Medical Image Synthesis via Monte Carlo Simulation

An Application of Statistics in Geometry

&

Building a Geometric Model with Correspondence

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Population Simulation Requires Statistical Profiling of Shape

Goal: Develop a methodology for generating realistic synthetic medical images *AND* the attendant “ground truth” segmentations for objects of interest.

Why: Segmentation method evaluation.

How: Build and sample probability distribution of shape.

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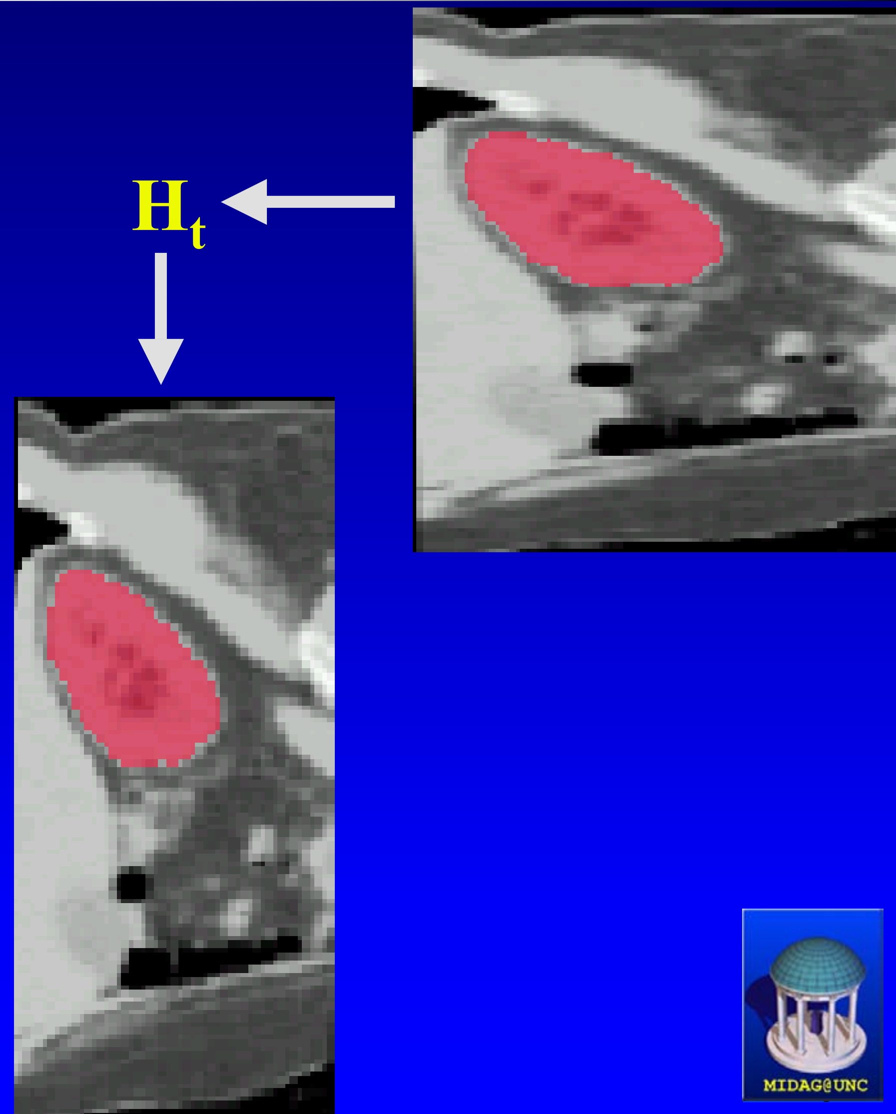
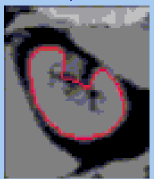
Basic Idea

- New images via deformation of template geometry and image.

- Characteristics
  - Legal images represent statistical variation of shape over a training set.
  - Image quality as in a clinical setting.

