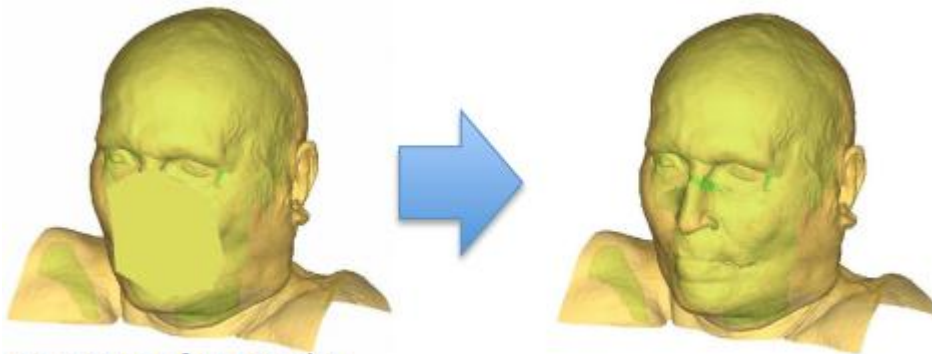


Extrapolation of Missing Craniofacial Skeletal Structure via Statistical Shape Models



Courtesy of Dr. Otake

Hsin-Hong Chiang

Robert Grupp

Dr. Yoshito Otake (Mentor)

Dr. Russell Taylor (Mentor)

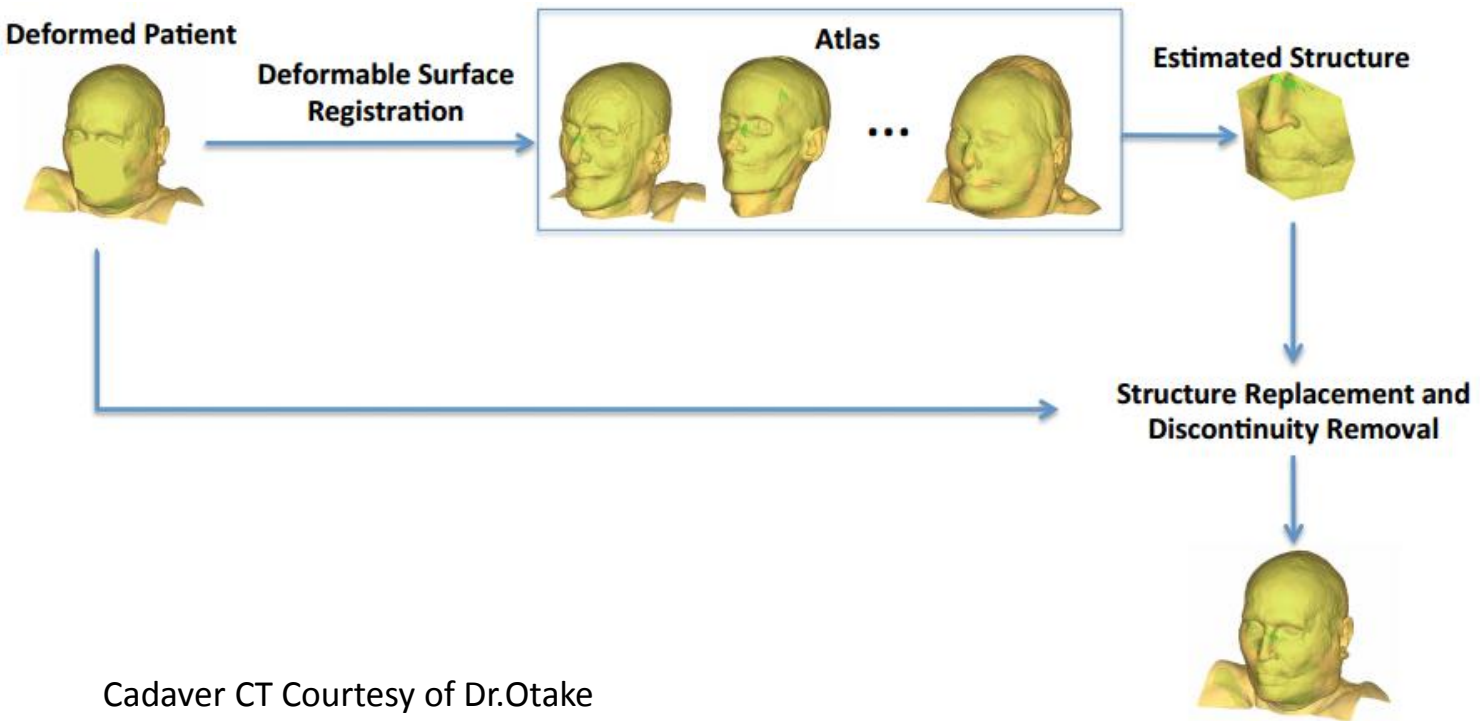
Dr. Mehran Armand (Mentor)

Ryan Murphy (Mentor)

- Brief Review and Project Relevance
- Article Choice
- Technical Summary
- Analysis

Brief Review

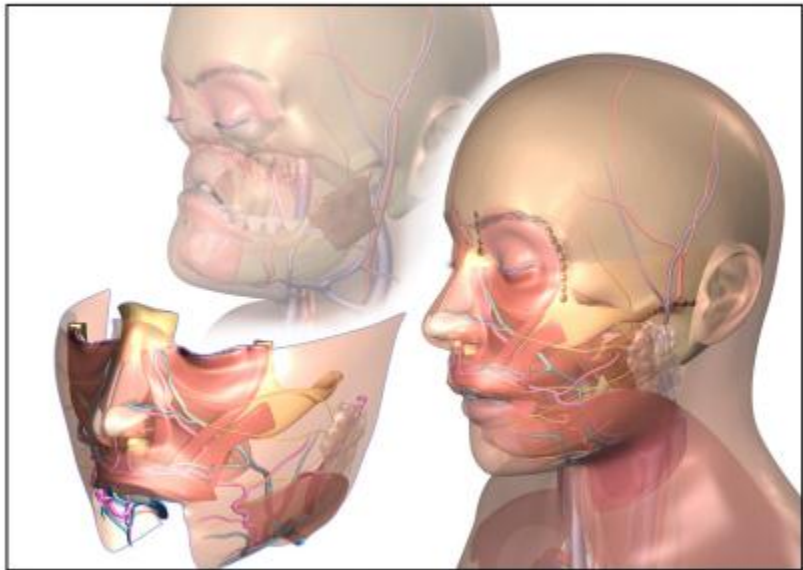
- **Project Goal**
 - Design and implement a method for extrapolating missing anatomical craniofacial skeletal structure with the use of a statistical shape model of the human cranium.



