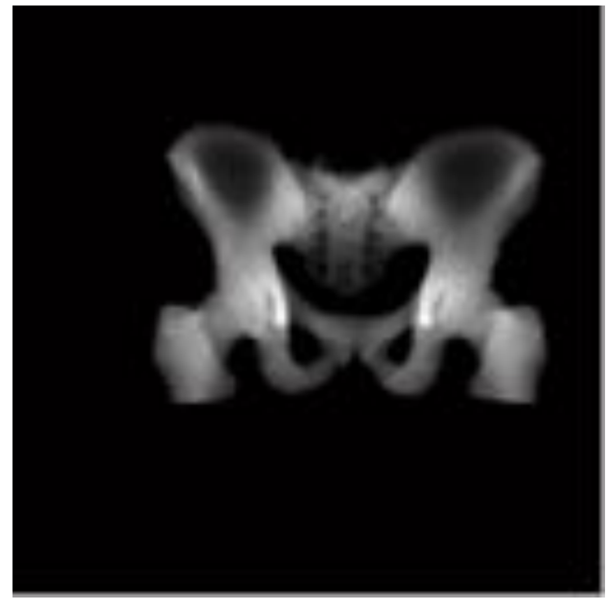
Separate Rigid

Combined Statistical Analysis

Multi-Component Hip Atlas


PC1

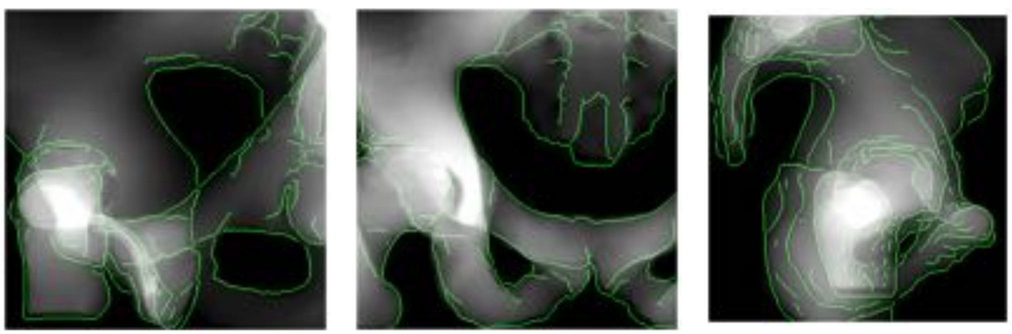

PC2


PC3

[1] Chintalapani *et al.* CAOS 2009

2D/3D Registration – Hip Model

- Registration with truncated images
  - FOV: 160mm
  - Three views
- Avg surface registration accuracy: 2.15 mm

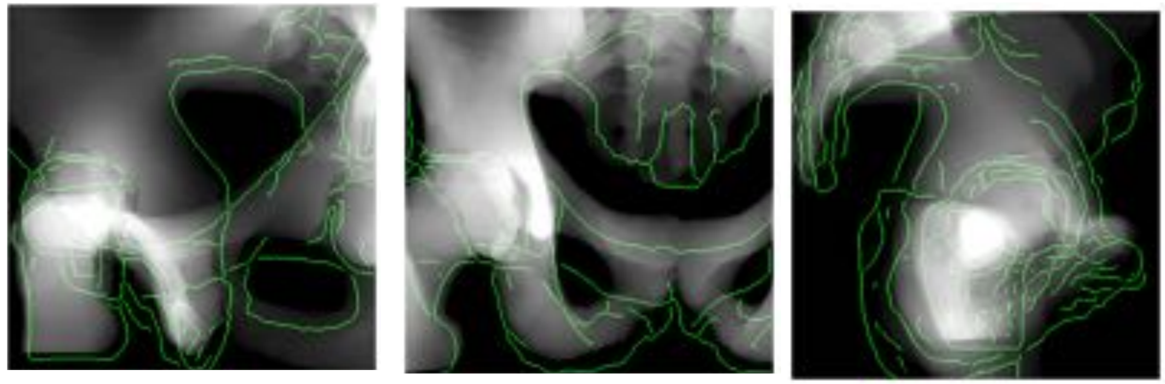


Atlas projections overlaid on DRR images after registration

2D/3D deformable registration

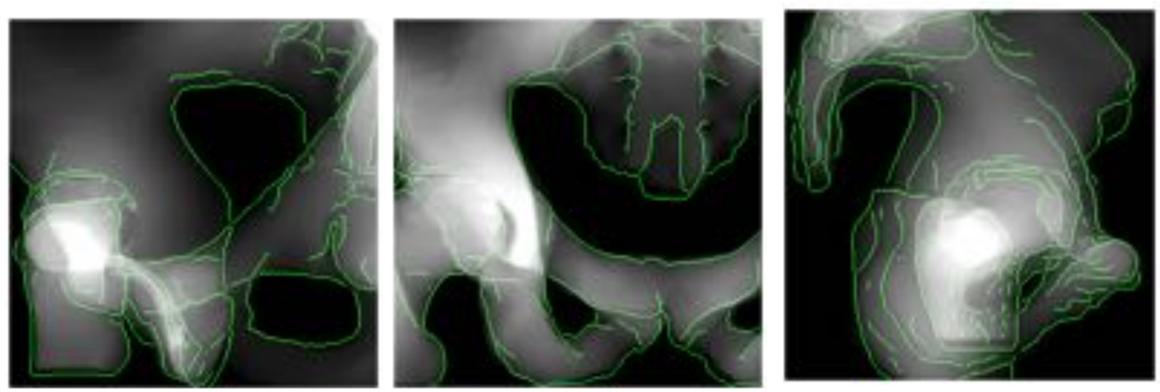
2D/3D Registration – Hip Model

- Registration with truncated images
  – FOV: 160mm
  – Three views



Atlas projections overlaid on DRR images before registration

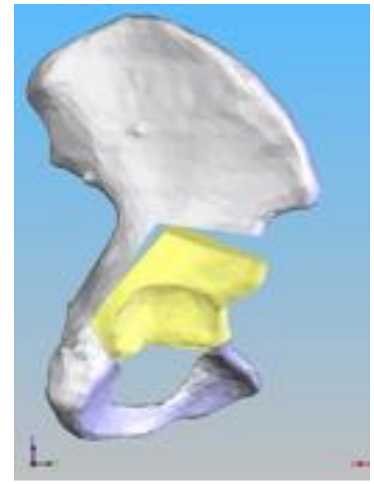
- Avg surface registration accuracy: 2.15 mm