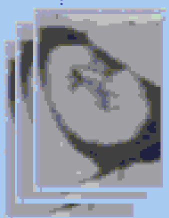


The Process



Template: I_0, S_0

Training: $\{I_t\}$



Registration

$I_t \cong H_t(I_0)$

Generate FPM

Analyze $\{H_t\}$ via PCA on {FPM displacements} to yield Pr(FPM)

Training

Generate random diffeomorphic H_s: Sample Pr(FPM) and interpolate

Template transformation

$H_{s,t} = H_s \cdot H_t^{-1}$

Synthetic images from template I_t:

$I_s' = H_{s,t}(I_t)$

$S_s' = S_s = H_s(S_0)$

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Sampling

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Registration

- Registration – Composition of Two Transformations
  - Linear – MIRIT, Frederik Maes
    - Affine transformation, 12 dof
  - Non-linear–Deformation Diffeomorphism, Joshi
- For all I_t , $I_t \cong \mathrm{H}_t(I_0)$ and $S_t \cong \mathrm{H}_t(S_0)$

Image Warp by Fluid Deformation

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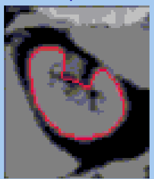
Consequence of an Erroneous H_t



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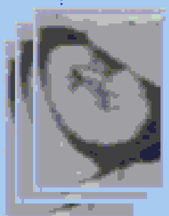

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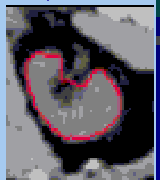

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Sampling

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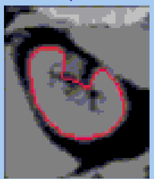
Generating the Statistics of H_t



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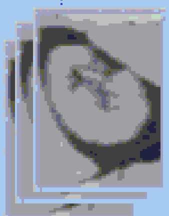

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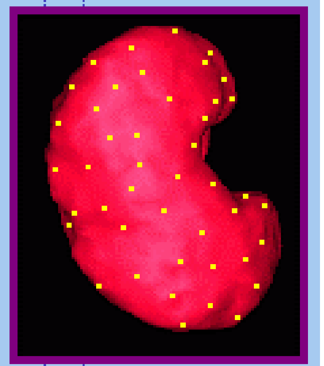

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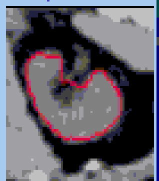

Generate random diffeomorphic H_s: Sample Pr(FPM) and interpolate

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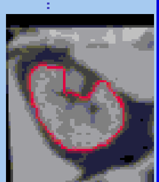

Sampling

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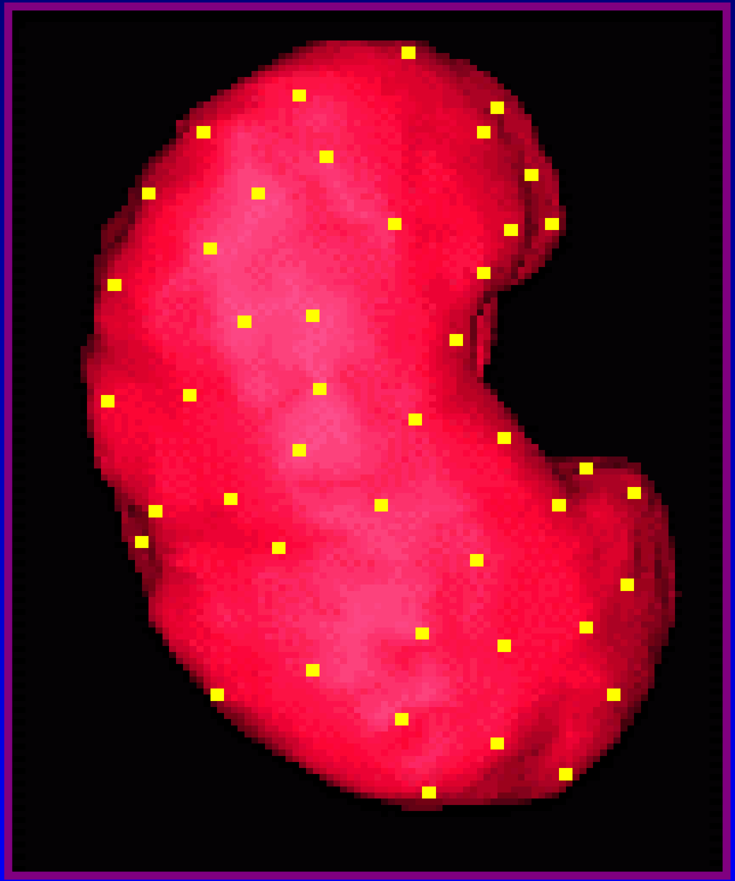
Fiducial Point Model

