Probabilistic Shape and Appearance Model for the Segmentation of Anatomic Structures within Tomographic Images of Laboratory Mice

HiRes 2001

New Developments in Small Animal Imaging Technology

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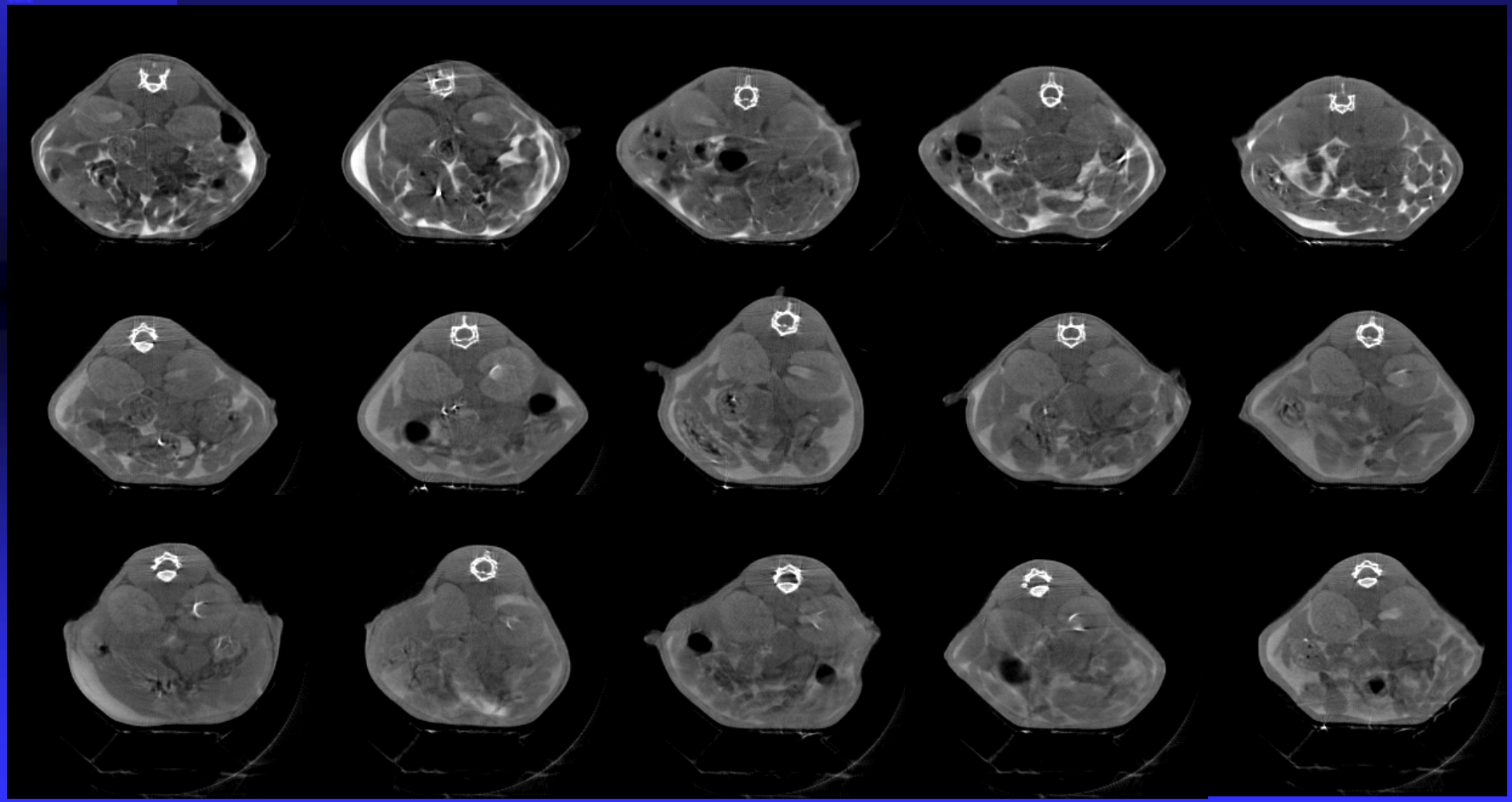
Outline

- Motivation for Research
- Starting Point: Active Shape Models (ASM)
- Development of a New Probabilistic Shape and Appearance Model (PSAM)
- Experimental Results on Medical Image Data
- Extension to 3D
- Conclusions

Motivation for Research

- We need a segmentation algorithm capable of :
  - handling semi-rigid objects within complex backgrounds
  - handling objects with faint, obscured, or partially missing object boundaries
  - combining the segmentation and recognition tasks into one (no post-processing for object ID)
  - using available a priori information on object shape & appearance
  - generating a segmentation confidence metric

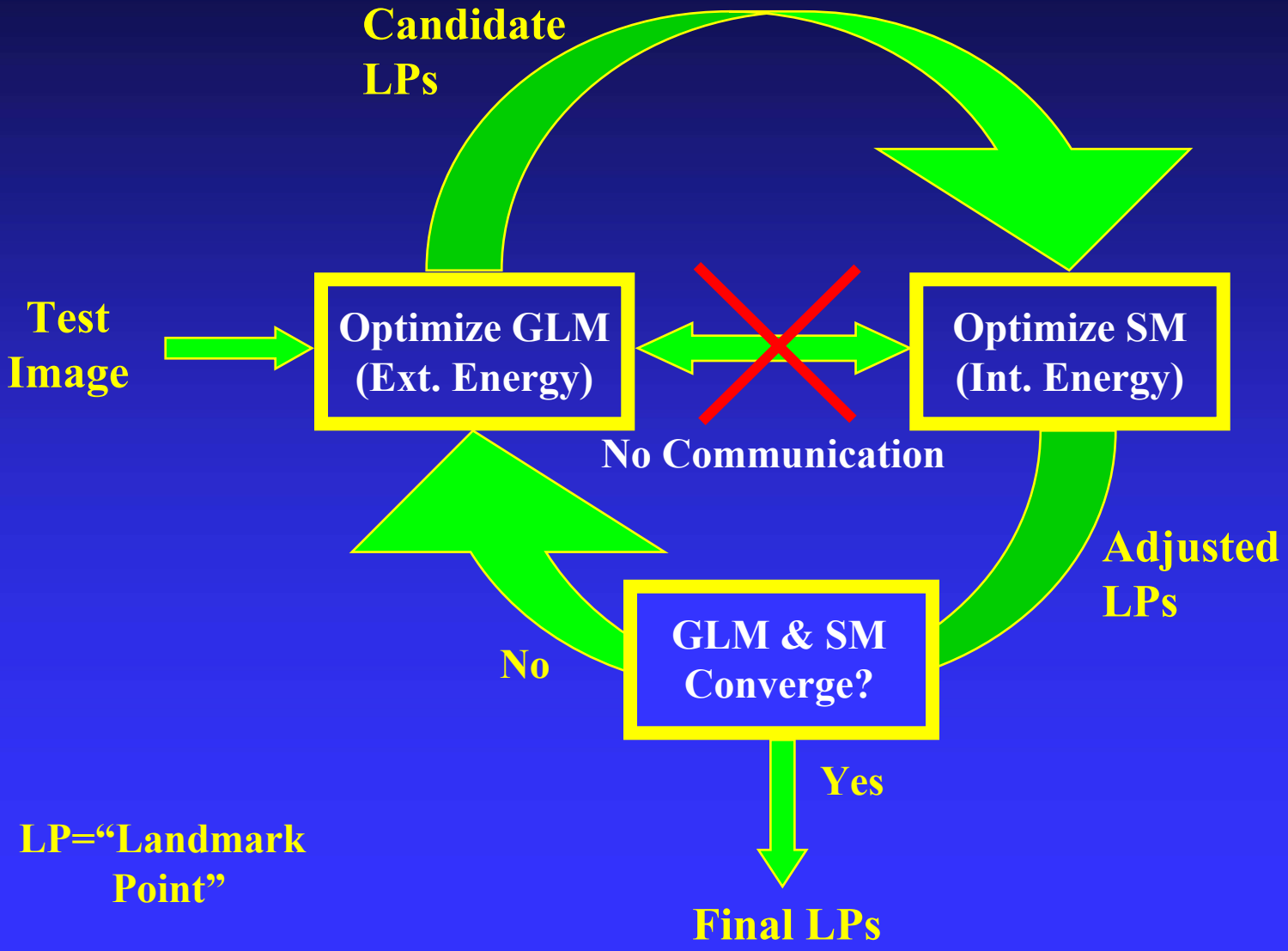
Semi-Rigid Objects on a Complex Background….