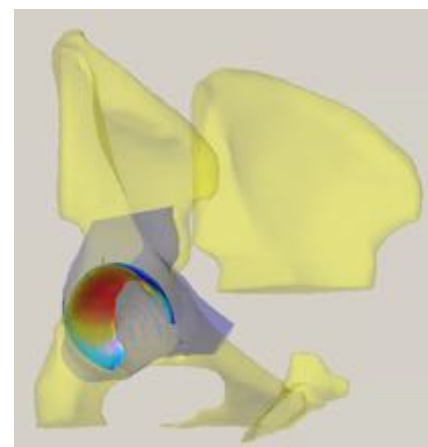


Atlas projections overlaid on DRR images after registration

Outline

- Statistical Atlases
  - Construction
  - Iterative Improvement
  - Validation
- Applications of atlases
  - Segmentation
  - 2D/3D Registration
  - Hip Osteotomy
  - C-arm Distortion Patterns
- Conclusions





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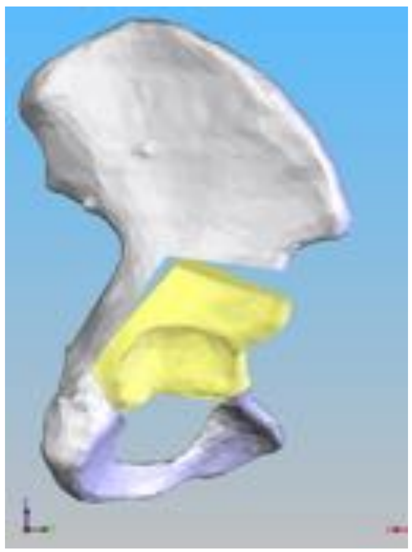
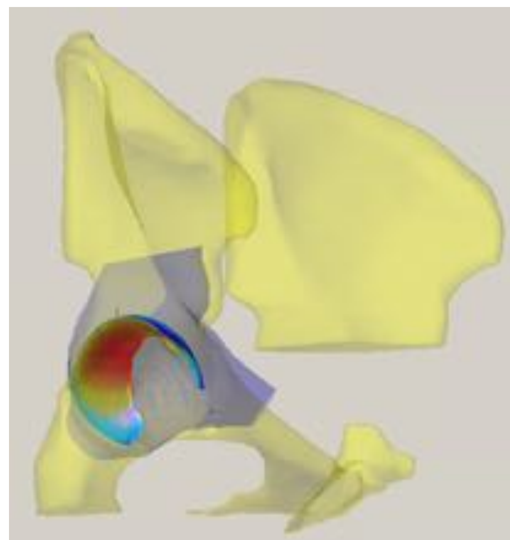
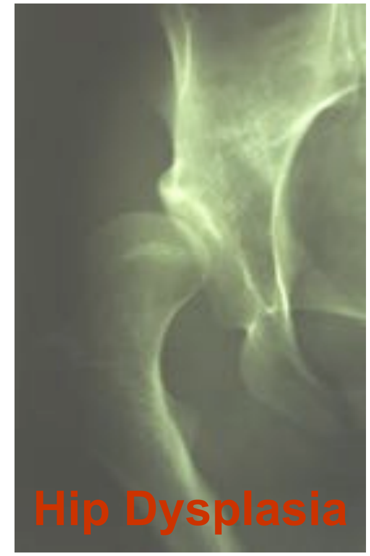
Applications – Hip Osteotomy

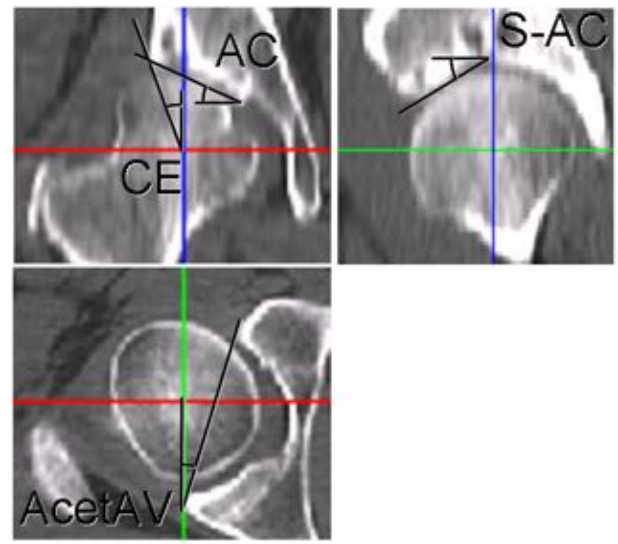




Background

- **Hip dysplasia:**
  - Malformation of the hip (normally a ball and socket joint)
  - Significant cause of osteoarthritis, especially in young adults
- **Surgery goals:**
  - Reduce pain symptoms
  - Realign joint to contain the femoral head
  - Diminish risk for degenerative joint changes
  - Improve contact pressure distribution
- **Periacetabular Osteotomy (PAO):**
  - Maintains pelvic structural stability
  - Preserves viable vascular supply
  - Technically challenging tool placement and realignment procedure
- **Limitations of current navigation systems:**
  - Lack the ability to track bone fragment alignment
  - Do not provide anatomical measurements
  - Omit biomechanical-based planning and guidance
  - Ignore the risk of reducing joint range-of-motion





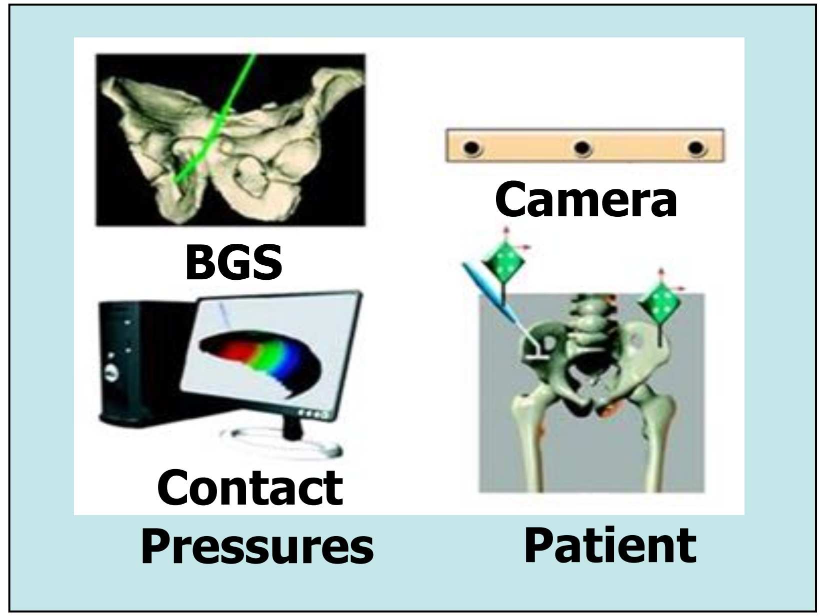
Anatomical measurements used to diagnose hip dysplasia