- H_t is *locally correlated*
- Fiducial point choice via greedy iterative algorithm
- H_t' determined by Joshi Landmark Deformation Diffeomorphism
- The Idea: Decrease

$$\frac{1}{T \bullet N_0} \sum_{t=1}^{T} \sum_{x \in S_0} | H_t(x) - H_t'(x) |$$



FPM Generation Algorithm

1. Initialize $\{\boldsymbol{F_m}\}$ with a few geometrically salient points on $\boldsymbol{S_0}$;
2. Apply the training warp function $\boldsymbol{H_t}$ on $\{\boldsymbol{F_m}\}$ to get the warped fiducial points: $\boldsymbol{F_{m,t}} = \boldsymbol{H_t}(\boldsymbol{F_m})$;
3. Reconstruct the diffeomorphic warp field $\boldsymbol{H'_t}$ for the entire image volume based on the displacements $\{\boldsymbol{F_{m,t}} - \boldsymbol{F_m}\}$;
4. For each training case t, locate the point $\boldsymbol{p_t}$ on the surface of $\boldsymbol{S_0}$ that yields the largest discrepancy between $\boldsymbol{H_t}$ and $\boldsymbol{H'_t}$;
5. Find most discrepant point $\boldsymbol{p}$ over the point set $\{\boldsymbol{p_t}\}$ established from all training cases. Add $\boldsymbol{p}$ to the fiducial point set;
6. Return to step 2 until a pre-defined optimization criterion has been reached.

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A locally accurate warp via FPM landmarks

- Volume overlap optimization criterion tracks mean warp discrepancy
- Under 100 fiducial points, of thousands on surface

Warped Image

and

Warped Segmentation

ATLAS WARP TRAINING

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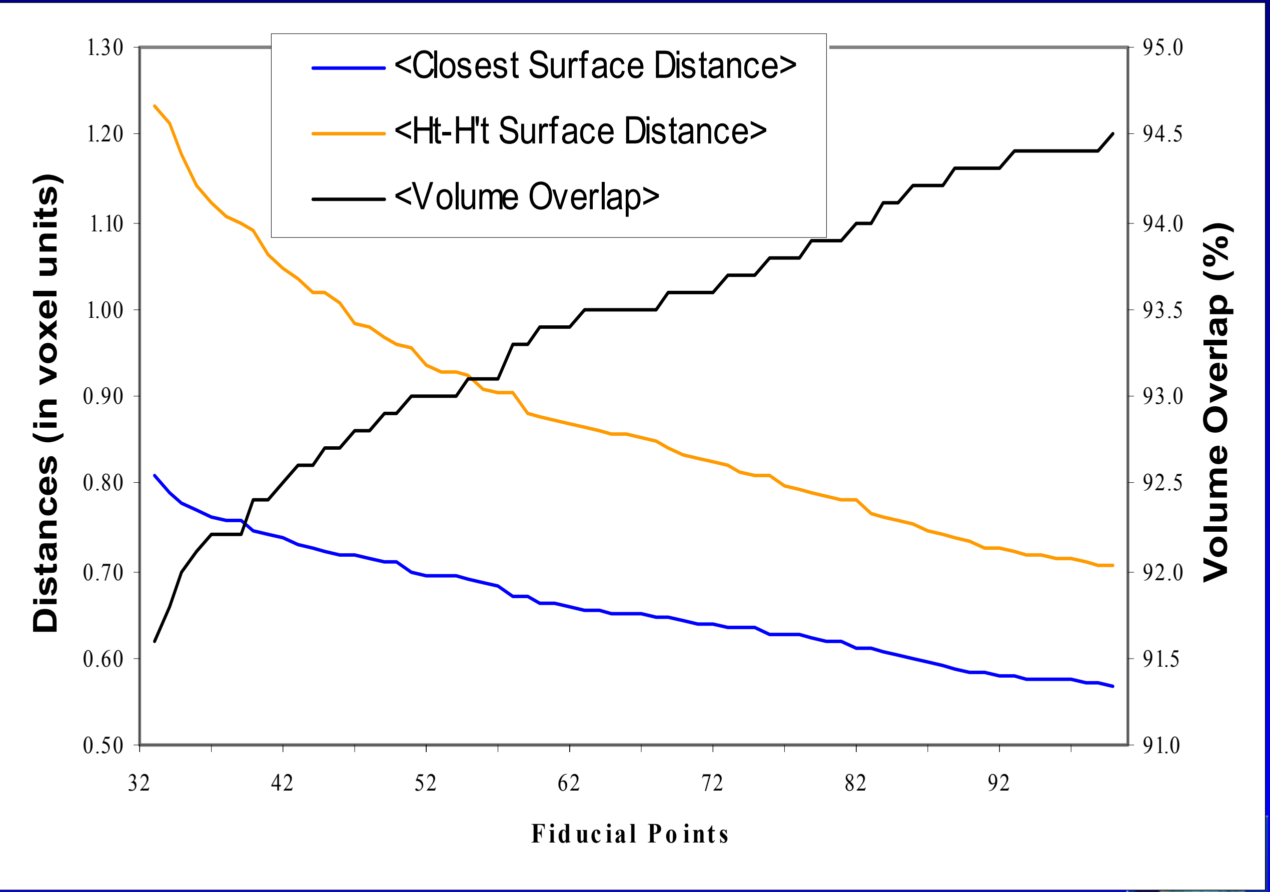
Human Kidney Example