Cadaver CT Courtesy of Dr.Otake

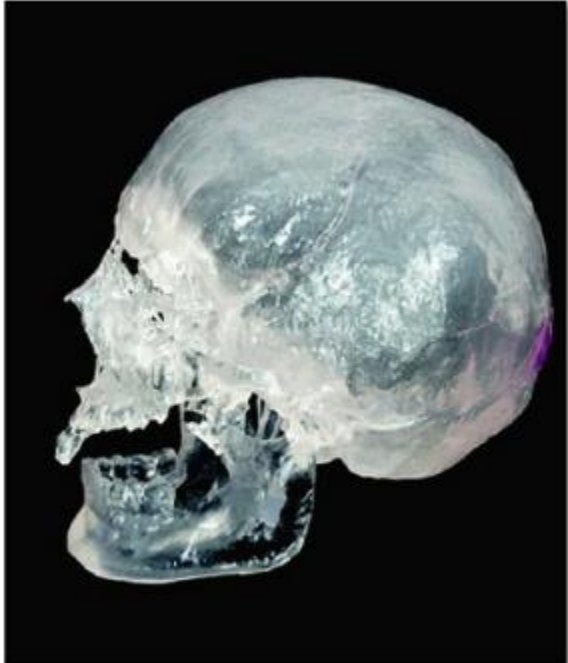
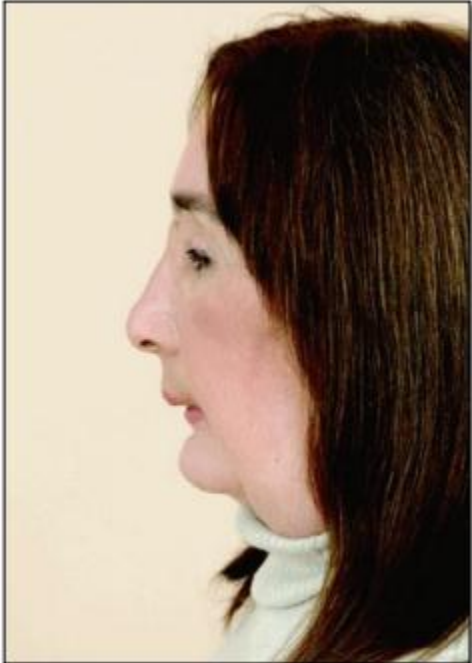
Project Relevance: Face Transplant Surgery

- Restore appearance
- Restore lost functionality



Cadaver CT Courtesy of Dr. Chad Gordon

Project Relevance: Face Transplant Surgery (cont.)



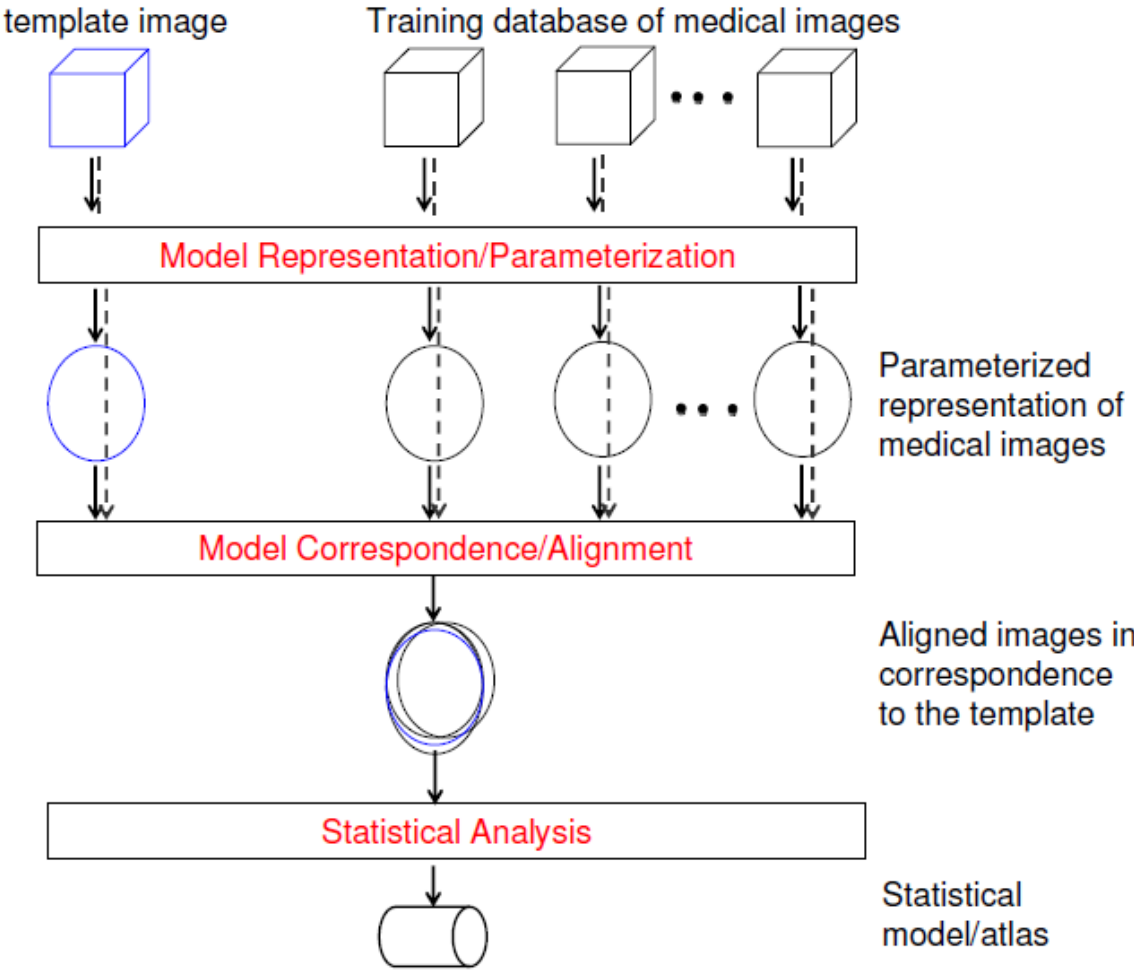
Cadaver CT Courtesy of Dr. Chad Gordon

Article Choice

- **Paper 1: “Statistical Atlases of Bone Anatomy Construction, Iterative Improvement and Validation”**
Authors: Gouthami Chintalapani, Lotta M. Ellingsen, Ofri Sadowsky, Jerry L. Prince, and Russell H. Taylor
Published at: Medical Image Computing and Computer-Assisted Intervention MICCAI 2007, 4791:499-506, 2007.
- **Paper 2: “Statistical Atlas Based Extrapolation of CT Data”**
Authors: Gouthami Chintalapani, Ryan Murphy, Robert S. Armiger, Jyri Lepistö, Yoshito Otake, Nobuhiko Sugano, Russell H. Taylor and Mehran Armand
Presented at: Medical Imaging 2010: Visualization, Image-Guided Procedures, and Modeling, February 13 2010, San Diego, California, USA