Starting Point: Active Shape Models [Cootes 95]

- Mid-level (both data- and model-driven) deformable model technique (good for semi-rigid objects)
- Landmark point (LP)-based boundary representation
- Training process results in a two-component ASM:
  - Gray-level model (GLM)
  - Global shape model (GSM)

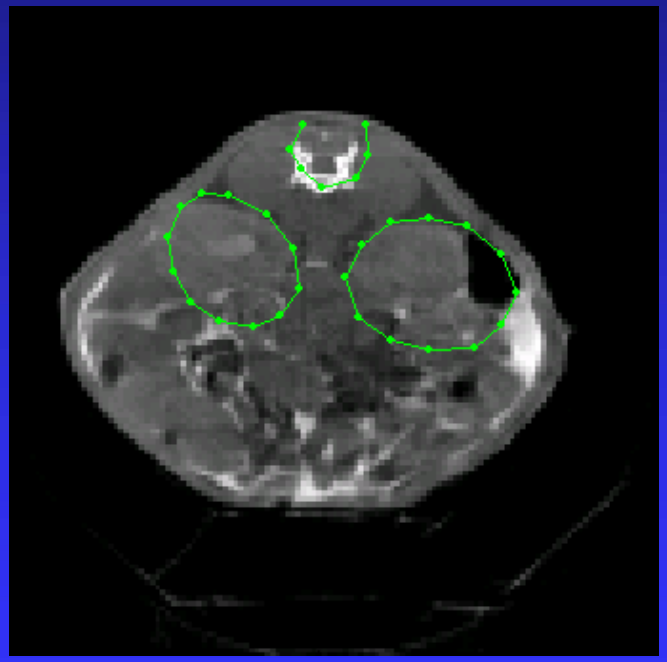
ASM Optimization Scheme

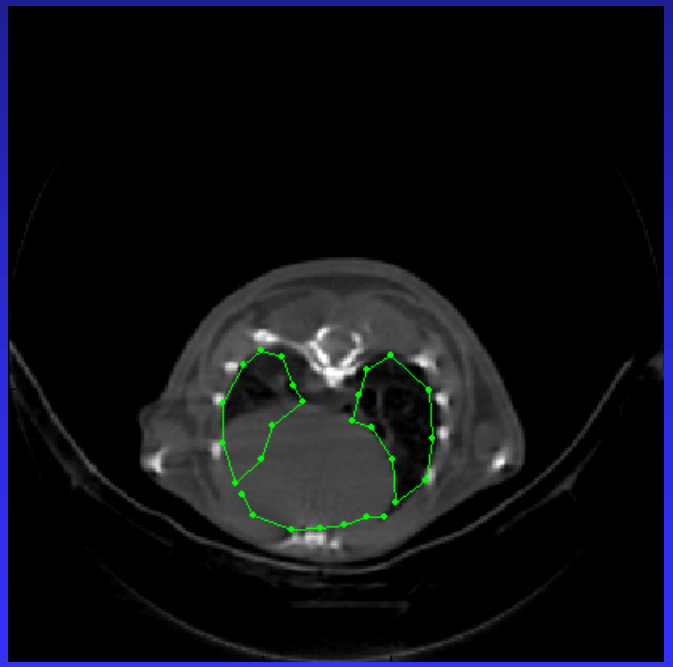


ASM Strengths

- Uses a priori information effectively
- Handles semi-rigid objects with faint boundaries
- Supports open and/or closed boundary models
- Mathematically straightforward

Fundamental Problems Still Limit ASM Performance





ASM Segmentation Results

Development of a New Probabilistic Shape and Appearance Model (PSAM)

The Goals for the New PSAM:

- Poses object segmentation/recognition as a probabilistic problem
- Theoretical framework is general:
  - Supports the use of a variety of image features
  - Generalizes previous work in probabilistic shape modeling techniques (e.g. Kervrann, Wang)
- Like ASM, formulation makes use of the a priori object information from a training set of:
  - (x, y) coordinate-based shape vectors (GSM)
  - gray-level profiles (GLM)
- Includes an effective model optimization strategy

PSAM Employs Compound Bayesian Decision Theory [Duda and Hart, 73]

- Bayes rule for single events:

$$P(\omega \mid \mathbf{x}) = \frac{p(\mathbf{x} \mid \omega) P(\omega)}{p(\mathbf{x})}$$

ω : an event

$\mathbf{x}$: a related observation

- Compound version of Bayes rule for multiple simultaneous events:

$$P(\boldsymbol{\omega} \mid \mathbf{X}) = \frac{p(\mathbf{X} \mid \boldsymbol{\omega}) P(\boldsymbol{\omega})}{p(\mathbf{X})}$$

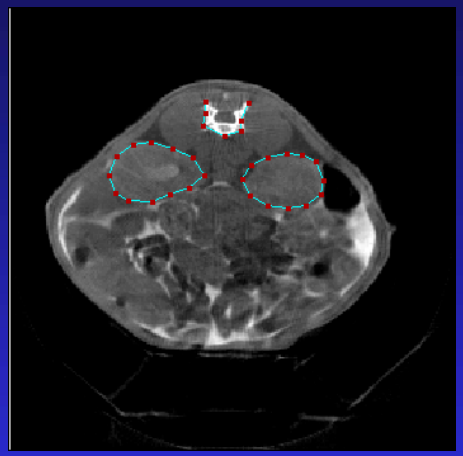
$\boldsymbol{\omega}$: a series of events

$\mathbf{X}$: a series of related observations

PSAM Events and Observations

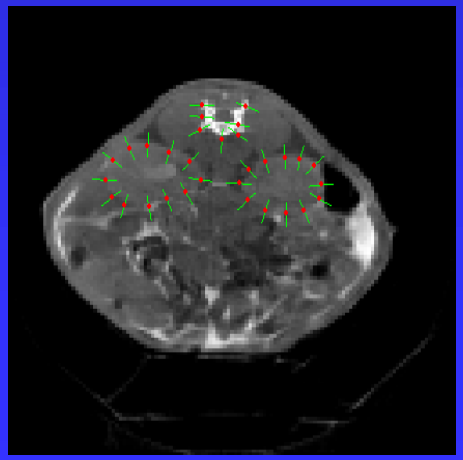
- Let our series of events be N (x, y) boundary LPs:

$$S_v = \begin{bmatrix} x_1 & y_1 \\ x_2 & y_2 \\ \dots & \dots \\ x_N & y_N \end{bmatrix}$$



- Let our series of observations be a N gray-level gradient profiles in the neighborhood of each LP:

$$G = \begin{bmatrix} g_1 \\ g_2 \\ \dots \\ g_N \end{bmatrix}$$



Compound Bayes Rule for PSAM

- Using our new set of events (boundary LPs) and our new set of observations (gray-level profiles):

$$P(S_v|G) = \frac{p(G|S_v)P(S_v)}{p(G)}$$

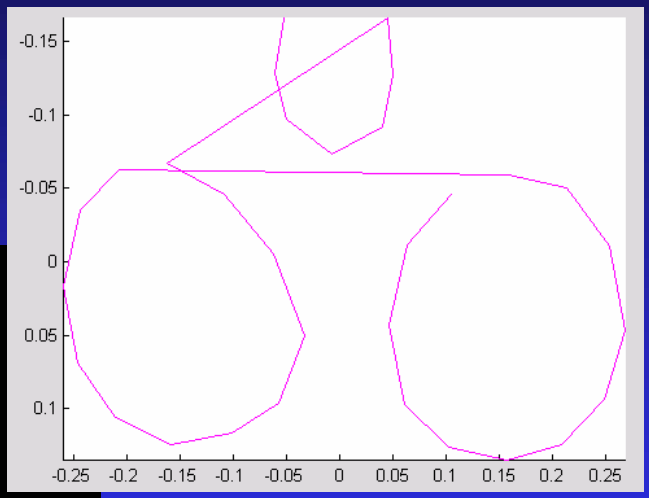
- Our goal is to find the boundary that corresponds to the maximum a posteriori probability (MAP):