- 36 clinical CT images in the training set
- Monotonic Optimization
- 88 fiducial points sufficiently mimick inter-human rater results (94% volume overlap)



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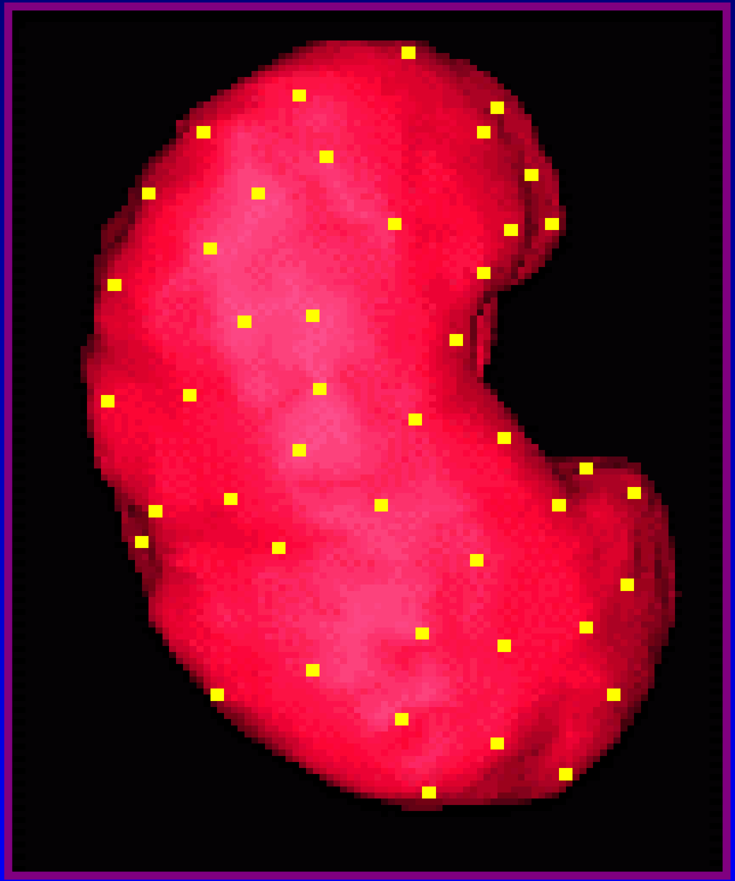
Fiducial Point Model Is an Object Representation with Positional Correspondence

- Positional correspondence is via the H' interpolated from the displacements at the fiducial points
- The correspondence makes this representation suitable for statistical analysis