Technical Summary: Atlas Creation Overview

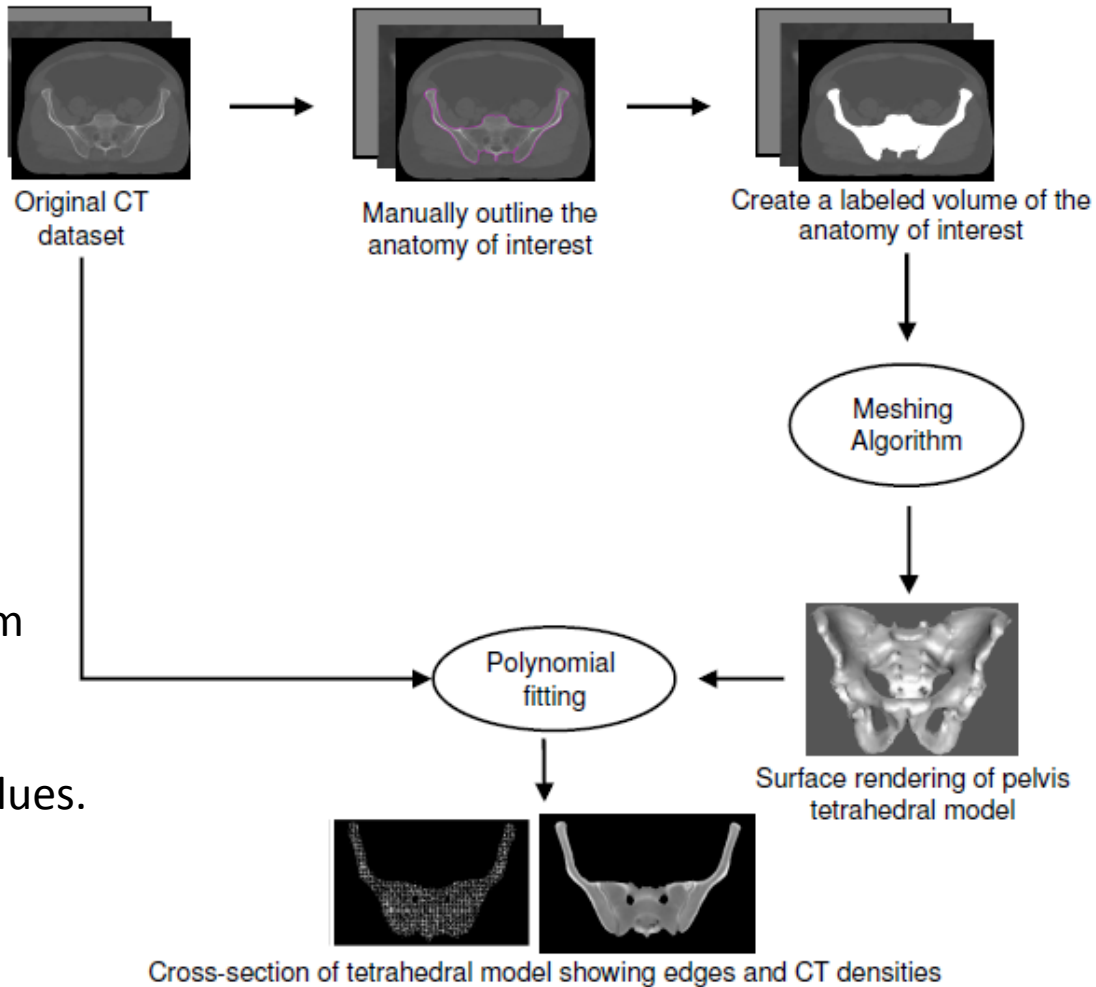
- **Alignment(Registration):**
ICP, mesh-based registration algorithm, volumetric image based registration algorithm...
- **Statistical Analysis:**
PCA, ICA,...



Source: Gouthami Chintalapann "Statistical Atlases of Bone Anatomy and Their Applications"

Technical Summary: Model Creation

- Segment the anatomy of interest, manually or semi-automatically
- Create the label volume according the segment result.
- Do the tetrahedral meshing algorithm
- Fit polynomials to the tetrahedral mesh to encode the CT intensity values.

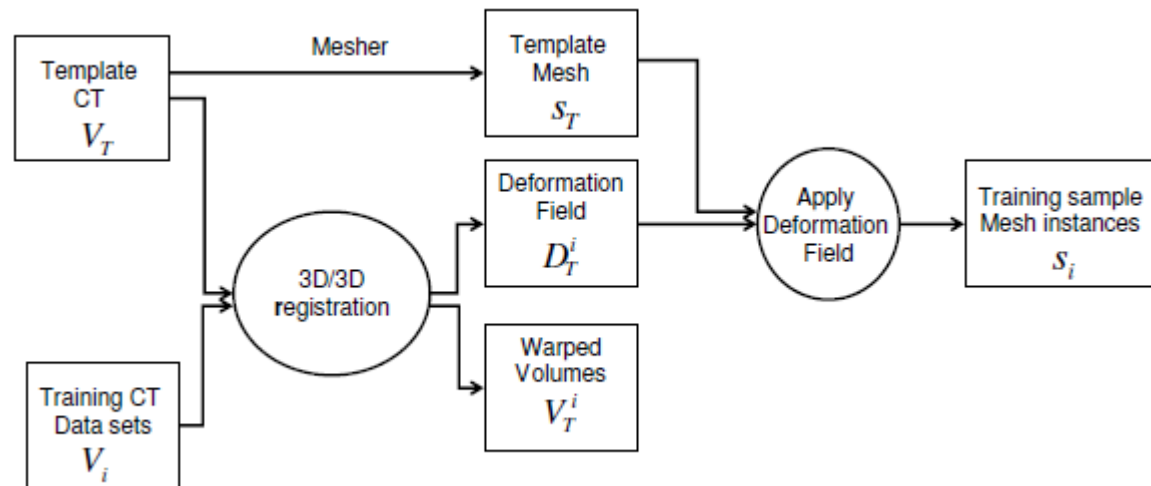


Source: Gouthami Chintalapann "Statistical Atlases of Bone Anatomy and Their Applications"

Technical Summary: Shape Correspondence

- **3D Grayscale Deformable Registration Method:**
Register the training CT volume to the template volume
- **Deformation Map:**
The deformation map consists of a vector flow field that maps every voxel on the template grid to a corresponding voxel in the subject image.