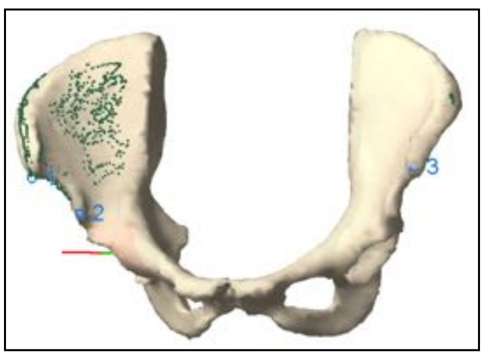
Slide src: Dr. Armand Mehran

Biomechanical Guidance System (BGS)

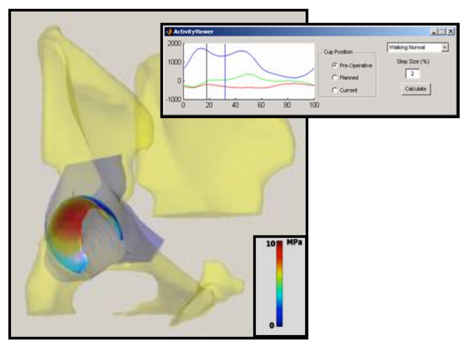
- **BGS Preoperatively:**
  - Plans surgical cuts
  - Optimizes contact pressures and joint realignment
  - Calculates anatomical-based angles that are meaningful to the surgical team

- **BGS Intraoperatively:**
  - Tracks surgical tools and bone fragment alignment
  - Computes resulting contact pressures
  - Calculates hip range-of-motion
  - Visualizes the surgical cuts
  - Displays radiation-free Digitally Reconstructed Radiographs (DRR)

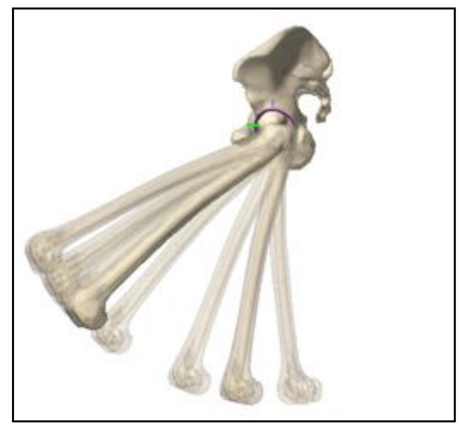




Model to Patient Registration



Joint contact-pressure after PAO

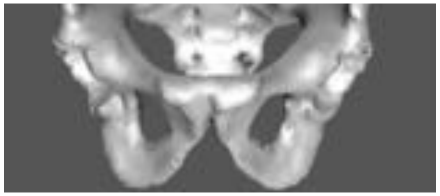


Hip-range-of-motion

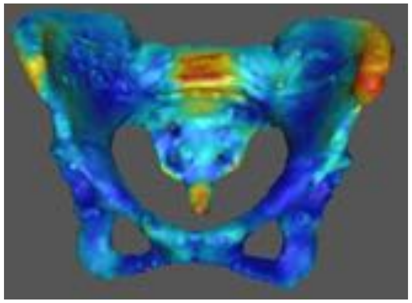
Slide src: Dr. Armand Mehran

Atlas Based Extrapolation of CT

- **Problem**: Partial CT scans of patients
  - Dose minimization for young female patients
  - But the BGS needs full pelvis CT for planning
- **My approach**: Use atlas to predict the missing data
  - Robust probabilistic atlases
  - Improve prediction using pre-op and intra-op x-ray images
- **Preliminary Results**
  - Comparable to the registration errors from full CT scans



Typical pre-operative CT scan of a dysplastic patient undergoing osteotomy



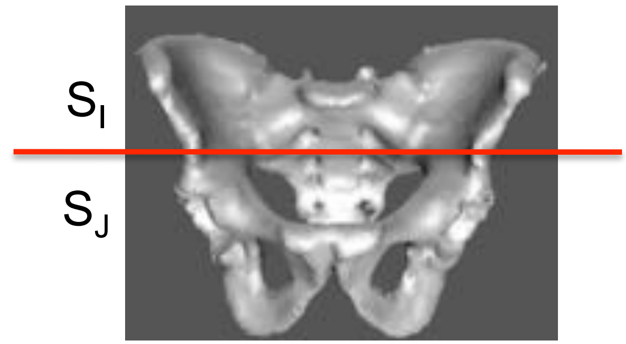
Distribution of surface registration errors of a patient pelvis model estimated from partial CT scan

Chintalapani *et al.* SPIE 2010

Revisiting PCA with Missing Data

- Let S_I be the available data and S_J be the missing data, such that

$$S = \begin{bmatrix} S_I \\ S_J \end{bmatrix} \qquad C = \begin{bmatrix} S_I S_I' & S_I S_J' \\ S_J S_I' & S_J S_J' \end{bmatrix}$$



- Rearrange U such that $U = \begin{bmatrix} U_I \\ U_J \end{bmatrix}$

- Solve $\dot{\lambda} = \arg\min_{\lambda} \| \hat{S}_I - U_I{}^T \lambda \|^2$

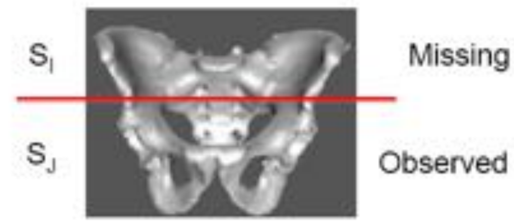
  s.t. $\lambda_{\min} \le \dot{\lambda} \le \lambda_{\max}$

where $\lambda_{\min}$ and $\lambda_{\max}$ are derived from the training database