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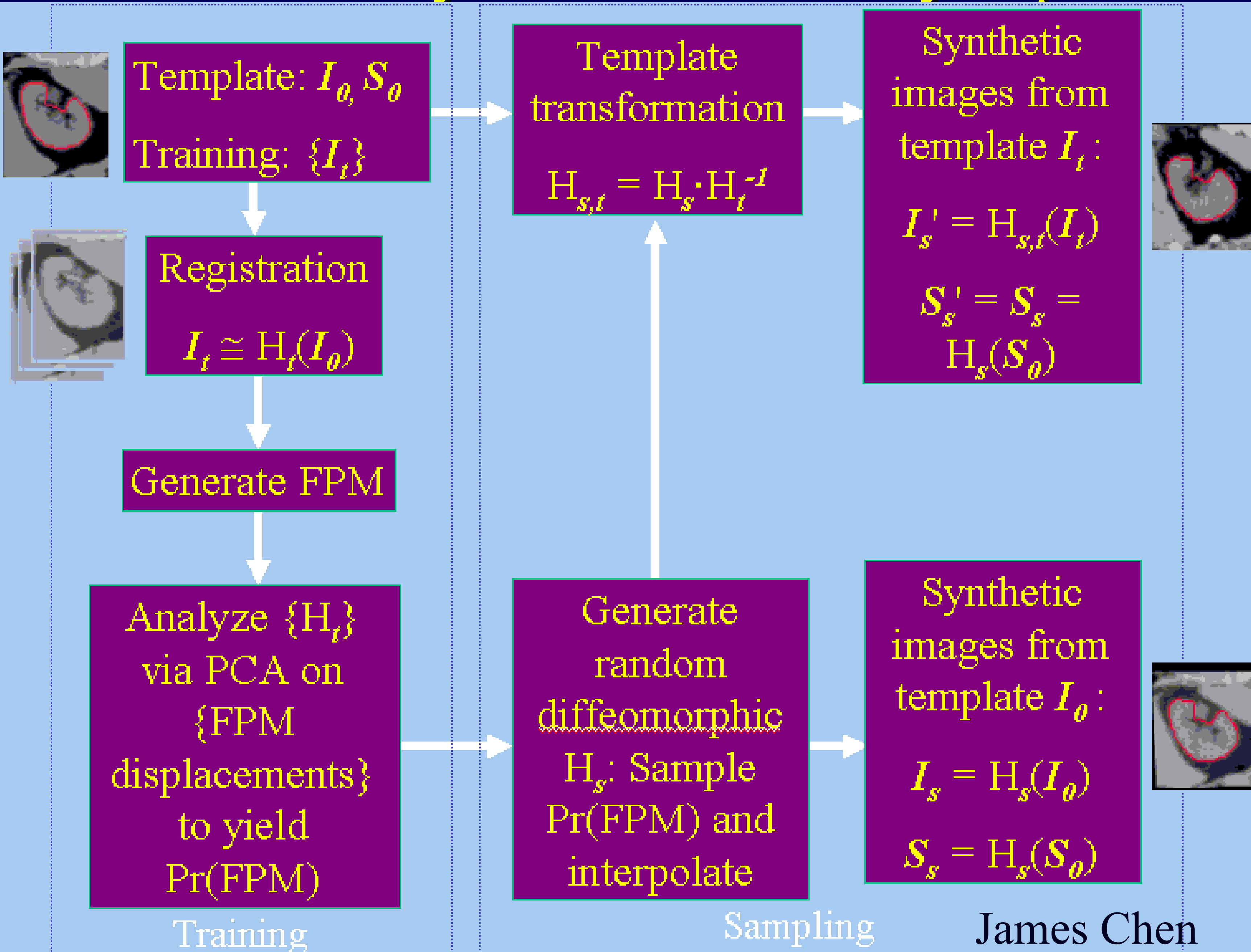
Statistical Analysis of the Geometry Representation



Principal Components Analysis of the FPM Displacements

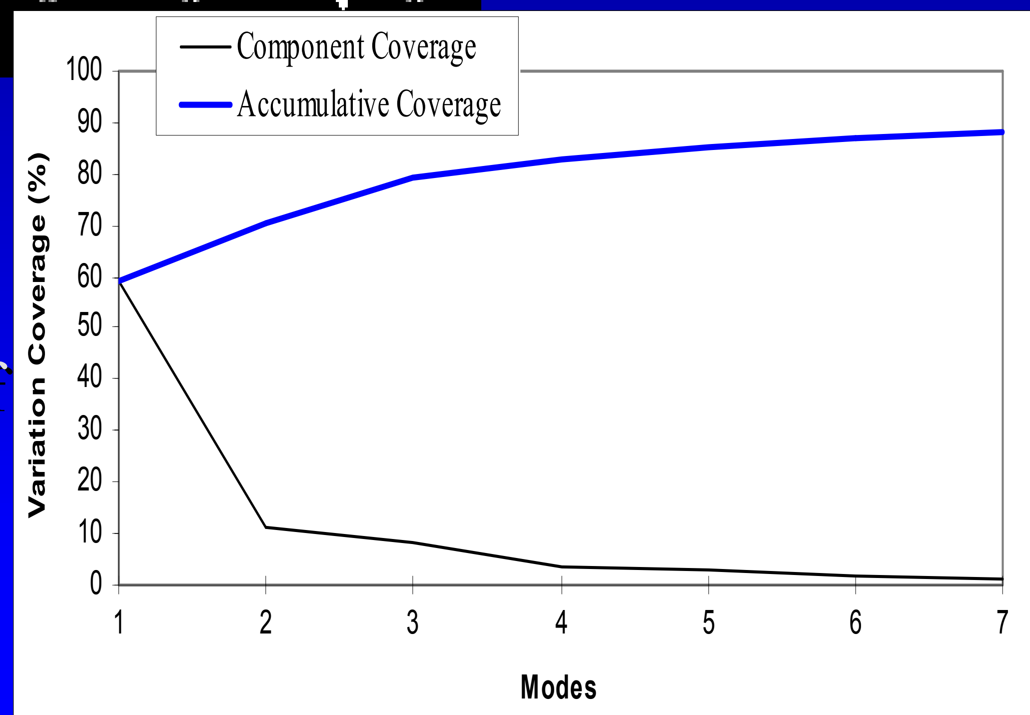
$$\vec{f}_0 = ((x_{f_1}, y_{f_1}, z_{f_1}), (x_{f_2}, x_{f_2}, x_{f_2}), \ldots, (x_{f_M}, y_{f_M}, z_{f_M}))$$