- With this approach, only the template image is segmented



Source: Gouthami Chintalapann "Statistical Atlases of Bone Anatomy and Their Applications"

Technical Summary: Statistical Analysis(PCA)

Given a set of N mesh instances , $\{S_1, S_2, S_3 \dots, S_N\}$

$$1. \bar{S} = \frac{1}{N} \sum_{i=1}^N S_i$$

$$2. S_i^m = S_i - \bar{S}$$

$$3. \tilde{S} = [S_1^m, S_2^m, S_3^m, \dots, S_N^m]$$

$$4. Cov = \frac{1}{N-1} \tilde{S} \tilde{S}^T$$

$$5. Cov = UDV^T$$

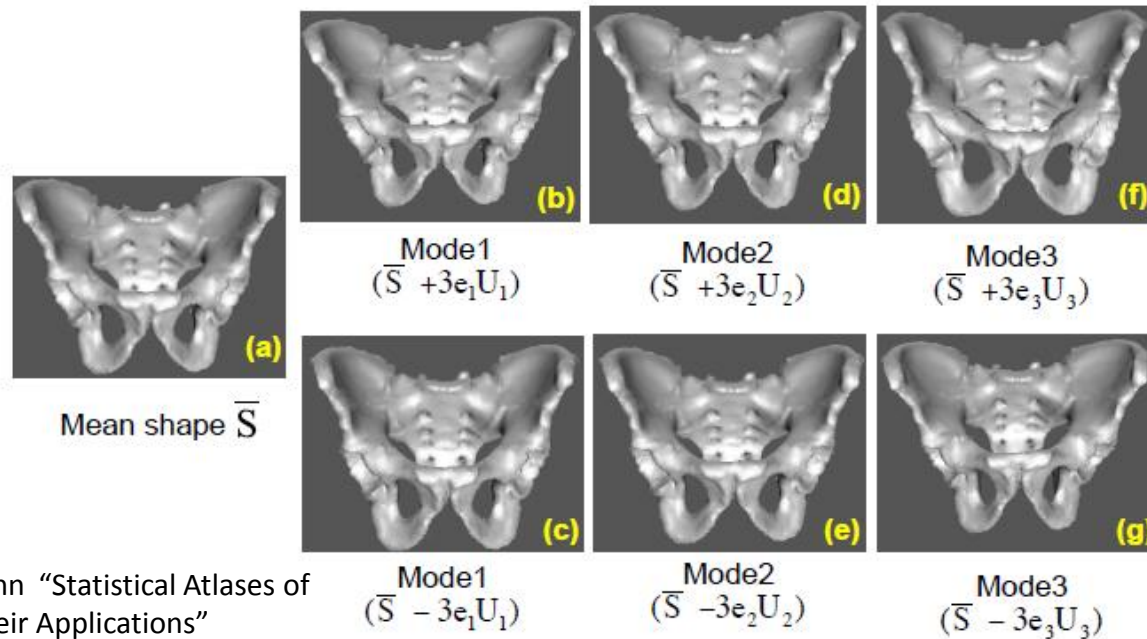
$$6. S^{est} = \bar{S} + \vec{\lambda} * U$$

We can compute the $\vec{\lambda}$
according the equation below:

$$\vec{\lambda} = U * (S^{true} - \bar{S})$$

Technical Summary: Result for Atlas Creation

- 110 male pelvis CT scans were acquired from the Department of Radiation Oncology, Johns Hopkins Medical Institutions.
- The datasets were resampled to isotropic voxels of size $1.875\text{mm} \times 1.875\text{mm} \times 1.875\text{mm}$
- A template was selected manually and meshing.
- 26875 vertices, 105767 tetrahedral, and 23414 outer surface triangles.



Source: Gouthami Chintalapann "Statistical Atlases of Bone Anatomy and Their Applications"

Technical Summary: Experiments for Atlas Creation

- **Leave-n-out Analysis:**

10 CT datasets are selected randomly and segmented manually.

These segmentations are used to create the mesh instances and consider as ground truth, S^{true} .

These instances were excluded from Atlas creation.

Use the first 15 eigenmodes to reconstruct the model from atlas.

avg (mm)	std (mm)	max (mm)	95% (mm)
1.80	1.46	10.91	4.71
1.51	1.24	12.60	3.77
1.66	1.36	8.41	4.31
1.50	1.14	5.87	3.77
1.52	1.24	10.81	3.80
1.48	1.16	8.06	3.57
1.61	1.23	8.79	3.93
1.54	1.14	9.46	3.69
1.99	1.46	10.25	4.72
1.66	1.36	8.41	4.31
1.63	1.28	9.36	4.06

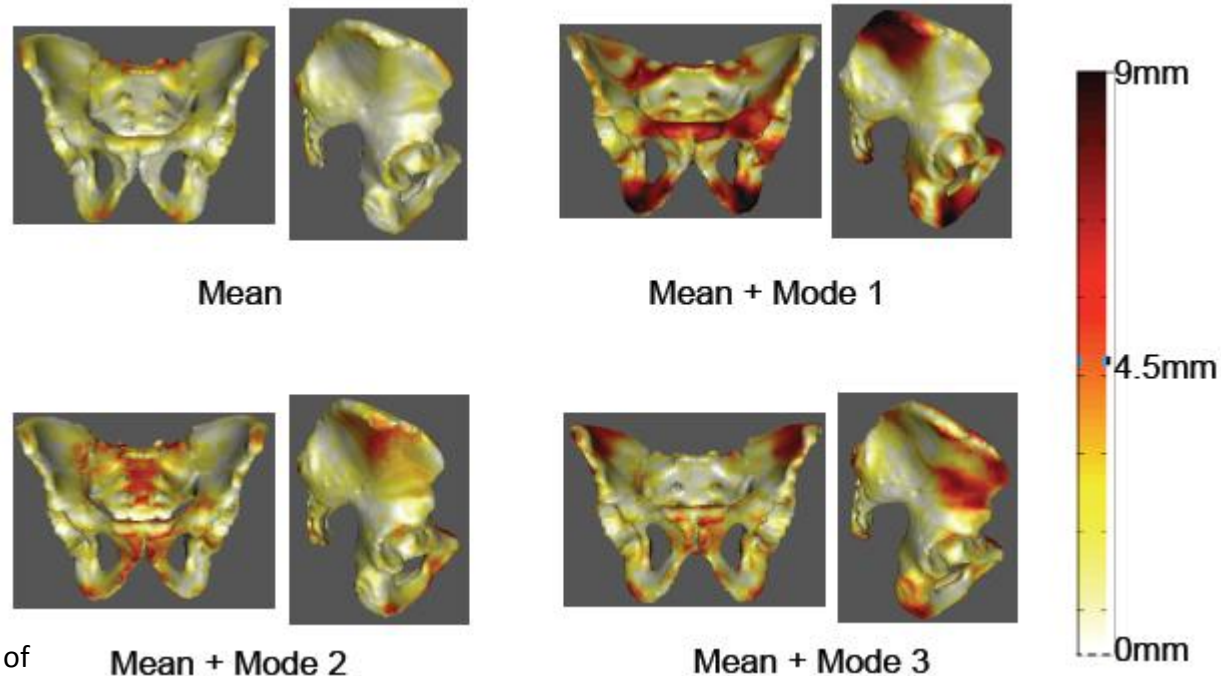
- **Surface Distance Error:**

$$d\{x, S^{true}\} = \min \|x - x'\|_2$$

Source: Gouthami Chintalapann "Statistical Atlases of Bone Anatomy and Their Applications"