$$P(S_v^*|G) = max_{S_v} \frac{p(G|S_v)P(S_v)}{p(G)}$$

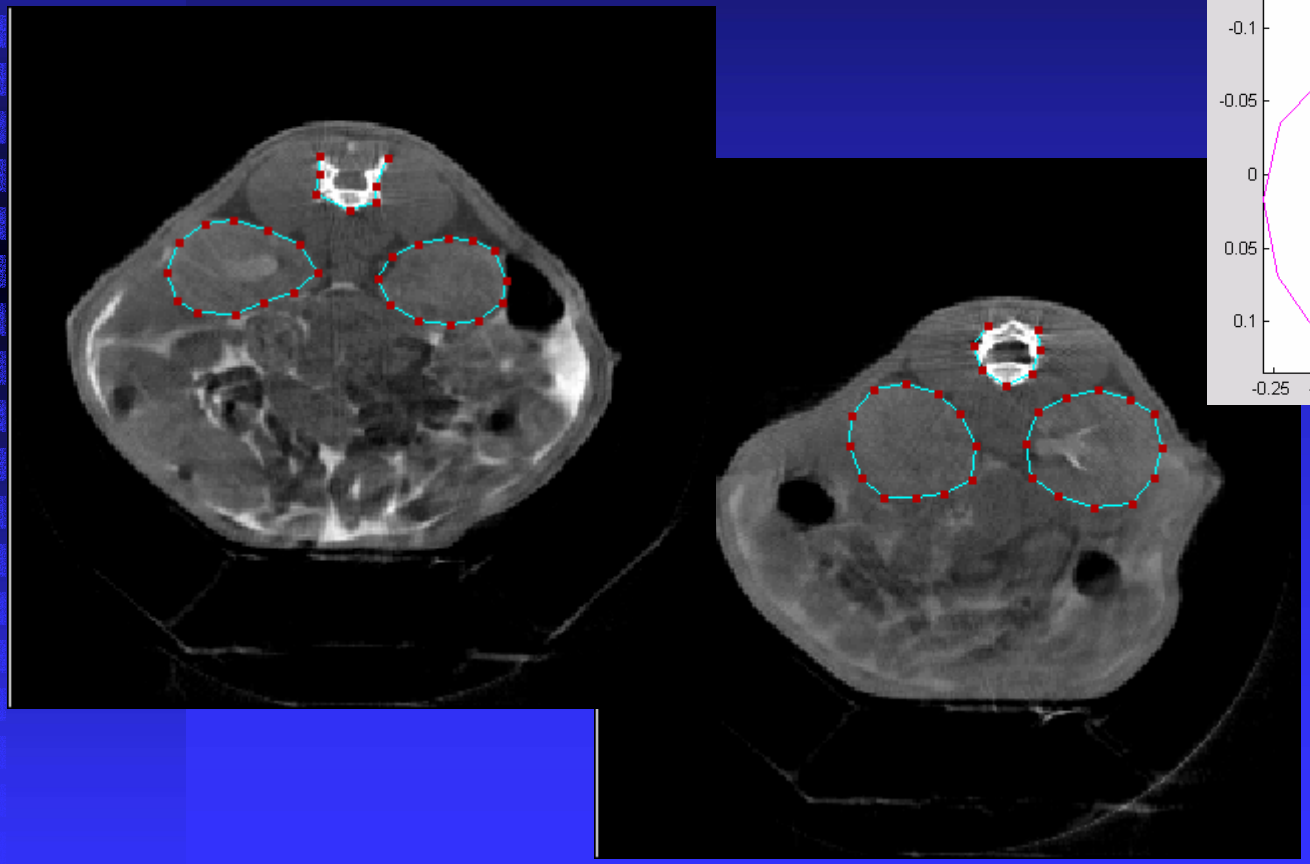
Objective Function

GSM: Uses an LP Training Set

Mean Global Shape

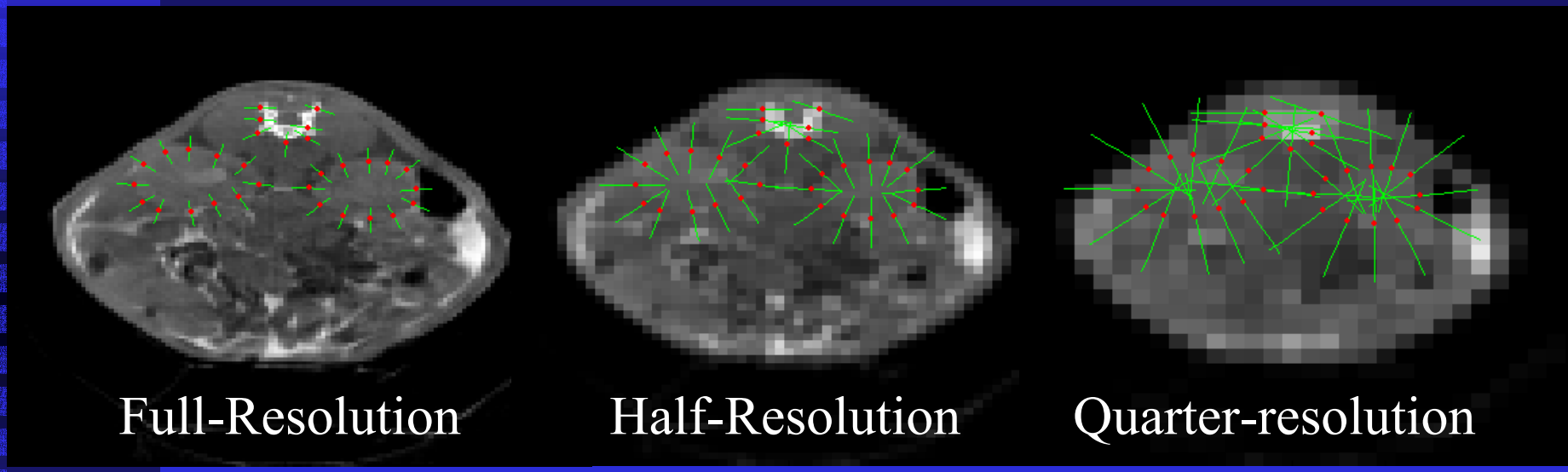


$\mathbf{x_1} = (x_1, x_2, \ldots, x_n, y_1, y_2, \ldots, y_n)^T$

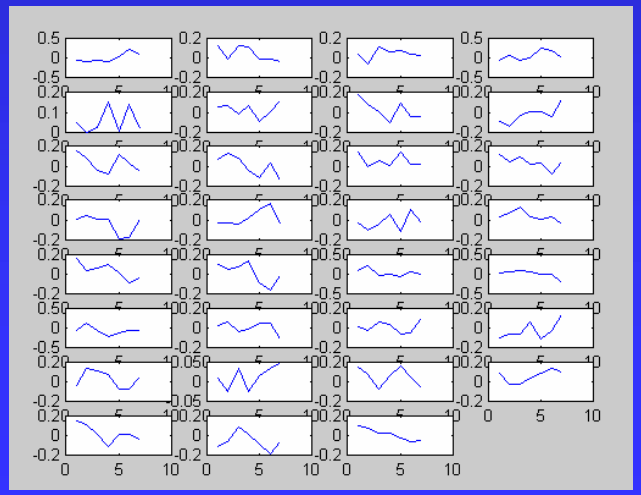


$\mathbf{x_2} = (x_1, x_2, \ldots, x_n, y_1, y_2, \ldots, y_n)^T$

GLM: Constructed from Gray-level Profile Training Set

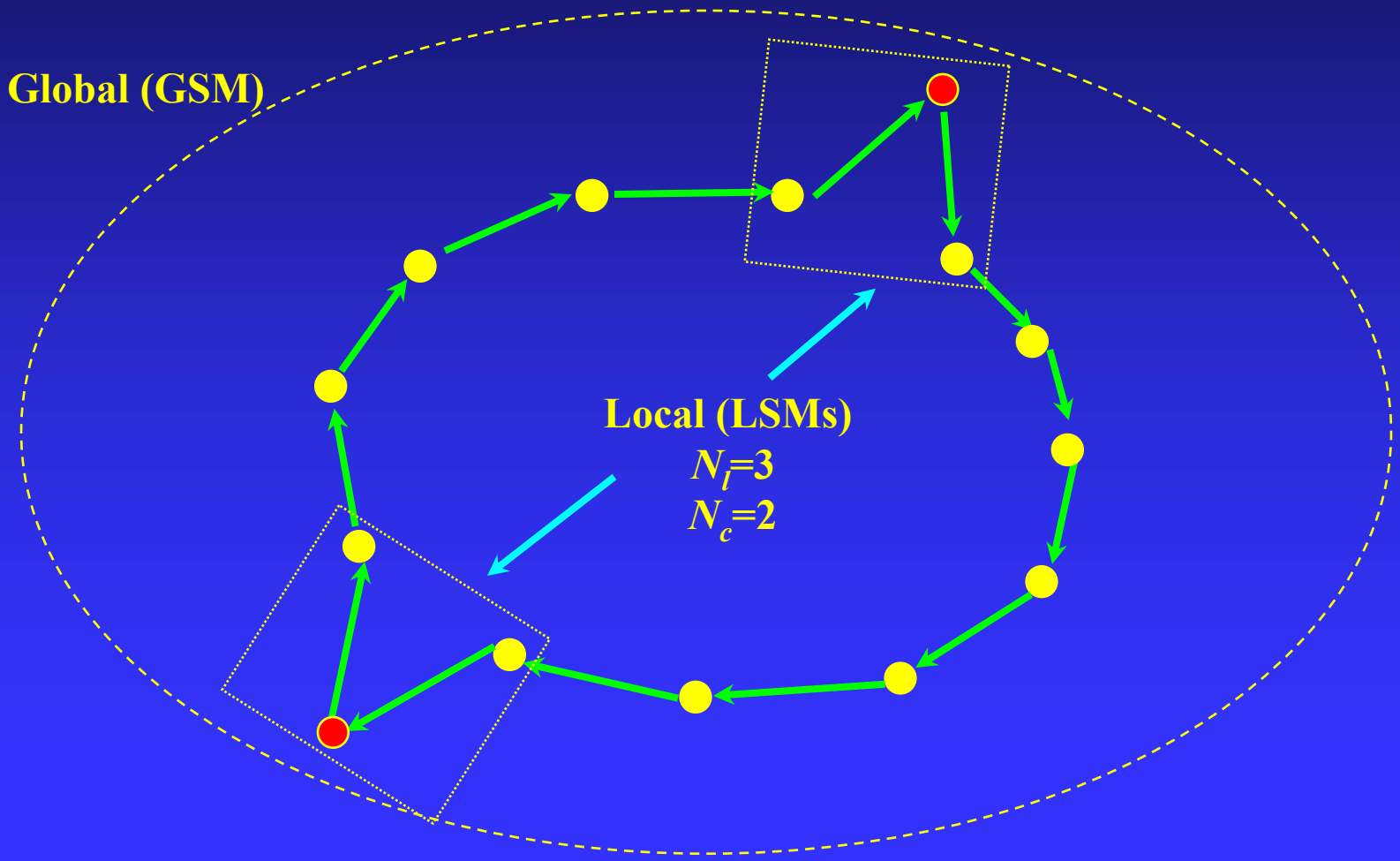


Gray-level Profiles



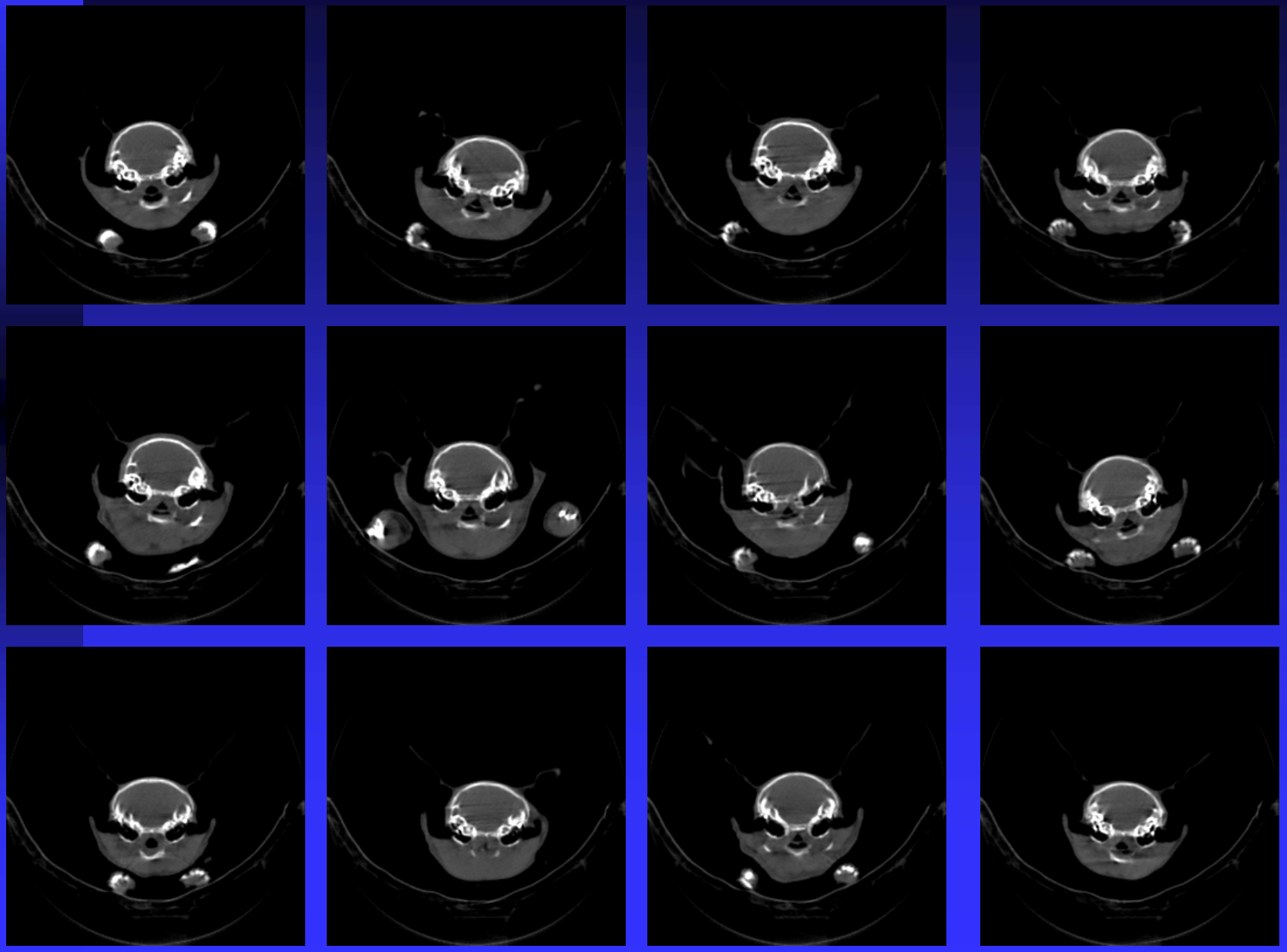
Local Shape Model (LSM) Component

Form N_l-LP Neighborhood LSM around each "critical" point ( )