- Estimated shape $S_i^{est} = \overline{S} + U^T \lambda$

Atlas Adaptation to Partial Data

- Surface based registration of the observed data
  - Rearrange $\bar{S}$ and U such that ; $\bar{S} = \begin{bmatrix} \bar{S}_I \\ \bar{S}_J \end{bmatrix}$ $U = \begin{bmatrix} U_I \\ U_J \end{bmatrix}$
  - Compute the rigid transformation (R, T) between the atlas and the patient data along with the mode weight parameters
  - Infer the missing region



$$S^{est} = \begin{bmatrix} S_I^{est} \\ \\ S_J^{est} \end{bmatrix} = \begin{bmatrix} \bar{S}_I \\ \\ \bar{S}_J \end{bmatrix} + \lambda \begin{bmatrix} U_I \\ \\ U_J \end{bmatrix}$$

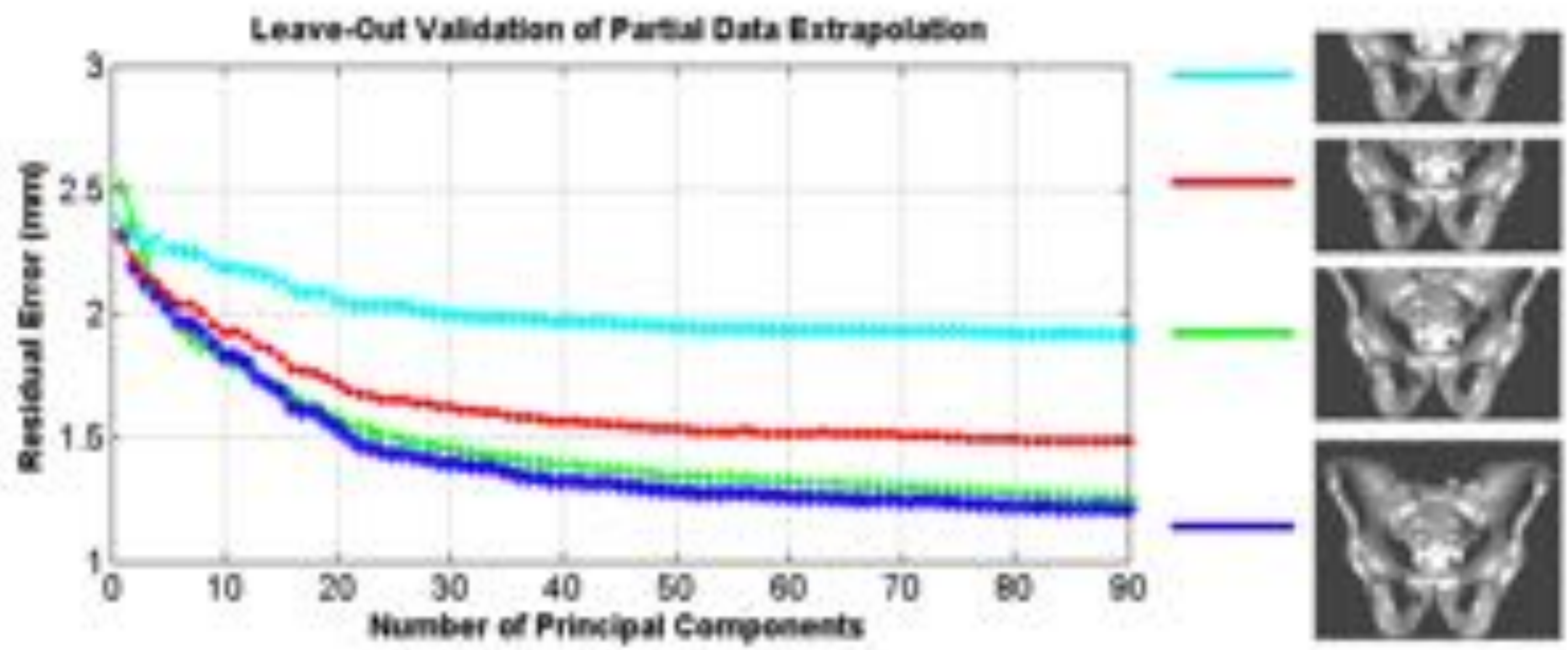
Atlas Adaptation to Partial Data with Xray Images

- 2D/3D registration[2] of inferred data with X-ray images

$$F, \Phi = \underset{(F,\Phi)}{\operatorname{argmax}} \sum_i MI\left(I_i, DRR\left(F.\left(\bar{S}_I + \Phi U_I\right)\right)\right)$$

- Final atlas extrapolated model is given as

Results


Leave-Out Validation of Partial Data Extrapolation
Residual Error (mm)
3
2.5
2
1.5
1
0
10
20
30
40
50
60
70
80
90
Number of Principal Components