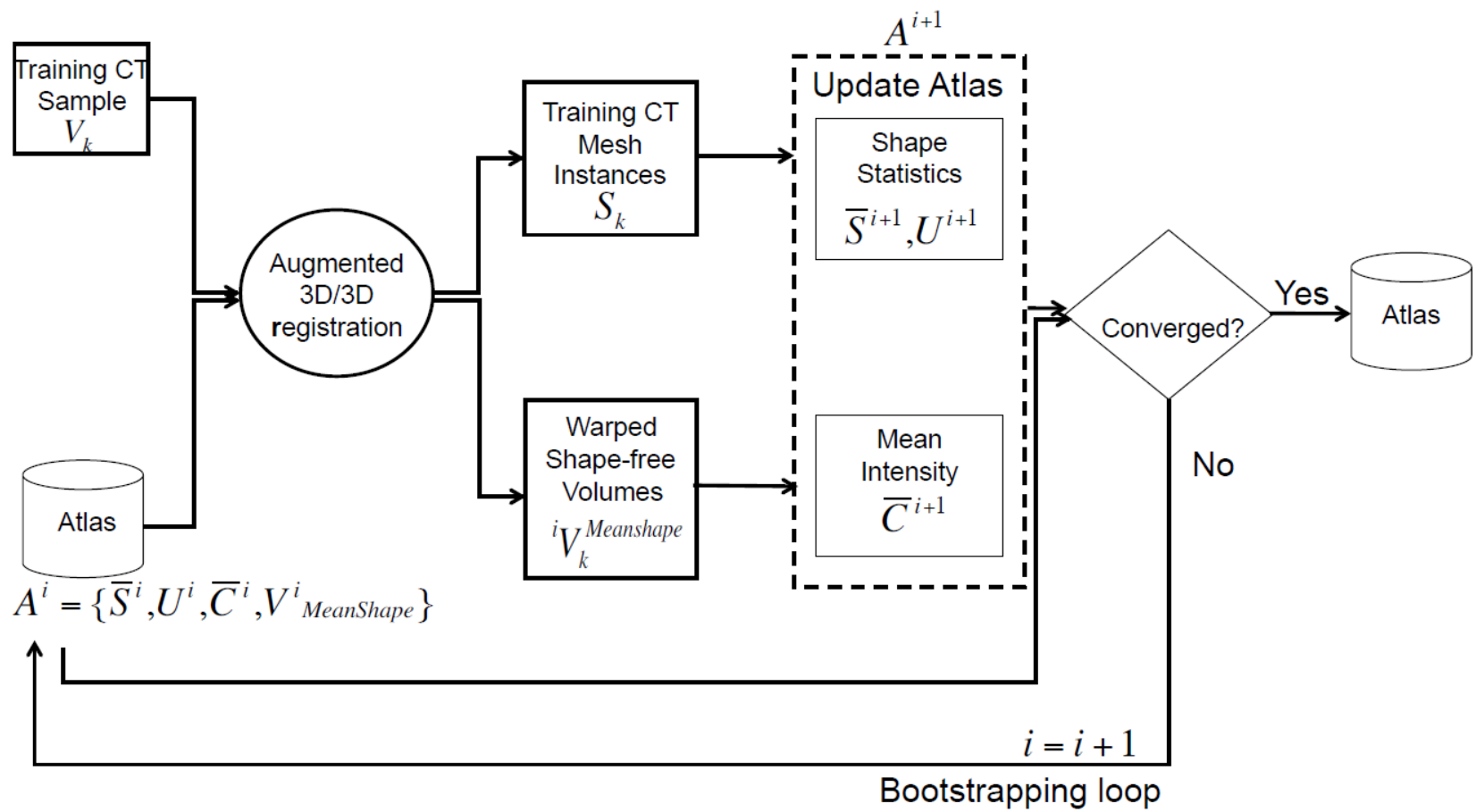
Technical Summary: Template Bias

- Template is important. The template represents the average anatomy in the given population more or less.
- Three images were selected at random from the training population as templates image and the three atlas were built by these template images.



Source: Gouthami Chintalapann "Statistical Atlases of Bone Anatomy and Their Applications"

Technical Summary: Iterative Bootstrapping Framework



Source: Gouthami Chintalapann "Statistical Atlases of Bone Anatomy and Their Applications"

Technical Summary: Algorithm for Iterative Bootstrapping Framework

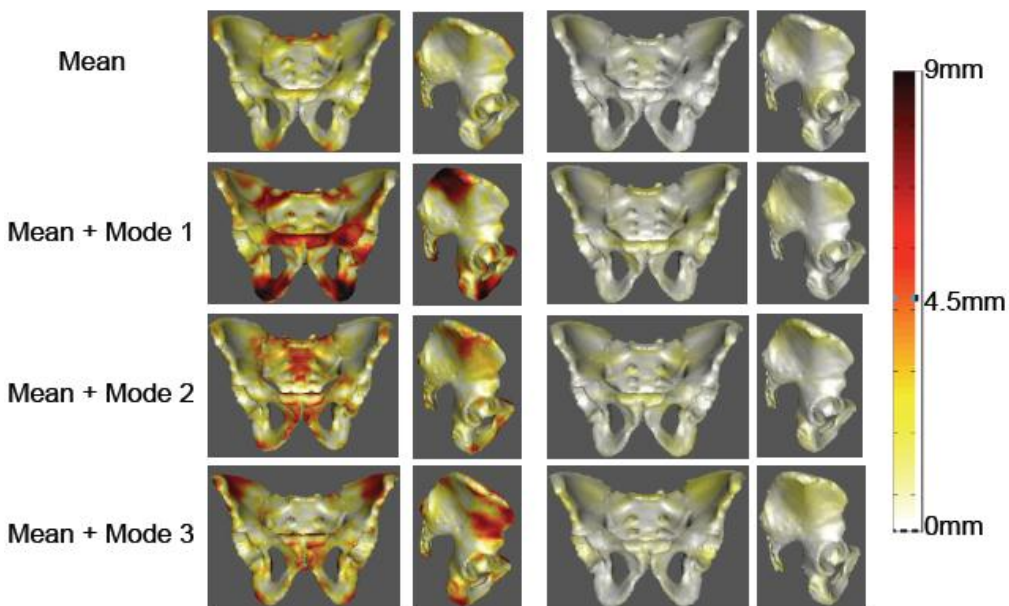
Iterative Bootstrapping Technique

Require: An atlas $A^0 = \{\bar{S}^0, U^0, \bar{C}^0\}$, training sample images, $V_k, k = 1..N$