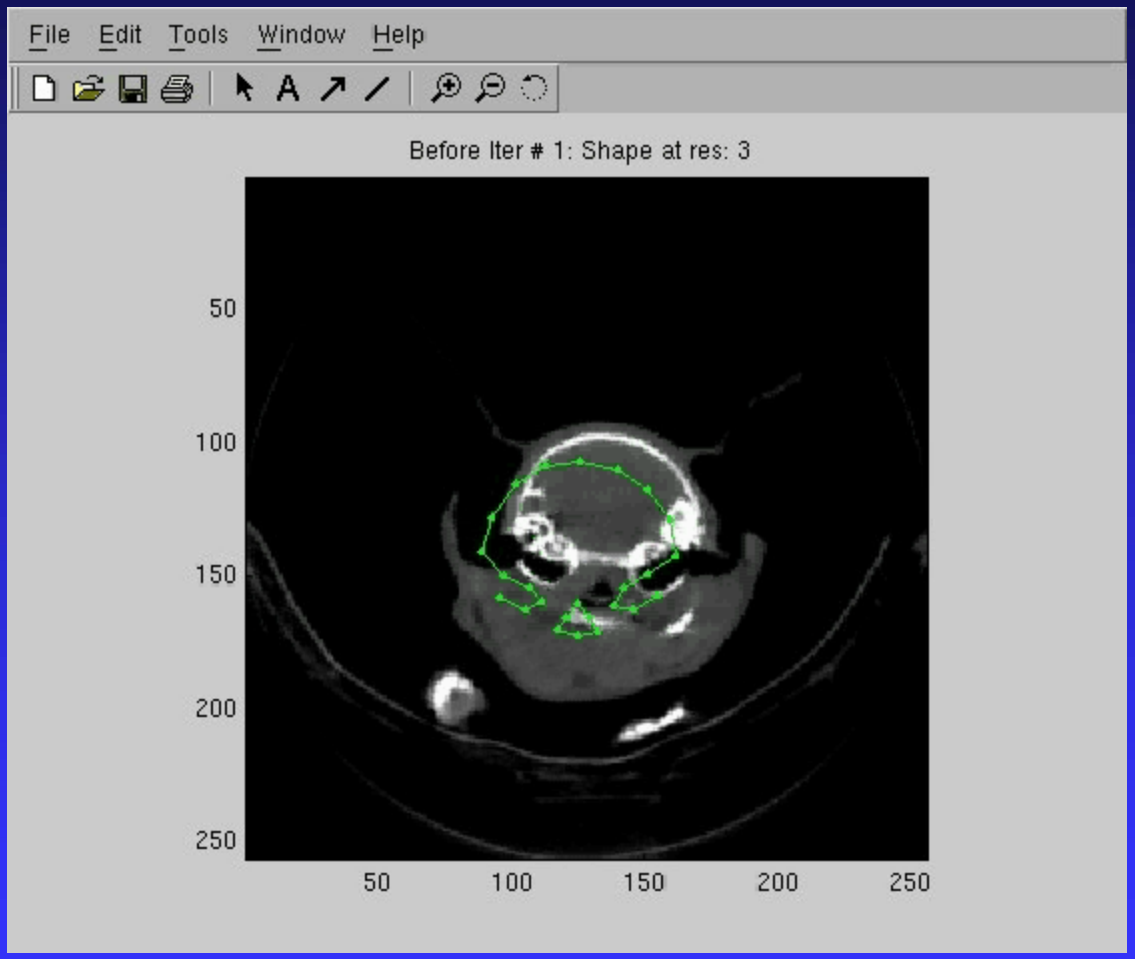


PSAM Results: Medical Images

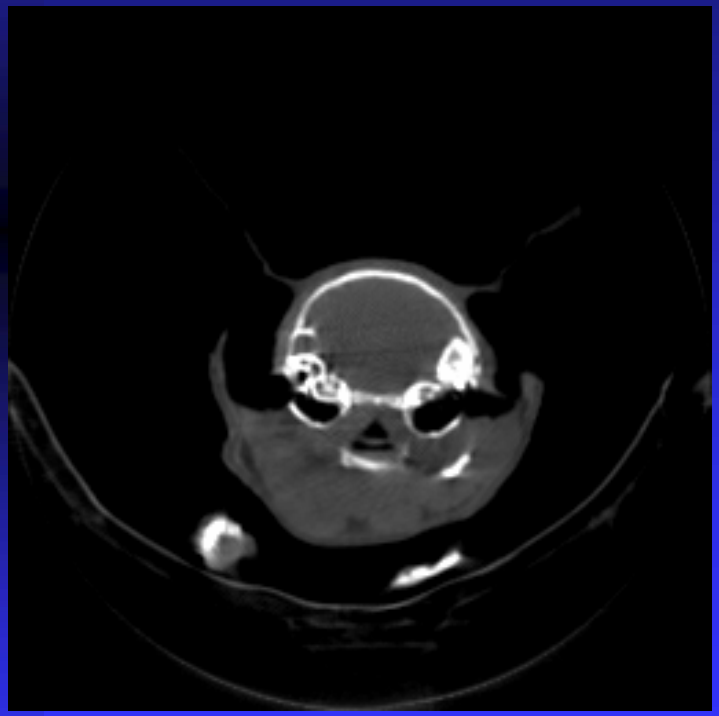
PSAM on Medical Images: Skulls

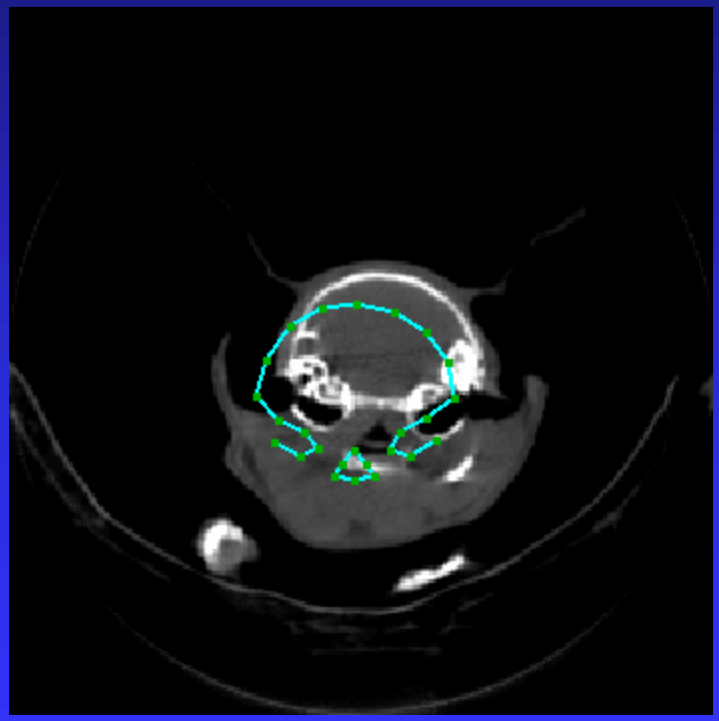


Results: Skeletal Structure

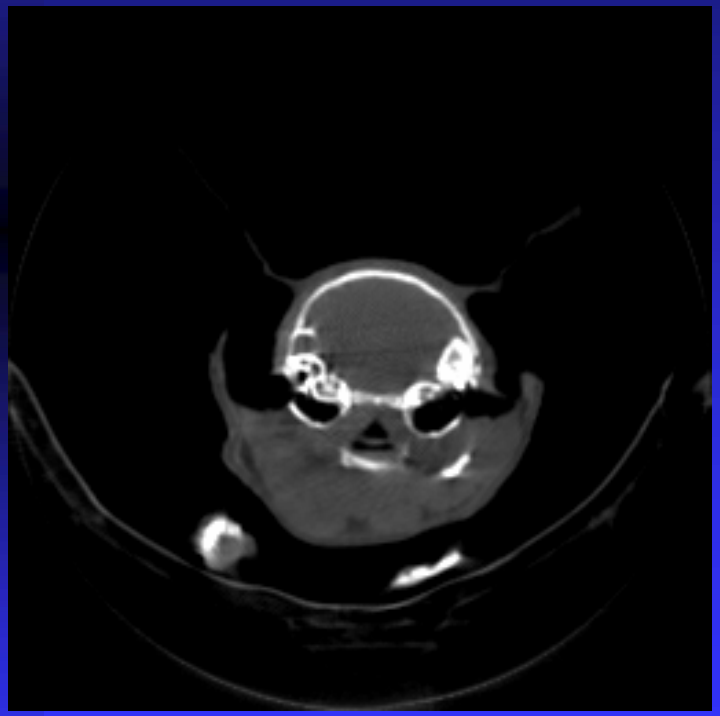