Results – Atlas Experiments

Atlas inferred CT using full CT scan

Atlas extrapolated CT using partial CT scan

Atlas extrapolated CT using partial CT scan and X-ray images

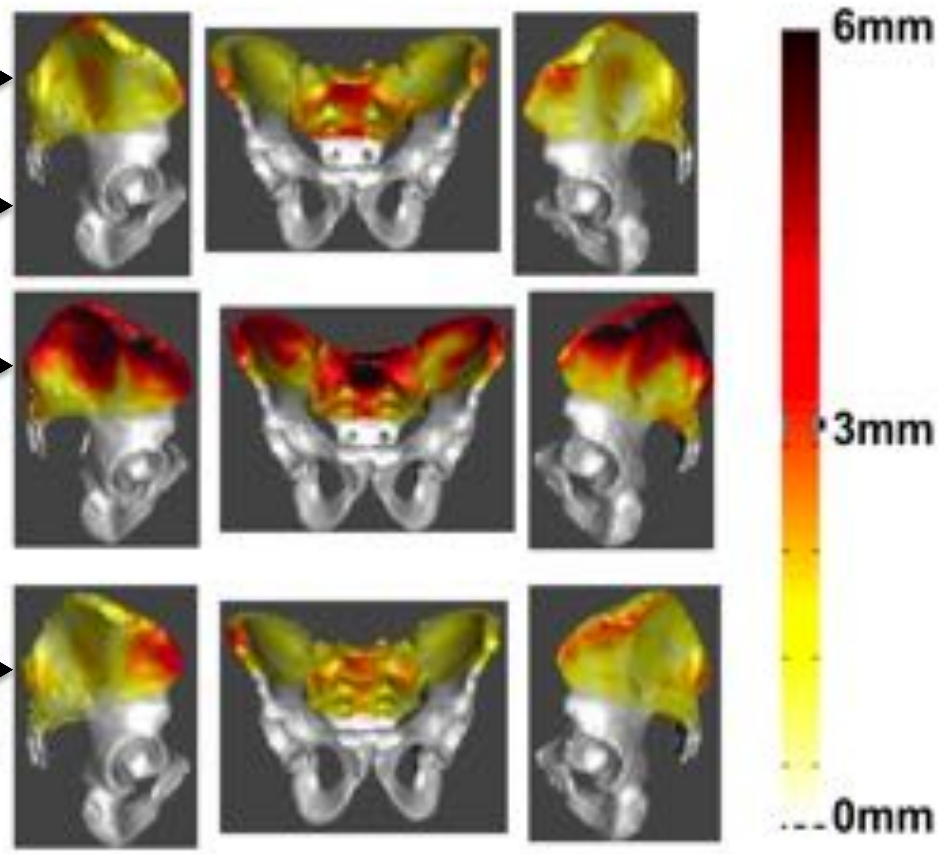
Results – Atlas Experiments

Inferred CT from full CT scan

True CT scan

Extrapolated CT from partial CT scan

Extrapolated CT from partial CT scan and X-ray images



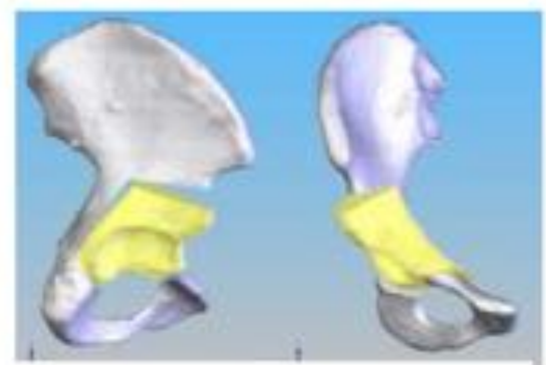
Distribution of surface errors between atlas extrapolated models and the true CT model

Osteotomy Simulations

- Atlas extrapolated model is used primarily for two reasons:

1. Model to patient registration
   - simulation experiments
   - six leave out experiments
   - FRE error metric

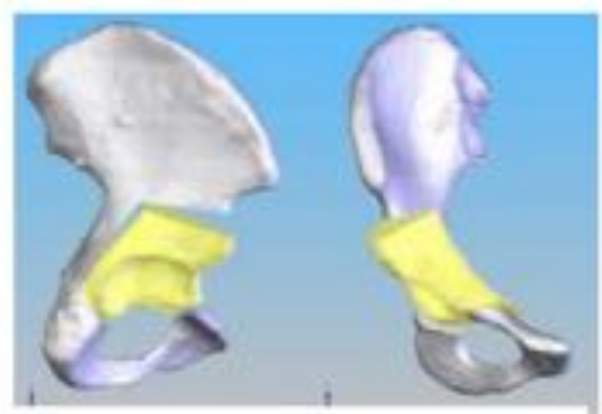
2. Fragment tracking
   - Simulated osteotomy cuts
   - Applied known transformation to the
   - Fragment
   - Computed the fragment transformation
   - Compared it to the known transformation



Results – Osteotomy Simulations

- Atlas extrapolated model is used primarily for two reasons:

1. Model to patient registration
2. Fragment tracking



Results – Osteotomy Simulations

#	Full CT				Partial CT				Partial CT + X-ray			
	rot (o)	trans (mm)	mean (mm)	max (mm)	rot (o)	trans (mm)	mean (mm)	max (mm)	rot (o)	trans (mm)	mean (mm)	max (mm)
1	2.63	1.03	1.68	5.86	4.23	2.17	2.05	7.55	2.56	2.73	1.65	5.86
2	1.29	0.97	1.42	5.56	2.62	3.39	1.77	7.15	2.18	3.90	1.85	8.26
3	1.66	3.58	1.46	5.94	8.37	6.27	1.87	6.41	3.06	3.92	1.50	5.87
4	0.87	0.91	1.21	4.16	2.00	2.32	1.64	5.96	1.42	2.64	1.46	6.35
5	1.27	1.09	0.95	3.68	4.96	5.87	1.61	5.47	2.20	1.87	1.22	4.53
6	1.64	1.97	1.58	6.93	4.32	4.12	1.84	8.75	1.46	2.74	1.44	6.17
avg	1.56	1.59	1.38	5.35	4.41	4.02	1.79	6.88	2.14	2.96	1.52	6.16

Results from ICP registration experiments

Results from Fragment Tracking Experiments

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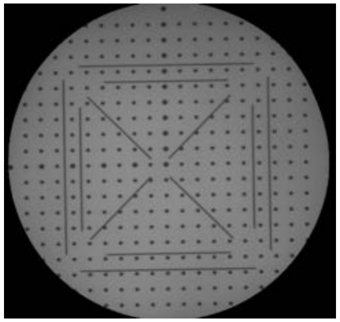
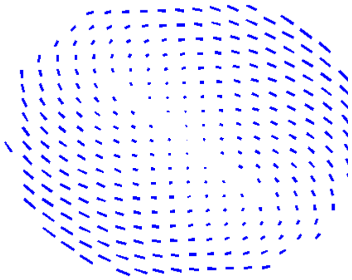
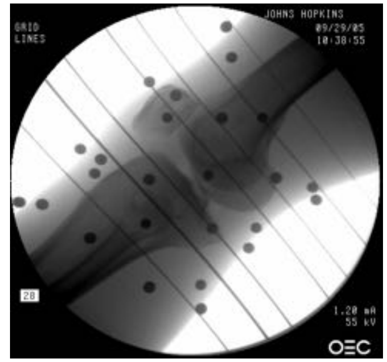




Thanks to GE for donating us an OEC 9600 C-arm

C-arm Distortion

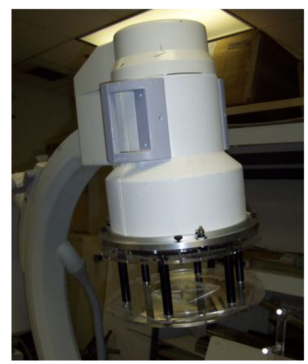
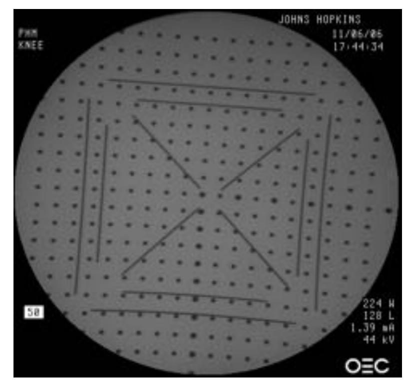
- What is distortion ?
  - –Avg distortion: **2.14** mm/pixel
  - –max distortion: **4.60** mm/pixel