- 1: Set $i = 0$
 - 2: ${}^iV_{meanshape} = \text{CreateMeanshapeVolume}(\bar{S}^i, \bar{C}^i)$
 - 3: **for** $k = 1$ to N **do** {each training image}
 - 4: [Deformably register the training images to the atlas mean shape volume and atlas shape modes]
 $\{ {}^iV_k^{Meanshape}, S_k \} = \text{DeformableRegistration}({}^iV_{MeanShape}, \bar{S}^i, U^i, V_k)$
 - 5: **end for**
 - 6: Update shape model, recompute mean shape and shape variational modes using principal component analysis. Let the new mean shape be \bar{S}^{i+1} and the shape modes be U^{i+1}
 - 7: Update the mean intensity polynomial. Refit the polynomials to the new mean shape mesh, $S^{\bar{i}+1}$ and the warped volumes, ${}^iV_k^{Meanshape}$. Let the new mean intensity polynomial be $C^{\bar{i}+1}$. The new updated atlas is given as follows:
 $A^{i+1} = \{\bar{S}^{i+1}, U^{i+1}, \bar{C}^{i+1}\}$
 - 8: $\Delta = \text{Compare}(A^i, A^{i+1})$
 - 9: If Δ is very small, return A^{i+1} . Otherwise, set $i = i+1$. Go to step 3.
-

Source: Gouthami Chintalapann "Statistical Atlases of Bone Anatomy and Their Applications"

Technical Summary: Experiments and Results



Summary of surface residual errors between the ground truth and the atlas reconstructed model with first 15 eigenmodes.

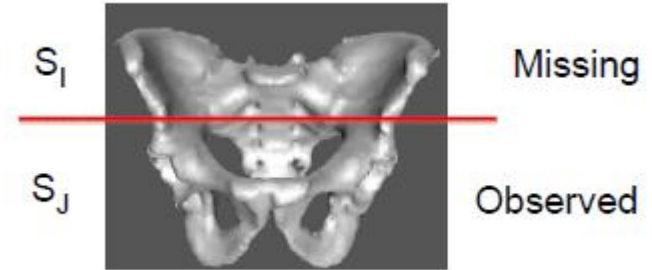
#	Iteration 1		Iteration 3		Iteration 5	
	avg (mm)	max (mm)	avg (mm)	max (mm)	avg (mm)	max (mm)
1	1.42	8.33	1.08	7.79	1.04	8.19
2	1.46	8.25	1.36	7.78	1.41	10.04
3	1.78	10.85	1.29	10.79	1.27	10.27
4	1.86	8.05	1.62	12.85	1.26	7.65
5	2.17	16.34	1.57	10.45	1.60	10.7
6	1.68	7.62	1.31	6.71	1.34	7.94
7	1.45	10.54	1.02	6.21	1.04	7.14
8	2.41	11.22	1.51	8.23	1.62	8.30
9	1.46	8.25	1.36	7.78	1.40	10.04
10	2.16	8.57	1.15	8.74	1.10	7.96
avg	1.79	9.80	1.33	8.7362	1.31	8.82

After the iterative bootstrapping, the mode Patterns exhibited by the three atlases were similar and leading to low registration error.

Source: Gouthami Chintalapann "Statistical Atlases of Bone Anatomy and Their Applications"

Technical Summary: Statistical Atlas-Based Extrapolation

The goal is to estimate the missing part from the observed part prior and a statistical model \bar{S} and U of full Anatomy.



If we know the $\vec{\lambda}$, we can estimate the full anatomy by \bar{S} and U .

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

We can compute the $\vec{\lambda}$ according the equation below:

$$\vec{\lambda} = U * (S^{true} - \bar{S})$$

Now, we just have part of S^{true} . How can we compute $\vec{\lambda}$ in this condition?

Source: Gouthami Chintalapann "Statistical Atlases of Bone Anatomy and Their Applications"

Technical Summary: Statistical Atlas-Based Extrapolation

- From the partial data, we manually segment and extract random sample points $p^k, k = 1, 2, \dots, m$, and try to register these points to observed part of the atlas. The transformation between the atlas and the partial data can be described in one equation as follows:

$$F^t * p^k \approx \bar{S}_j^k + \vec{\lambda}^t * U_j^k$$

Now, we can estimate the $\vec{\lambda}^t$ according these points by solving the above equation.

- Having computed the optimal λ , we can estimate the missing region as follows

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

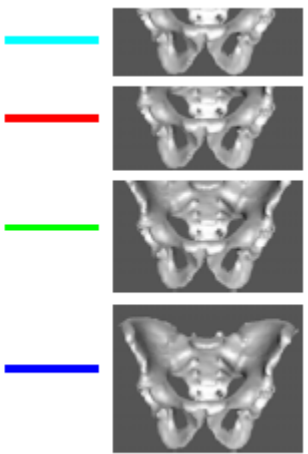
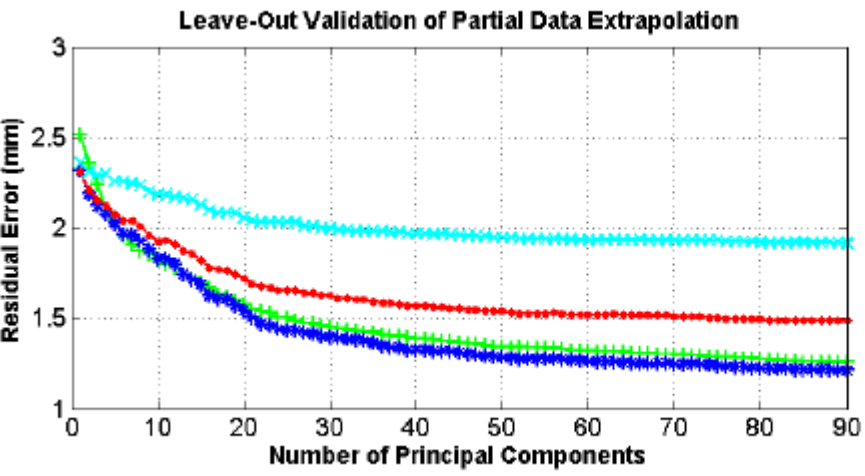
- Since we already have exact information for the observed part from the CT, we replace the estimated observed part with the true data

$$S^{est} = \begin{bmatrix} S_I^{est} \\ S_J^{true} \end{bmatrix}$$

Technical Summary: Experiments and Results

- This time , we do leave-n-out analysis for 6 datasets.
- Use surface distance error as error metric.