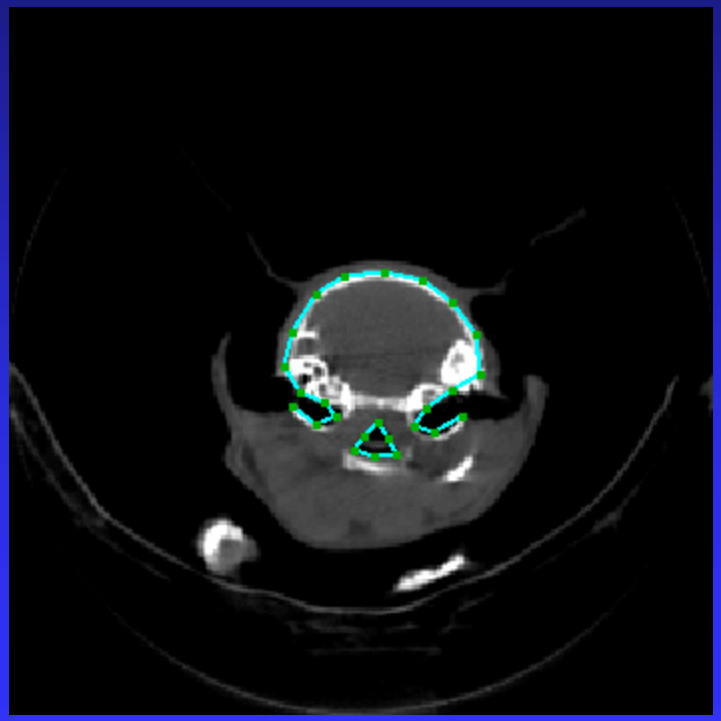
Results: Skeletal Structure



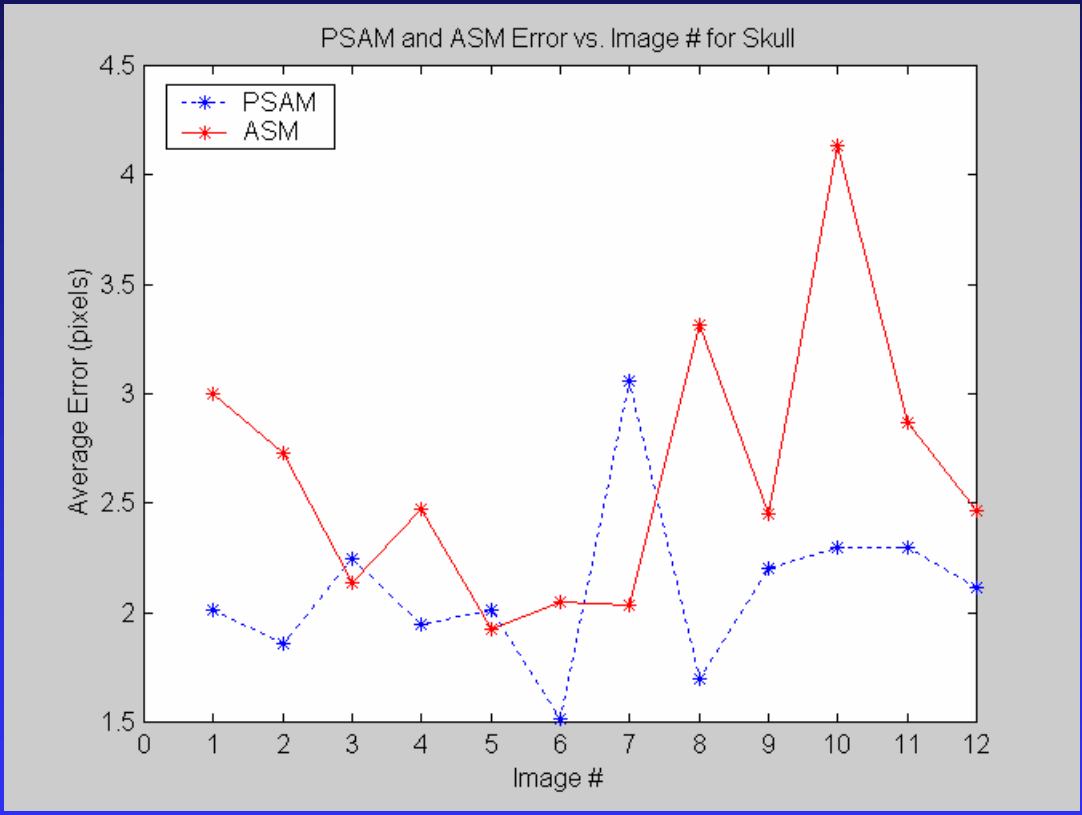


Results: Skeletal Structure



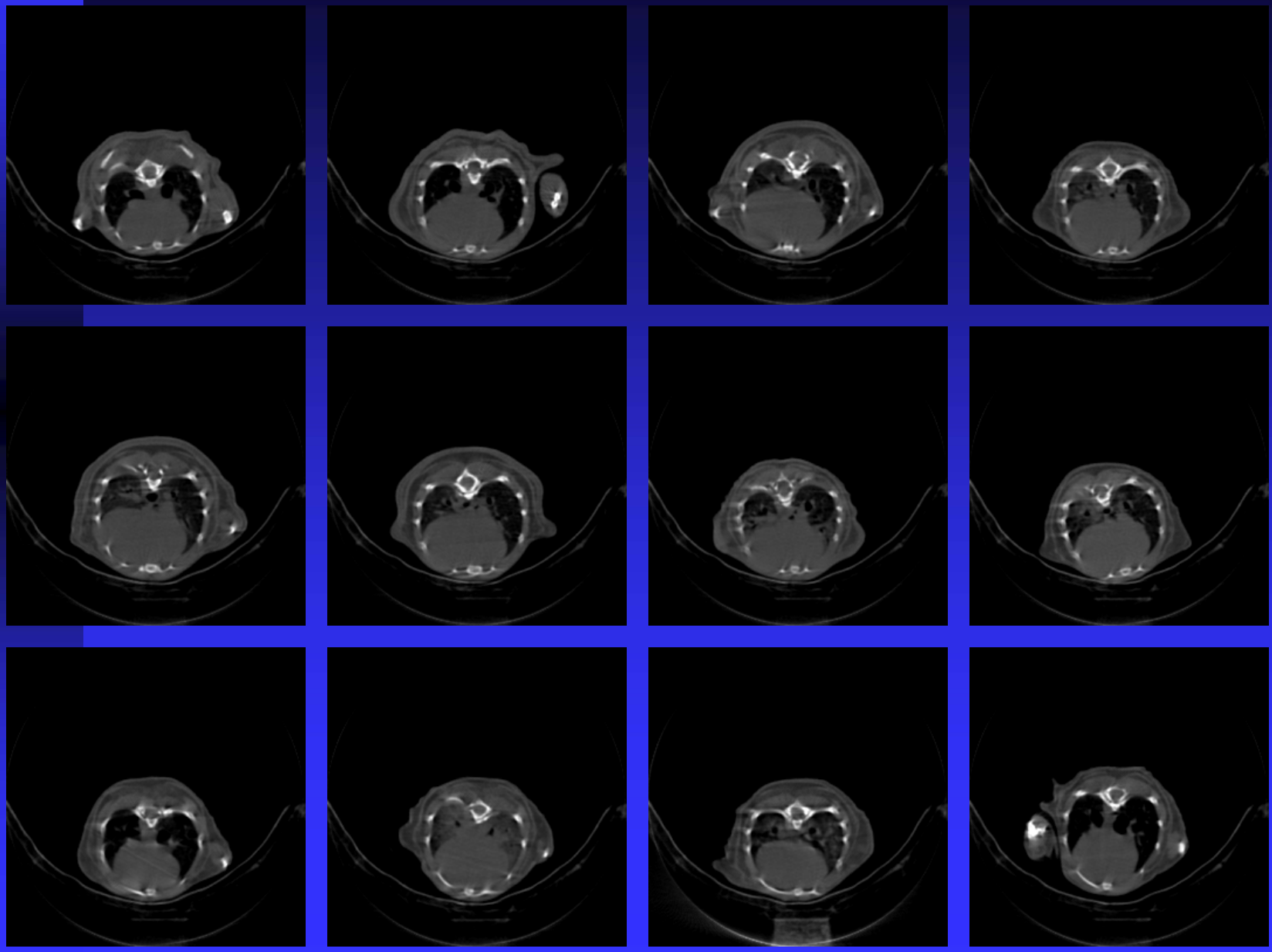


PSAM vs. ASM Boundary Error: Skull Data

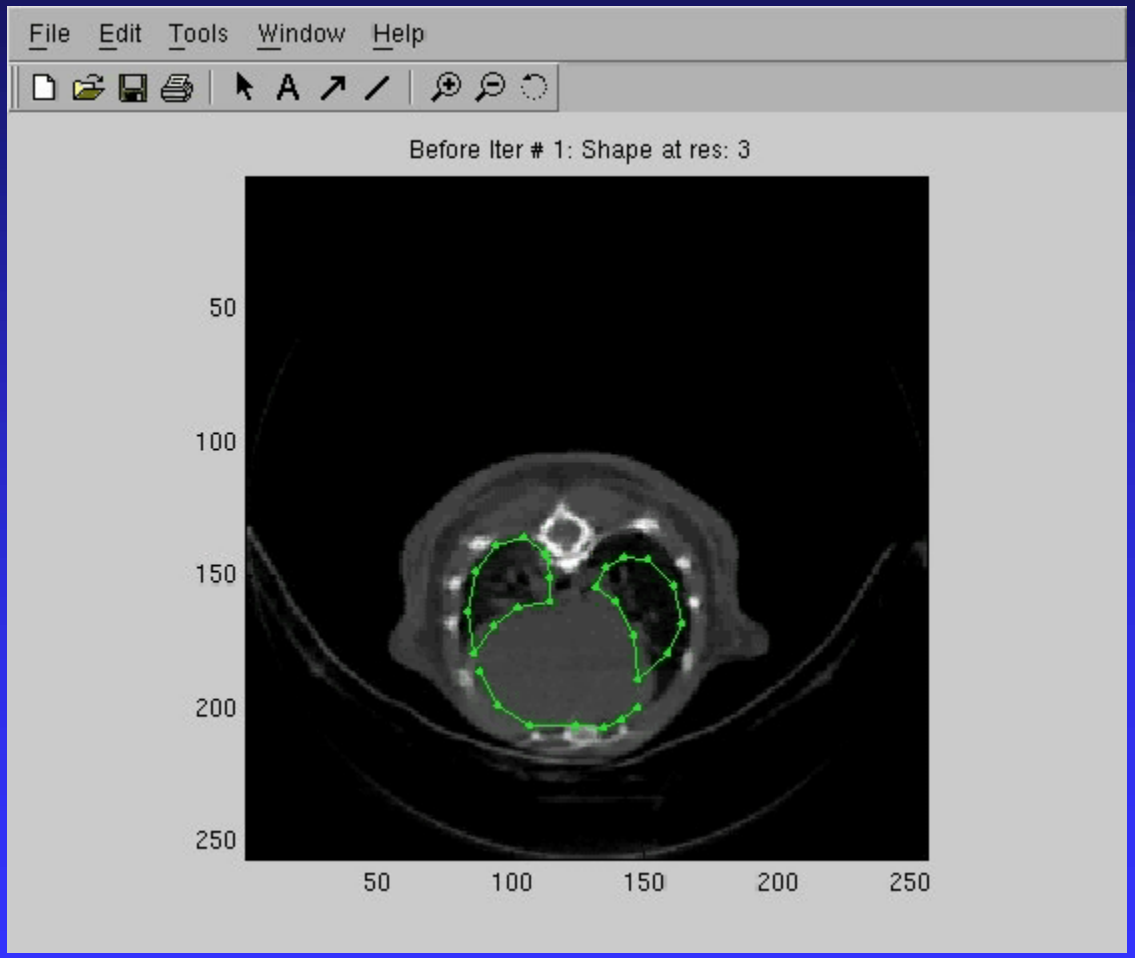