$$\vec{f}_t = H_t(\vec{f}_0)$$

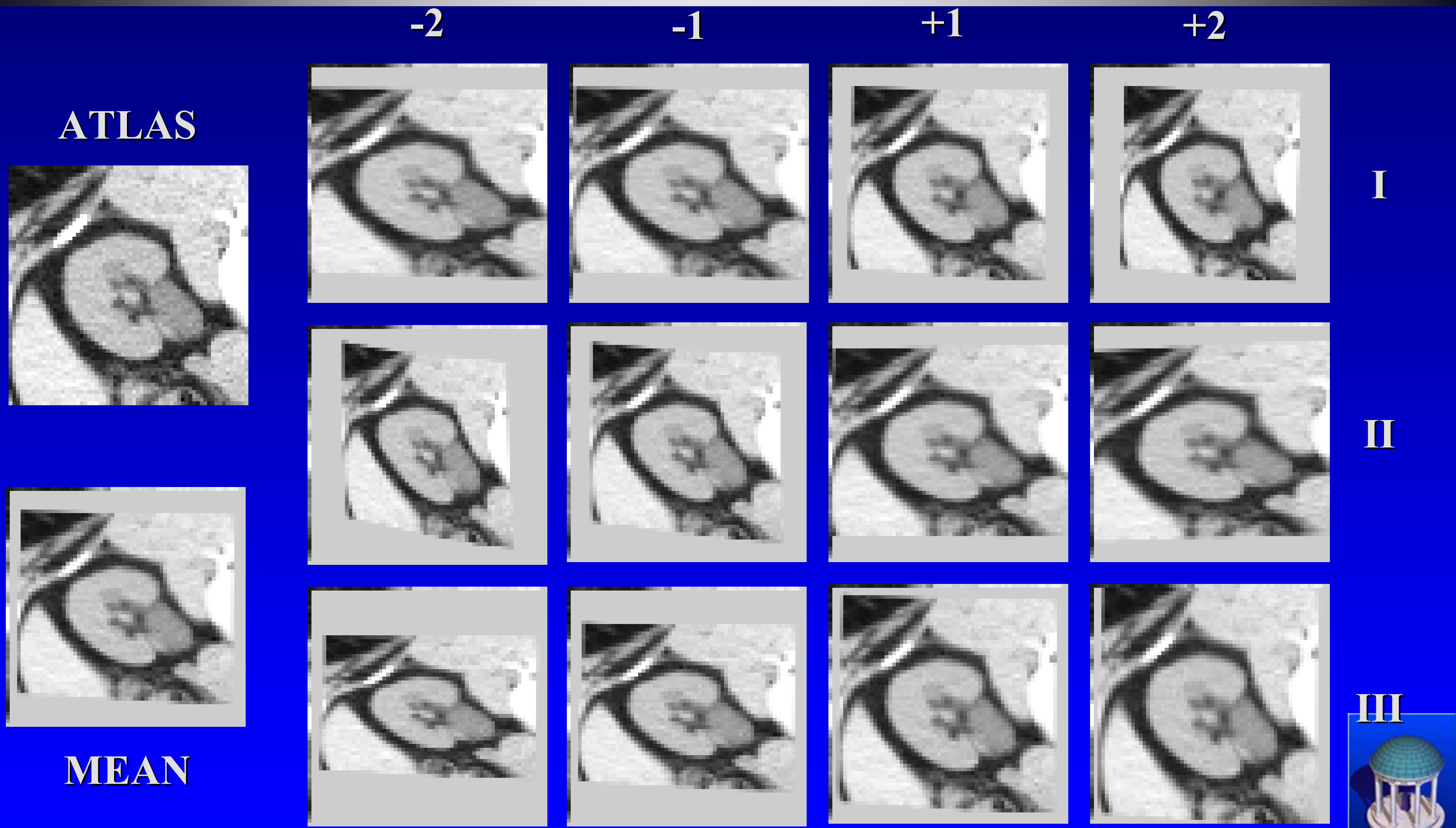
$$\vec{f}_s = <\vec{f}> + \sum_{k=1}^{n} b_k \cdot \vec{p}_k \qquad -3\sqrt{\lambda_k} \leq b_k \leq 3\sqrt{\lambda_k}$$

- Points in 3M-d space
- Analyze deviation from mean

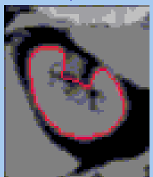
- Example: first *seven modes* of FPM cover 88% of the total variation.