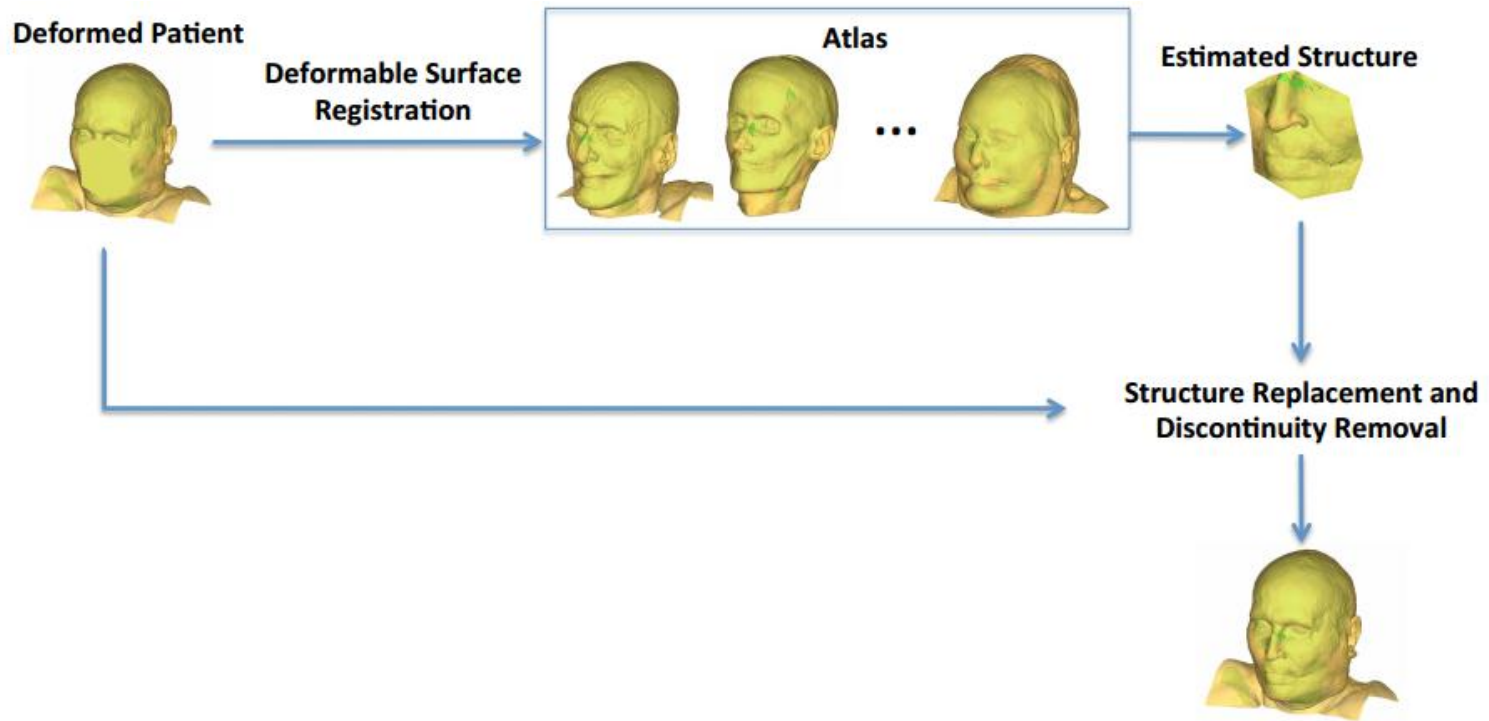
#	Full CT				Partial CT			
	mean	max	std	95%	mean	max	std	95%
1	1.41	8.20	1.06	3.45	1.97	14.06	1.69	5.17
2	1.88	7.25	1.42	4.71	2.15	12.25	1.73	5.28
3	1.55	7.72	1.20	3.77	2.45	11.33	2.08	6.89
4	1.32	5.77	1.01	3.27	1.69	9.06	1.43	4.58
5	1.72	8.29	1.17	3.79	1.92	9.87	1.24	3.93
6	1.69	10.58	1.55	4.78	2.64	14.87	2.27	7.18
avg	1.59	7.96	1.23	3.96	2.08	11.40	1.74	5.50



Leave-out analysis of proposed method for varying amount of the observed data.

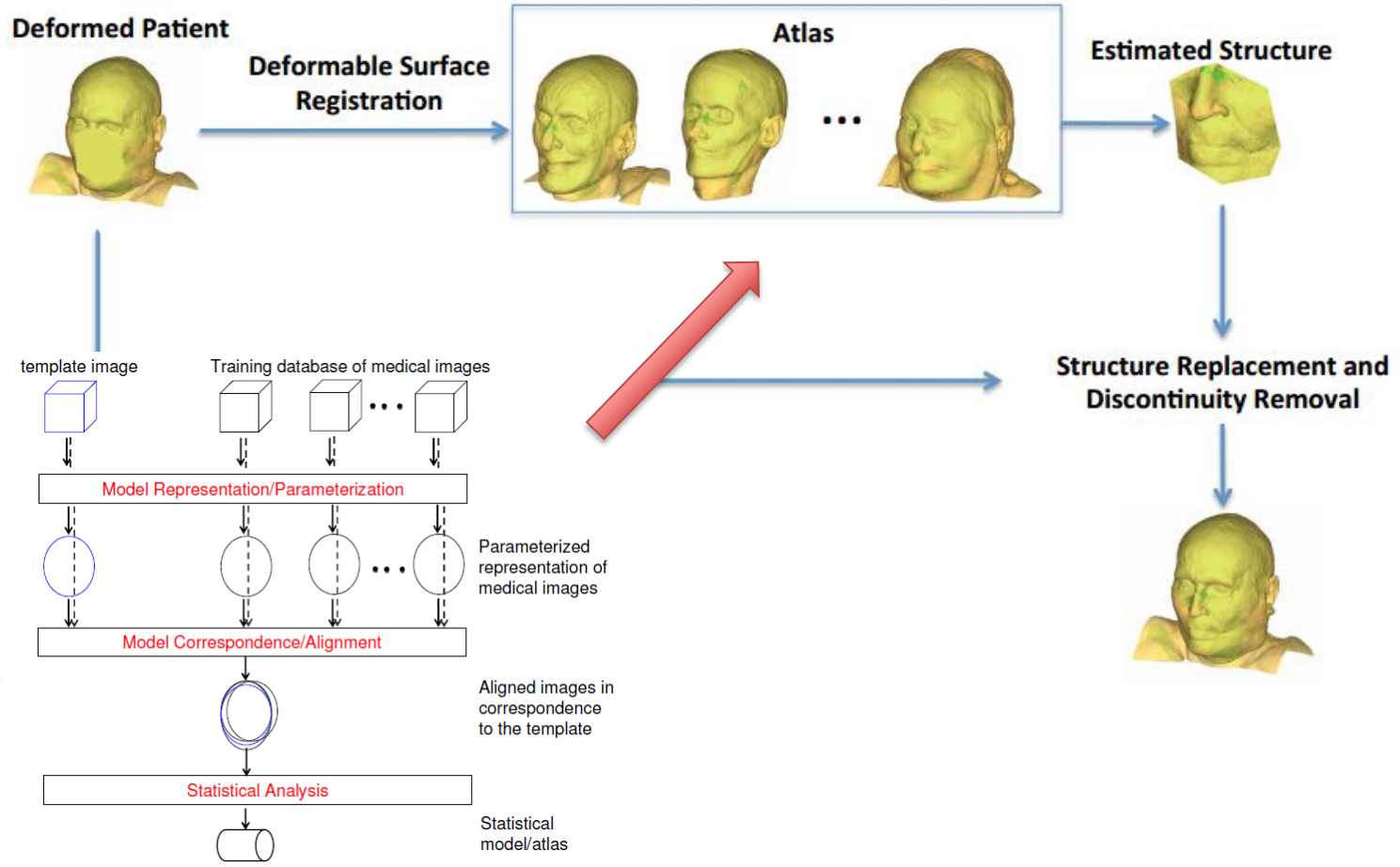
Source: Gouthami Chintalapann "Statistical Atlases of Bone Anatomy and Their Applications"