Total boundary error for ASM was on average 25% higher on the 12 skull images

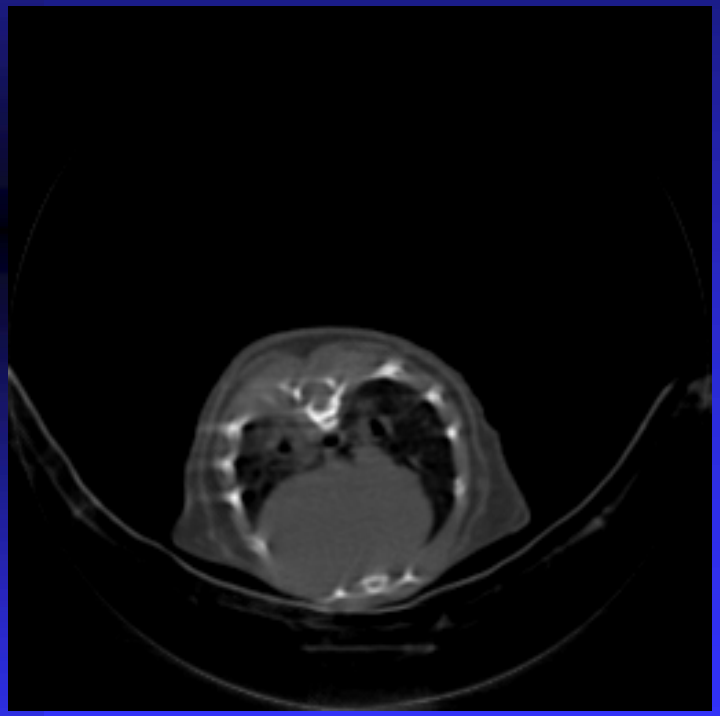
PSAM on Medical Images: Heart/Lungs

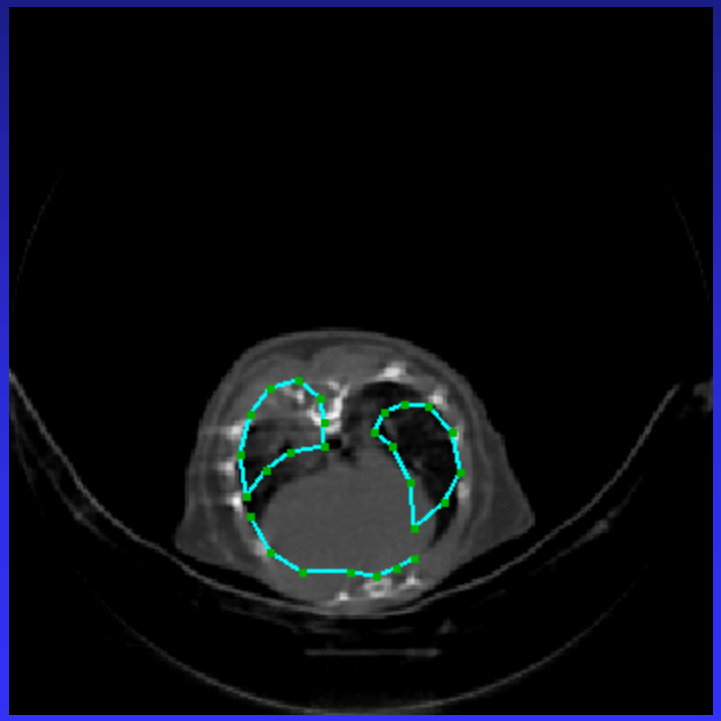


Results: Heart/Lung

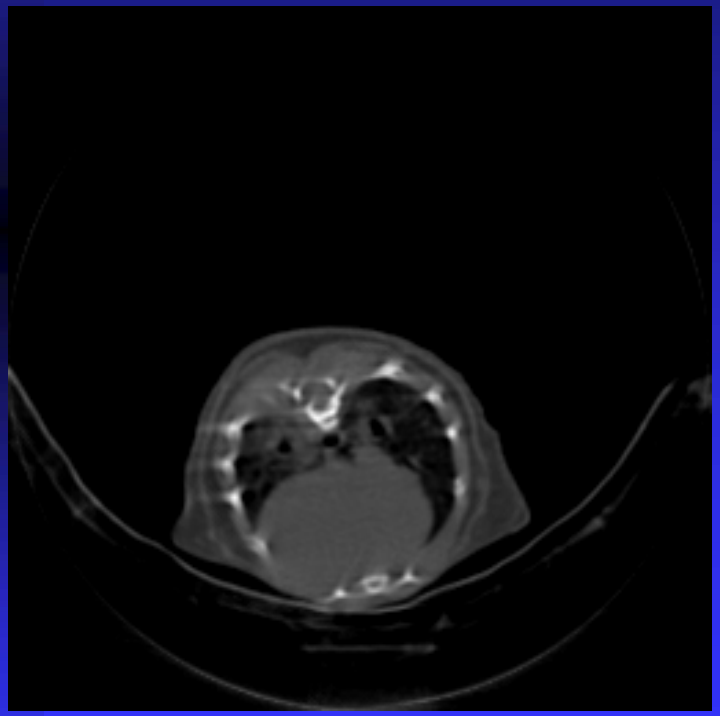


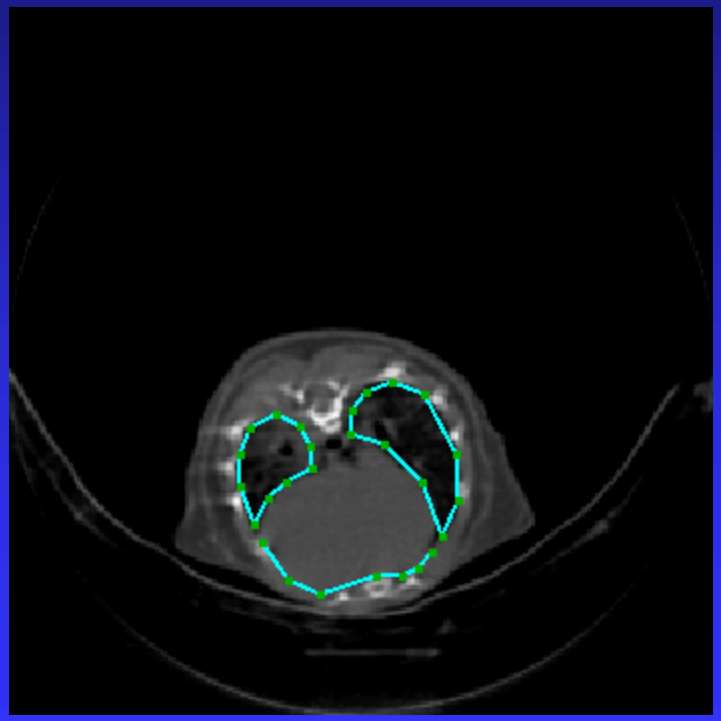