Modes of Variation – Human Kidney



Generating Samples of Image Intensity Patterns



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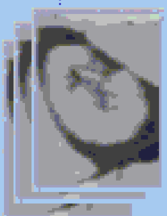

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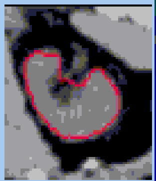

Synthetic images from template I_0:

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Sampling

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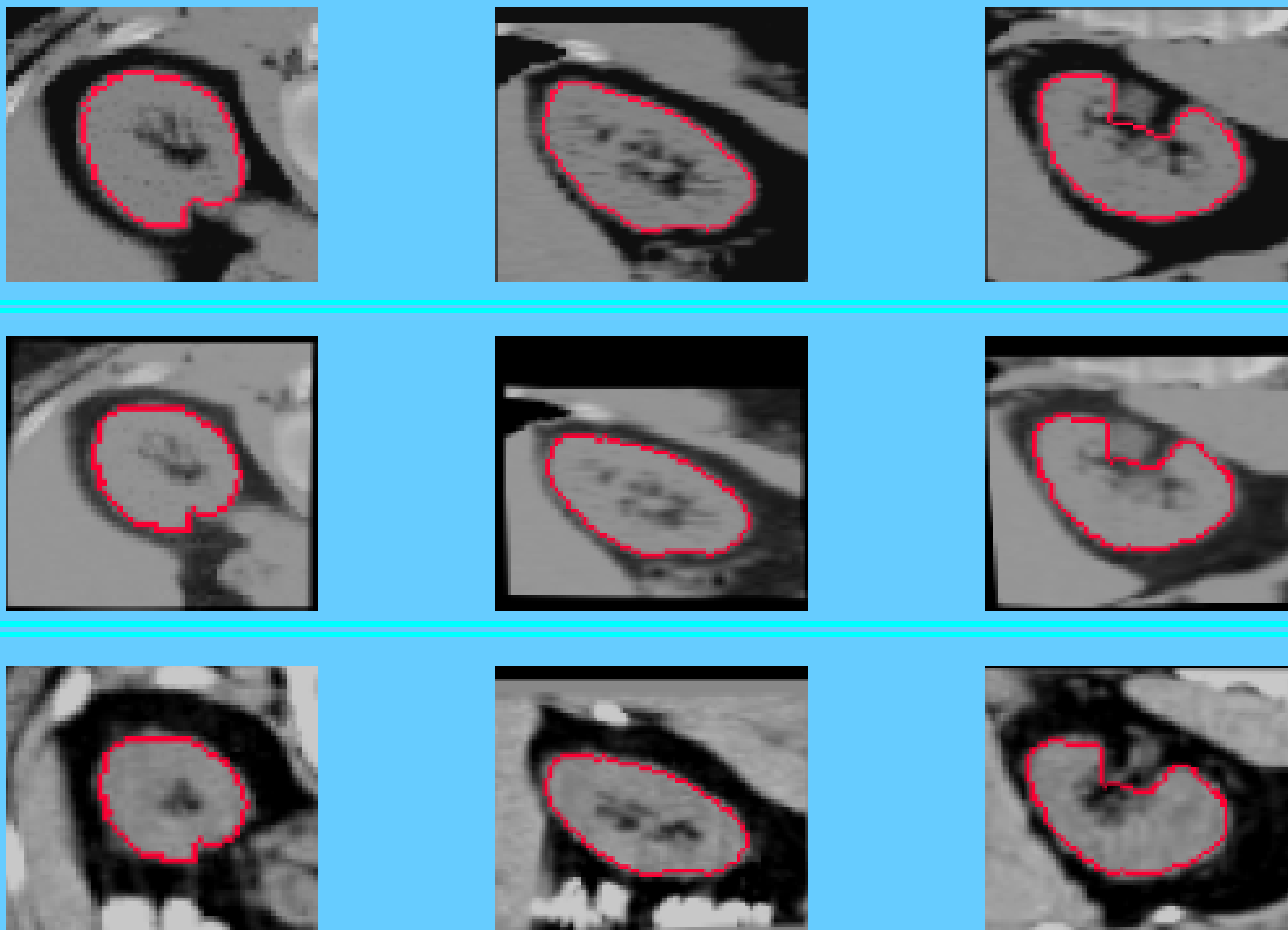
Results