Example C-arm images showing distortion, straight metal wires appear curved due to distortion

- How to rectify images ?
  - Phantom based correction
  - Polynomial functions to model distortion

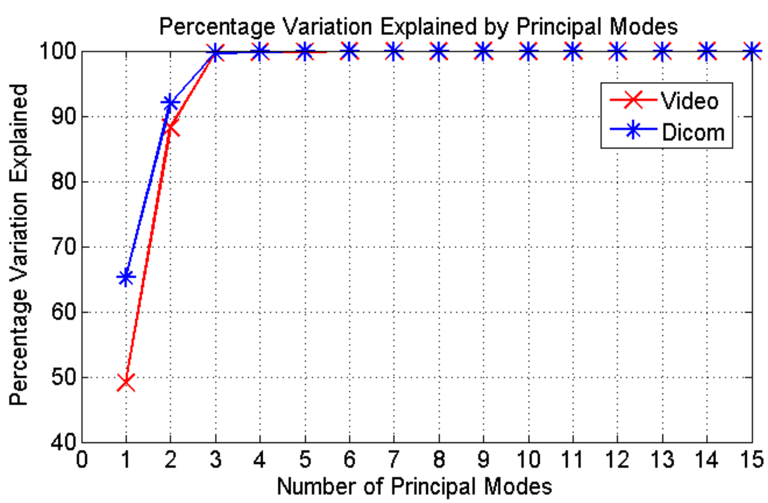
$$(u_d, v_d) = \sum_{i=0}^{n} \sum_{j=0}^{n} C_{ij} B_{ij}(u_0, v_0)$$

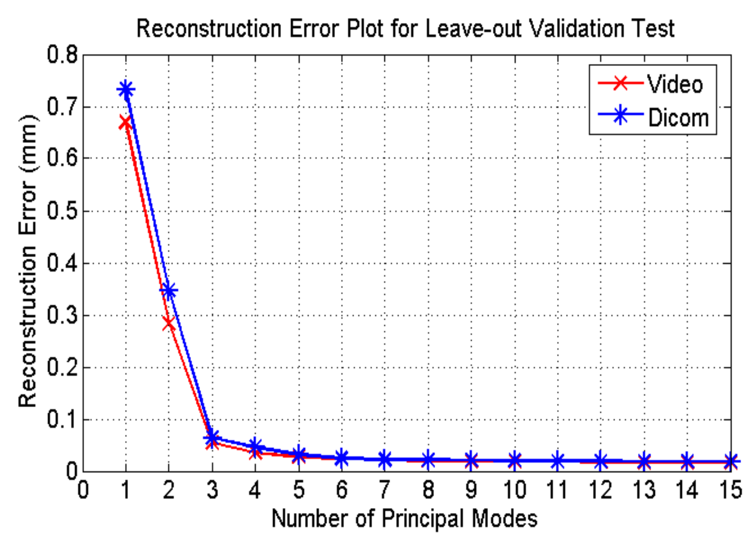



Typical bi-planar phantom used for C-arm calibration

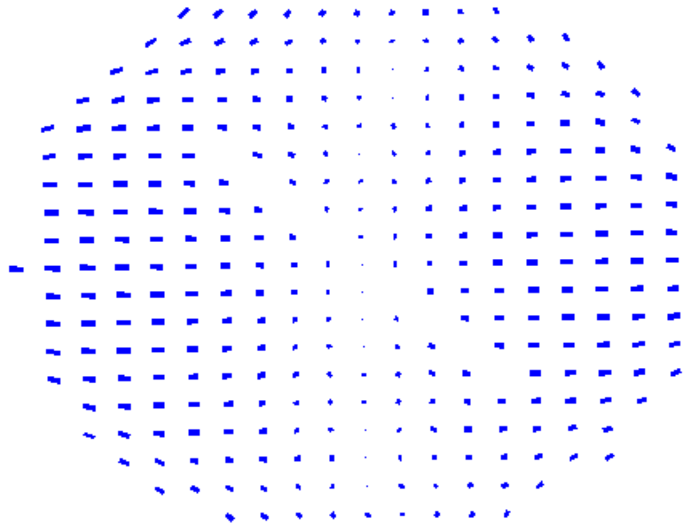
Statistical Characterization of C-Arm Distortion correction using PCA

- Principal componet analysis on distortion maps
  - 120 images, one every 3 degrees approx., along propeller axis (similar to the full sweep data used for 3D reconstruction)
  - 200 images to span the sphere defined by the "C" of the c-arm