Results: Heart/Lung



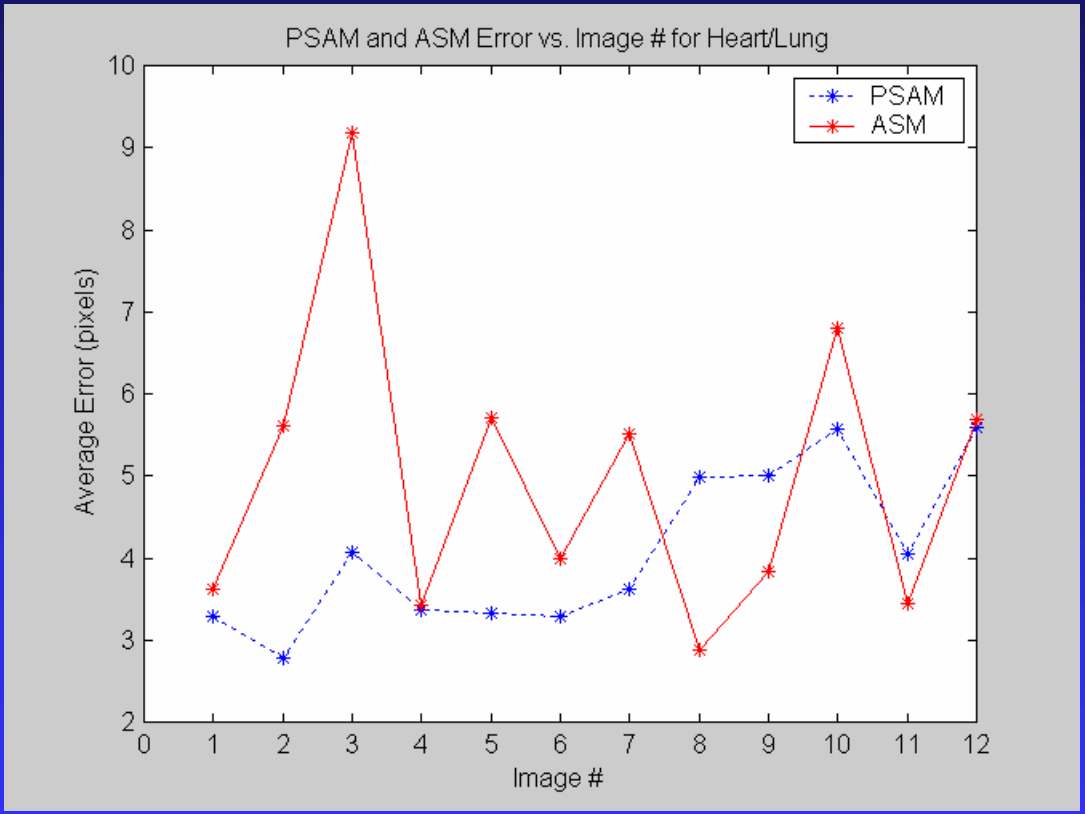


Results: Heart/Lung



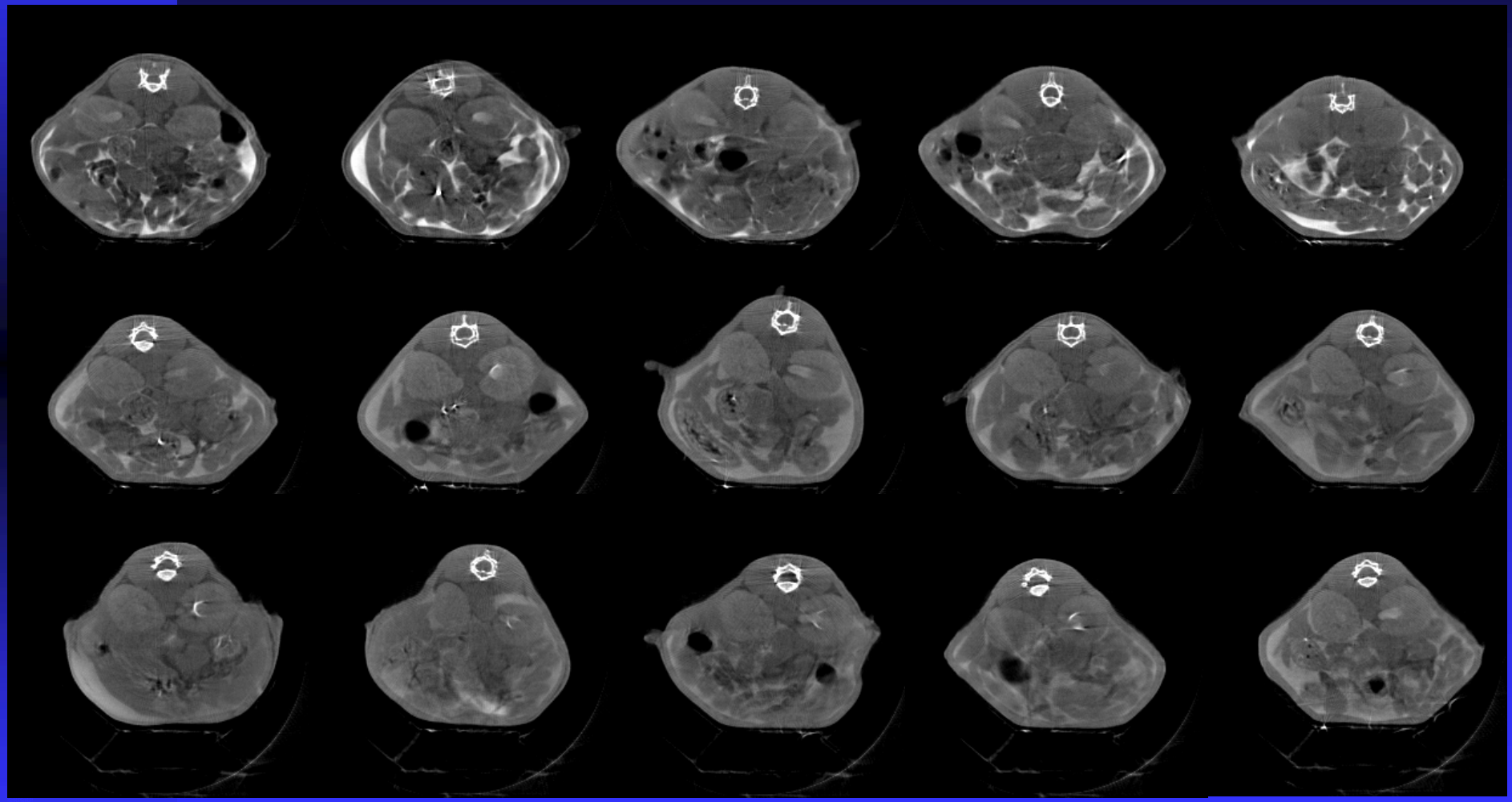


PSAM vs. ASM Boundary Error: Heart/Lung Data

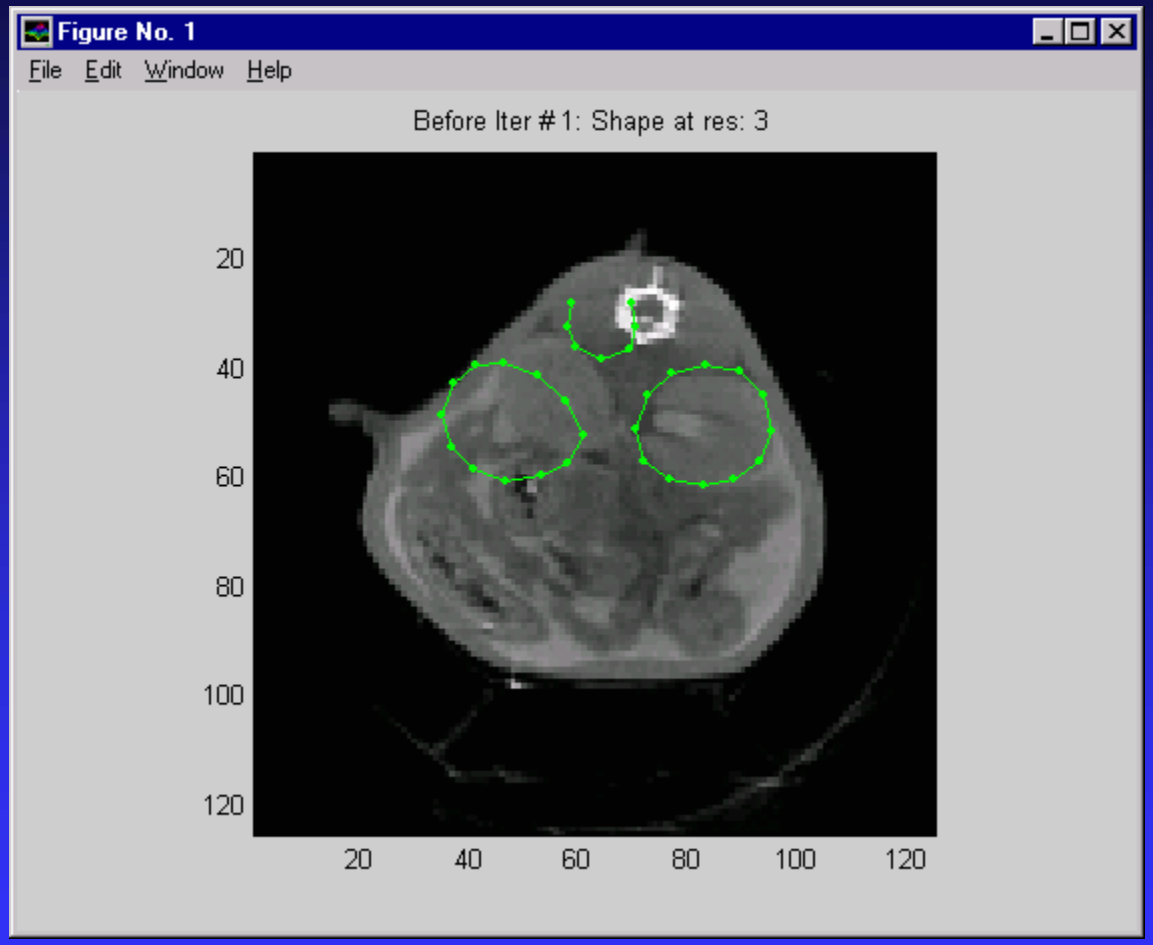


Total boundary error for ASM was on average 22% higher on the 12 heart/lung images