Synthesis of CT images of kidney region



Template

Synthesized from $H_s(I_0)$

Synthesized from $H_{s,t}(I_t)$

Axial Sagittal Coronal

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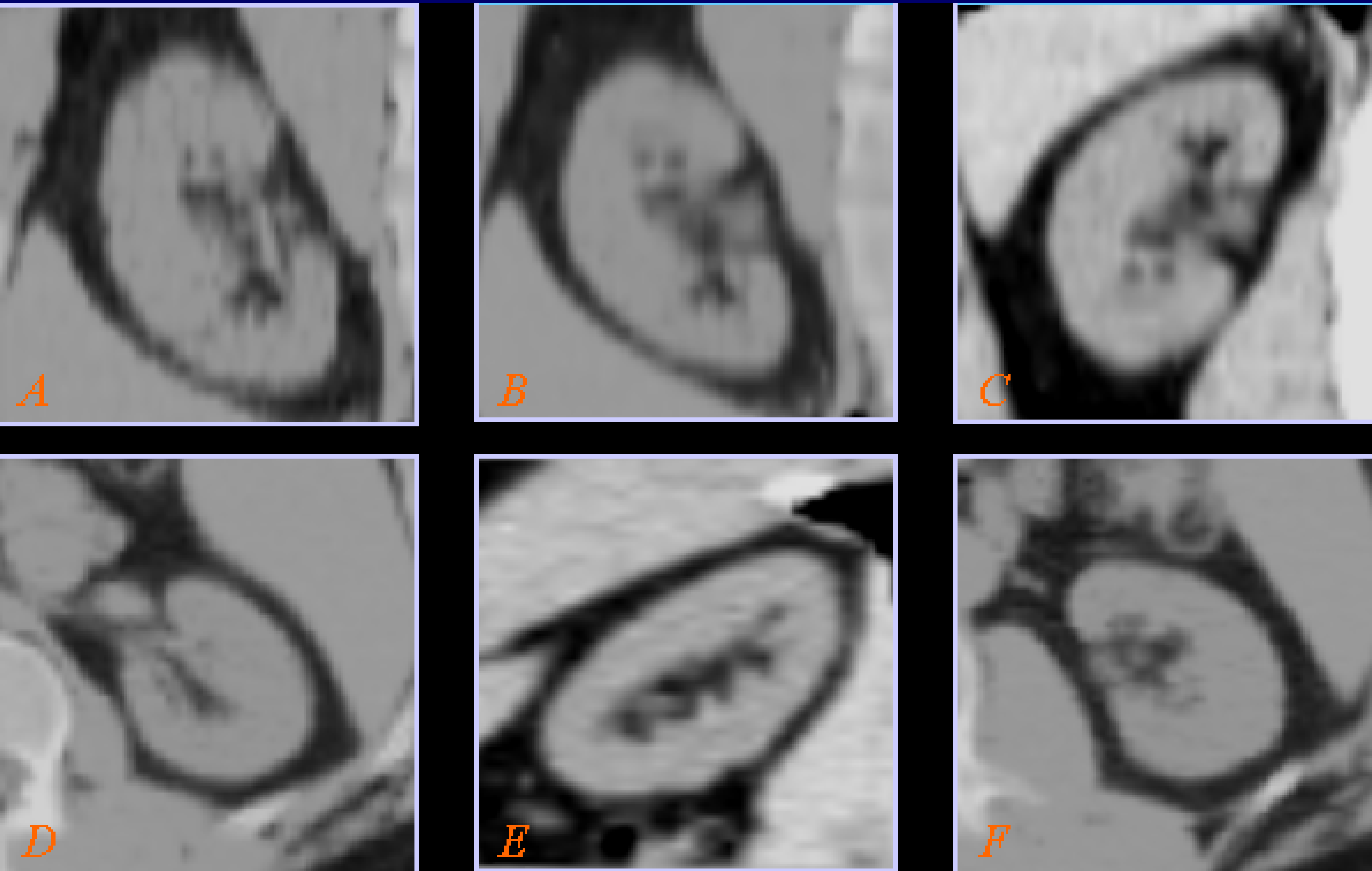
Results



Miscellaneous

- National Cancer Institute Grant P01 CA47982

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