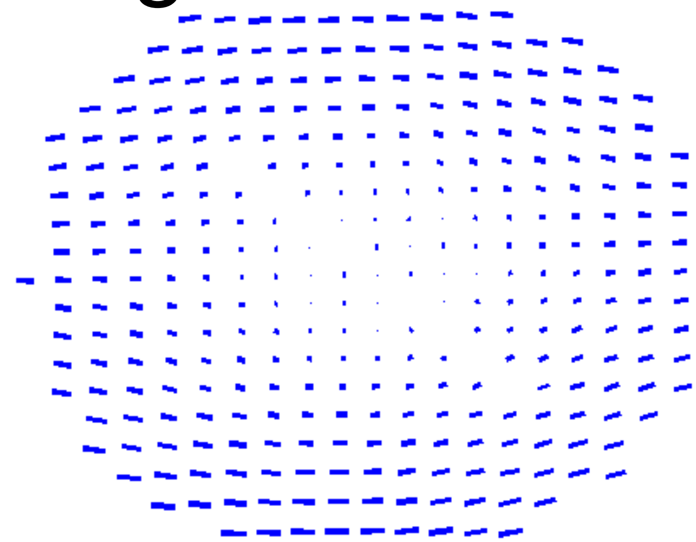




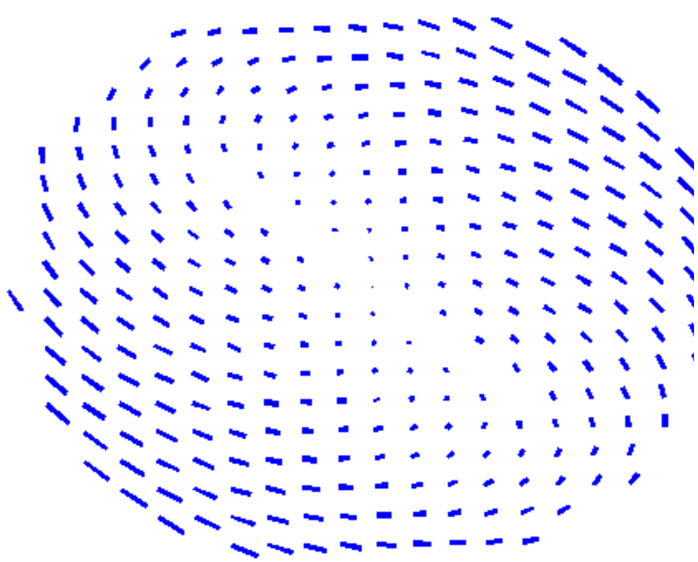
Distortion Pattern from Eigen Modes



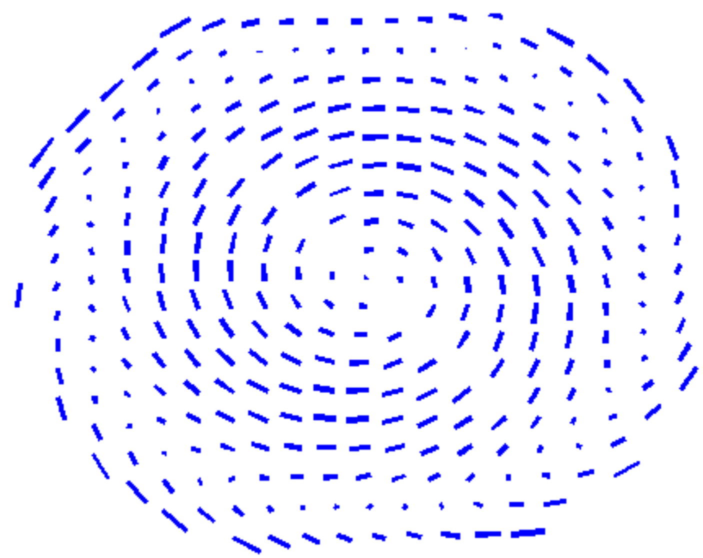
Mean distortion map



$+3\sigma_1$Mode1

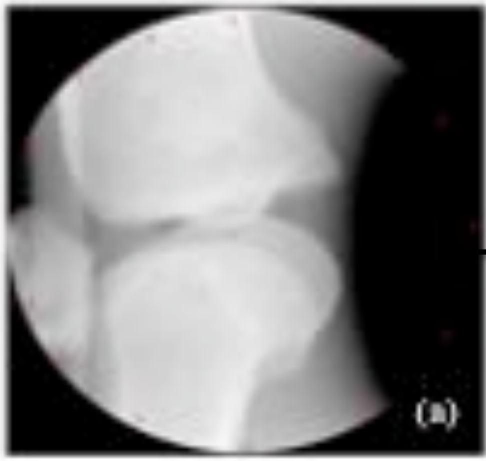


$+3\sigma_2$Mode2

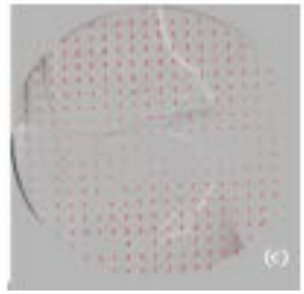


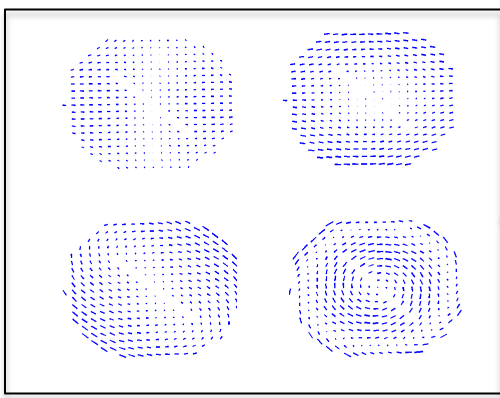
$+3\sigma_3$Mode3

Small Phantom based Distortion Correction



Example patient image with a small phantom

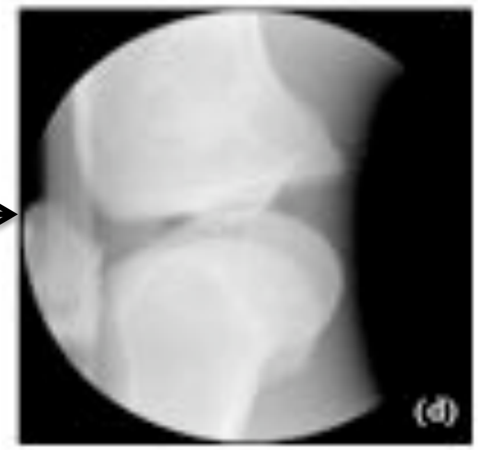




Prior distortion model

Distortion mode matching

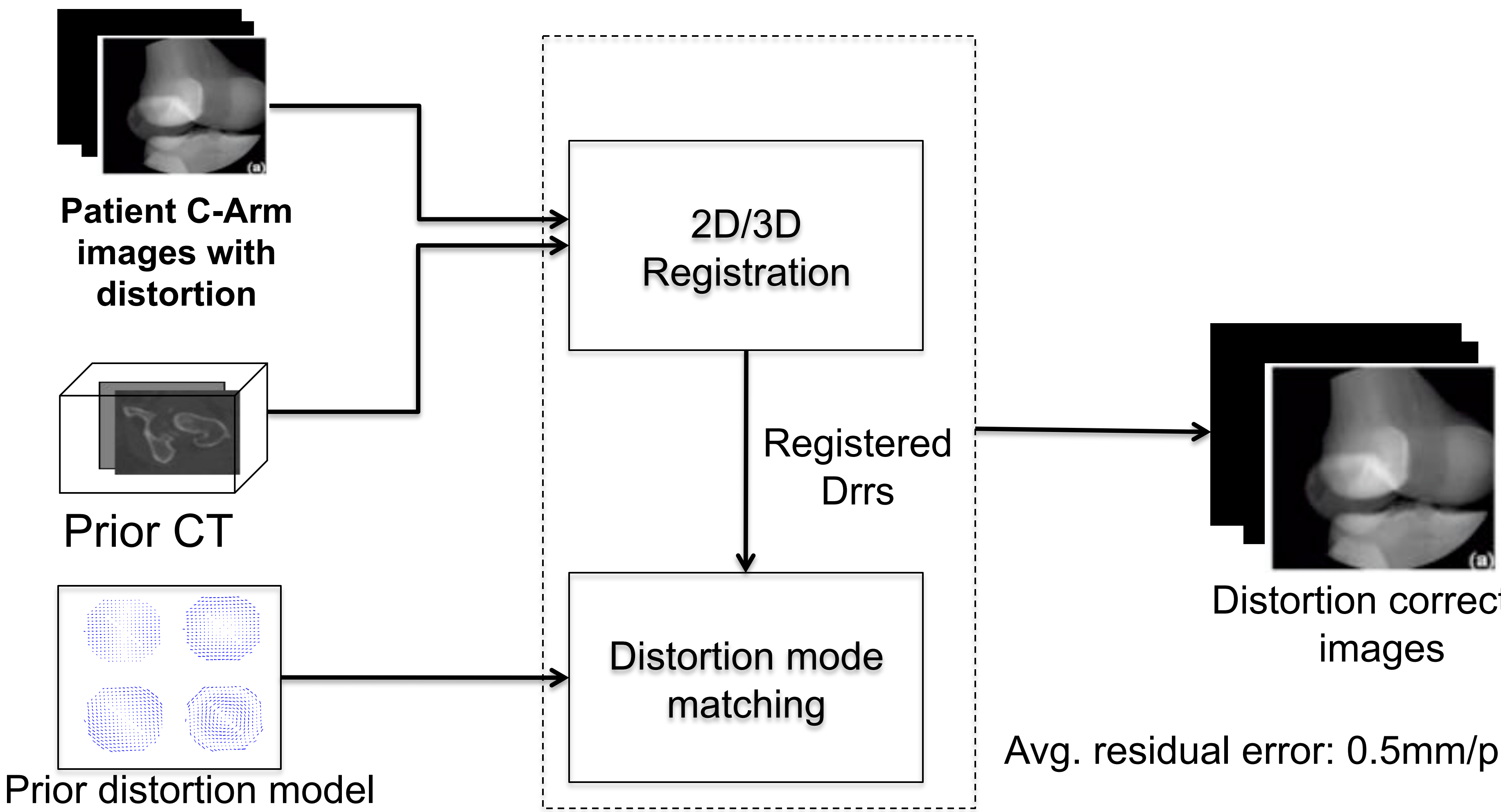