Analysis



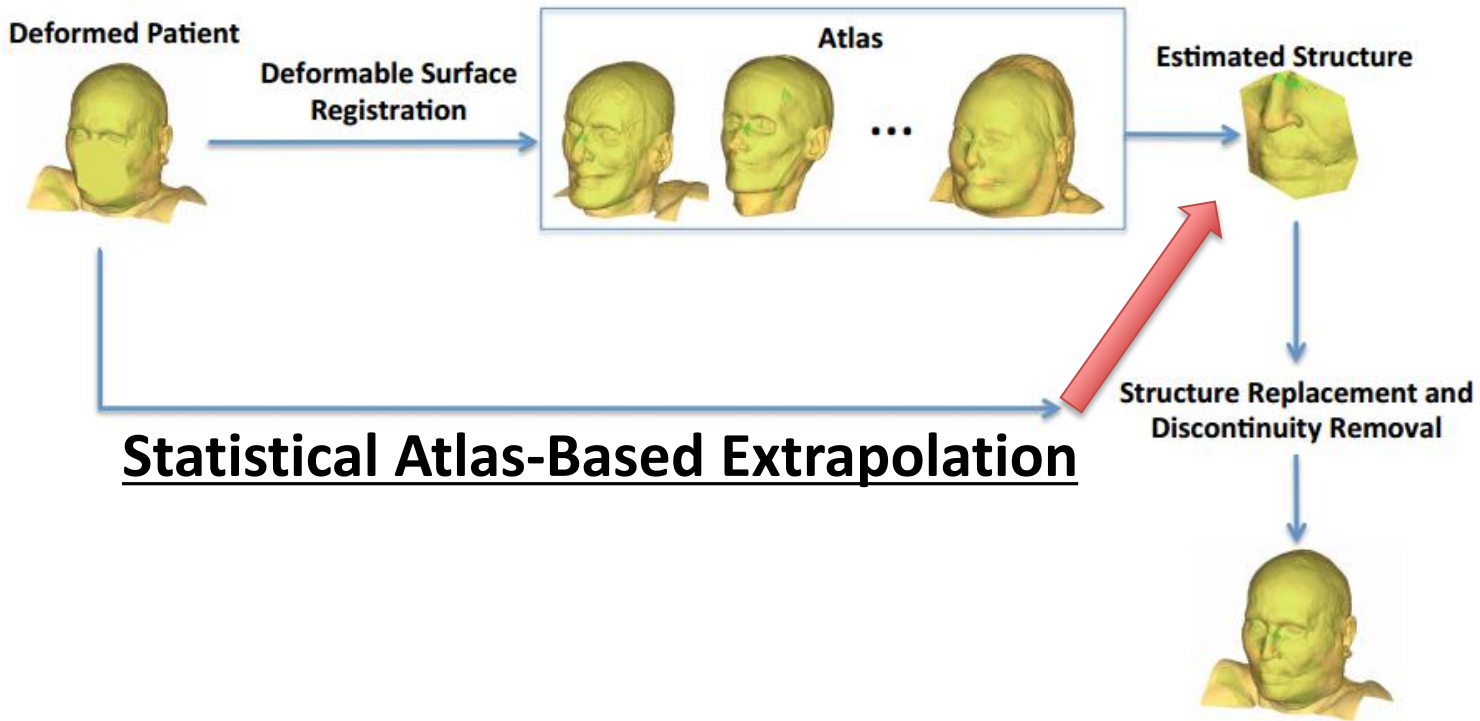
Cadaver CT Courtesy of Dr. Otake

Analysis



Cadaver CT Courtesy of Dr.Otake

Analysis



Cadaver CT Courtesy of Dr.Otake

Iterative Bootstrapping Technique

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 - 4: [Deformably register the training images to the atlas mean shape volume and atlas shape modes]
 $\{ {}^iV_k^{Meanshape}, S_k \} = \text{DeformableRegistration}({}^iV_{MeanShape}, \bar{S}^i, U^i, V_k)$
 - 5: **end for**
 - 6: Update shape model, recompute mean shape and shape variational modes using principal component analysis. Let the new mean shape be \bar{S}^{i+1} and the shape modes be U^{i+1}
 - 7: Update the mean intensity polynomial. Refit the polynomials to the new mean shape mesh, $S^{\bar{i}+1}$ and the warped volumes, ${}^iV_k^{Meanshape}$. Let the new mean intensity polynomial be $C^{\bar{i}+1}$. The new updated atlas is given as follows:
 $A^{i+1} = \{\bar{S}^{i+1}, U^{i+1}, \bar{C}^{i+1}\}$
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-

Iterative Bootstrapping Technique

Require: An atlas $A^0 = \{\bar{S}^0, U^0, \bar{C}^0\}$, training sample images, $V_k, k = 1..N$

- 1: Set $i = 0$
- 2: ${}^iV_{\text{meanshape}} = \text{CreateMeanshapeVolume}(\bar{S}^i, \bar{C}^i)$
- 3: for $k = 1$ to N do {each training image}
- 4: [Deformably register the training images to the atlas mean shape volume and atlas shape modes]
 $\{ {}^iV_k^{\text{Meanshape}}, S_k \} = \text{DeformableRegistration}({}^iV_{\text{MeanShape}}, \bar{S}^i, U^i, V_k)$
- 5: end for
- 6: Update shape model, recompute mean shape volume and principal component analysis. Let the principal component modes be U^{i+1}
- 7: Update the mean intensity polynomial and mean shape mesh, \bar{S}^{i+1} and the warped volume. Let the mean intensity polynomial be \bar{C}^{i+1} . The new updated atlas $A^{i+1} = \{\bar{S}^{i+1}, U^{i+1}, \bar{C}^{i+1}\}$
- 8: $\Delta = \text{Compare}(A^i, A^{i+1})$
- 9: If Δ is very small, return A^{i+1} . Otherwise, set $i = i+1$. Go to step 3.

- Currently, we just use triangular meshes to represent the surface of the face.
- Therefore, we can't compute the intensity polynomial and mean shape volume in each iteration.

Question?