Distortion corrected image



Avg. residual error: 0.2mm/pixel
Max. residual error: 0.8mm/pixel

Chintalapani *et al.* SPIE 2007

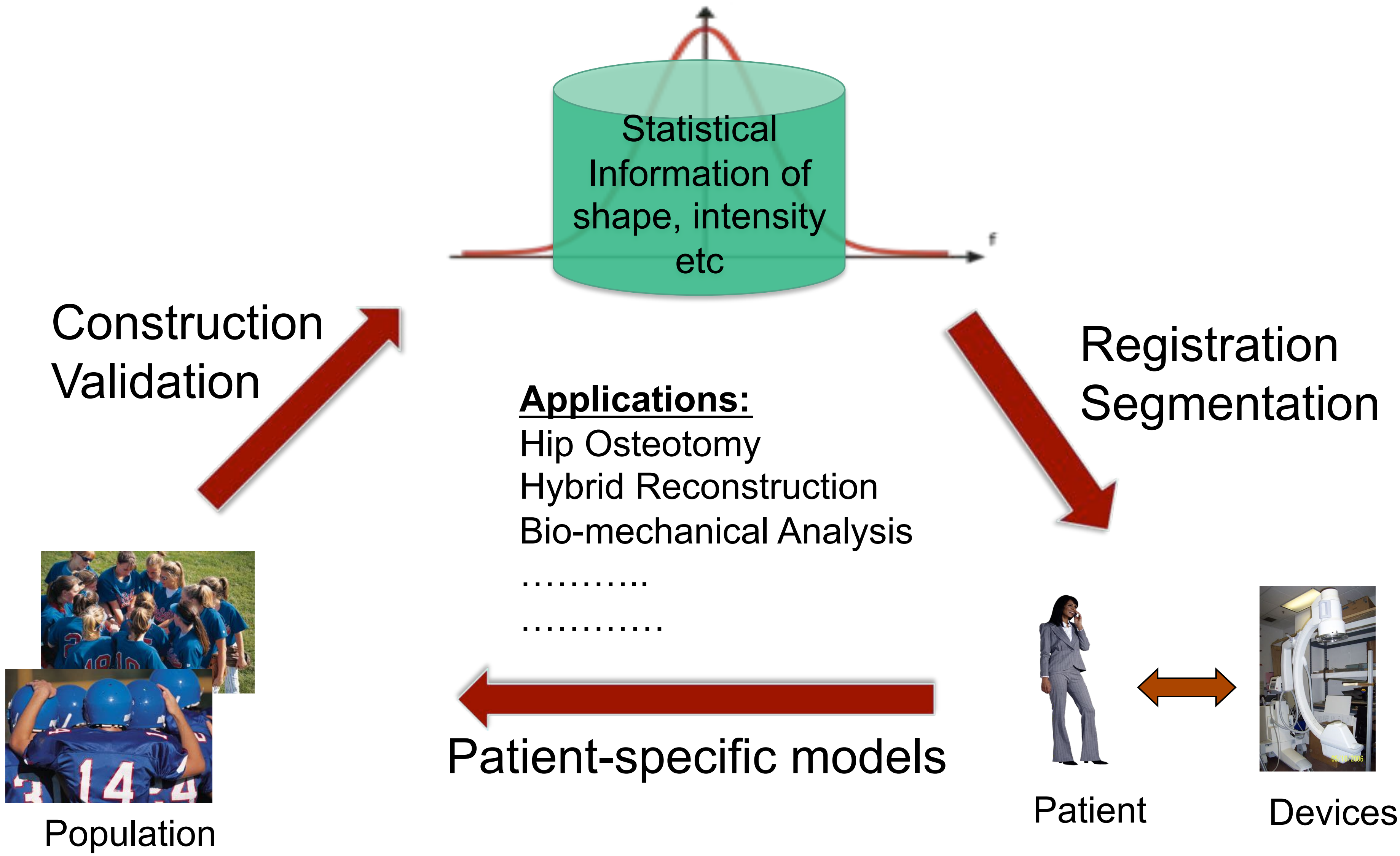
Using Patient CT as Fiducial



Avg. residual error: 0.5mm/pixel

Chintalapani *et al.* ISBI 2007

Conclusions



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  - Russell H. Taylor, Jerry L. Prince, Ofri Sadowsky, Lotta Ellingsen, Pauline Pelletier, Junghoon Lee
- Prostate brachytherapy, JHU
  - Gabor Fichtinger, Jerry L. Prince, Ameet Jain, Anton Deguet, Iulian Iordachita
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Thank You !