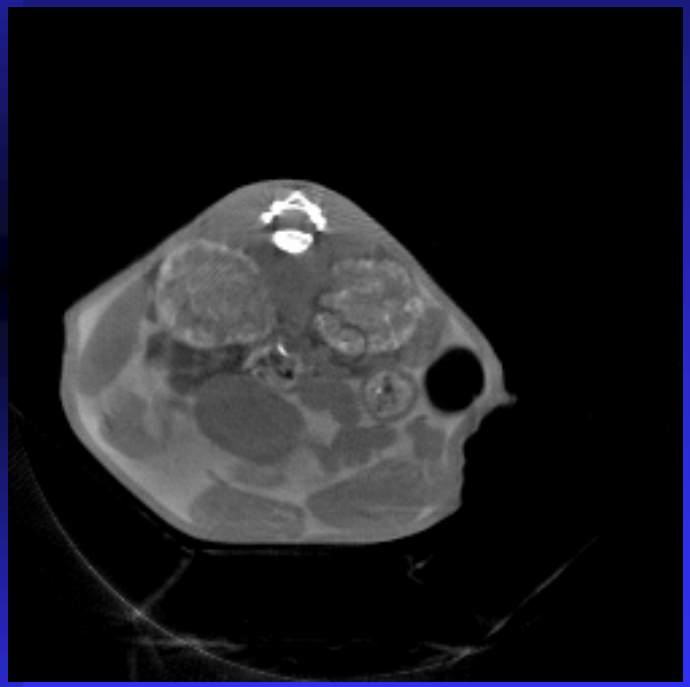
PSAM on Medical Images: Kidneys

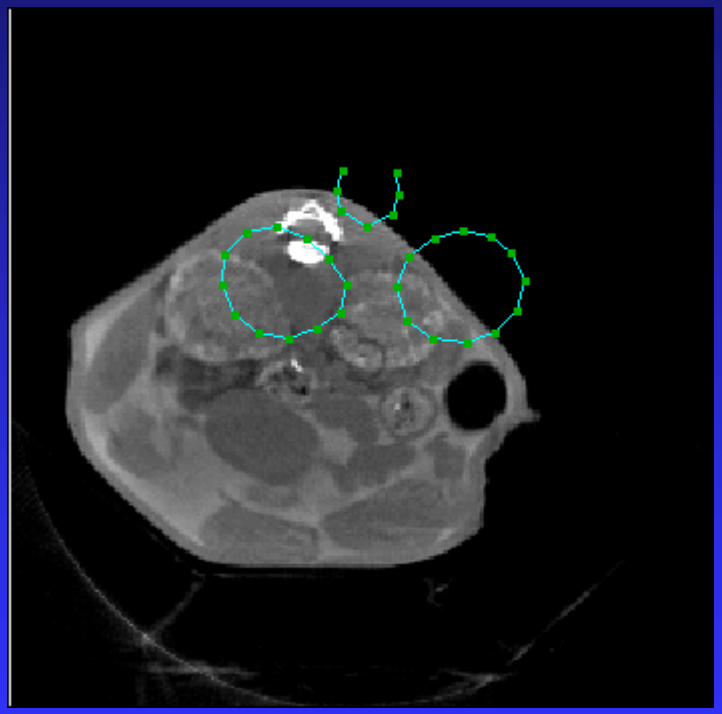


Results: Kidneys

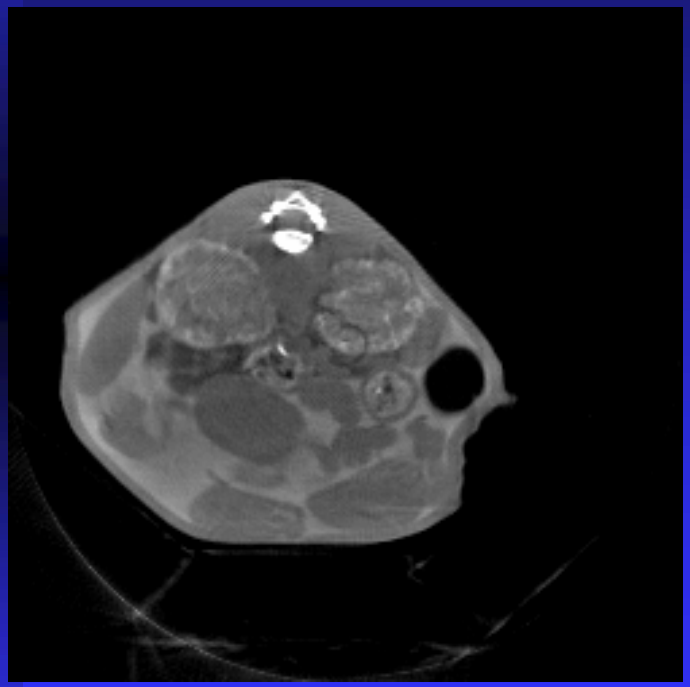


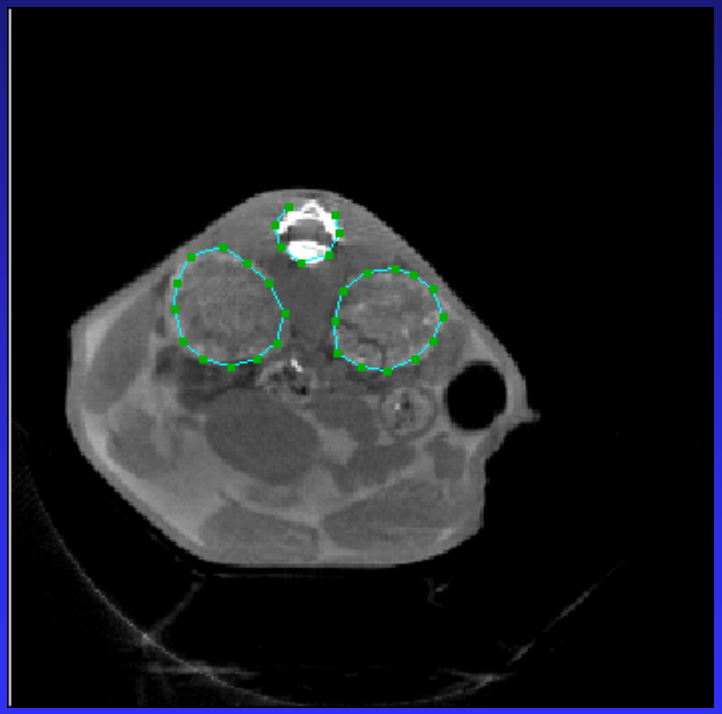
Results: Kidneys (PKD)



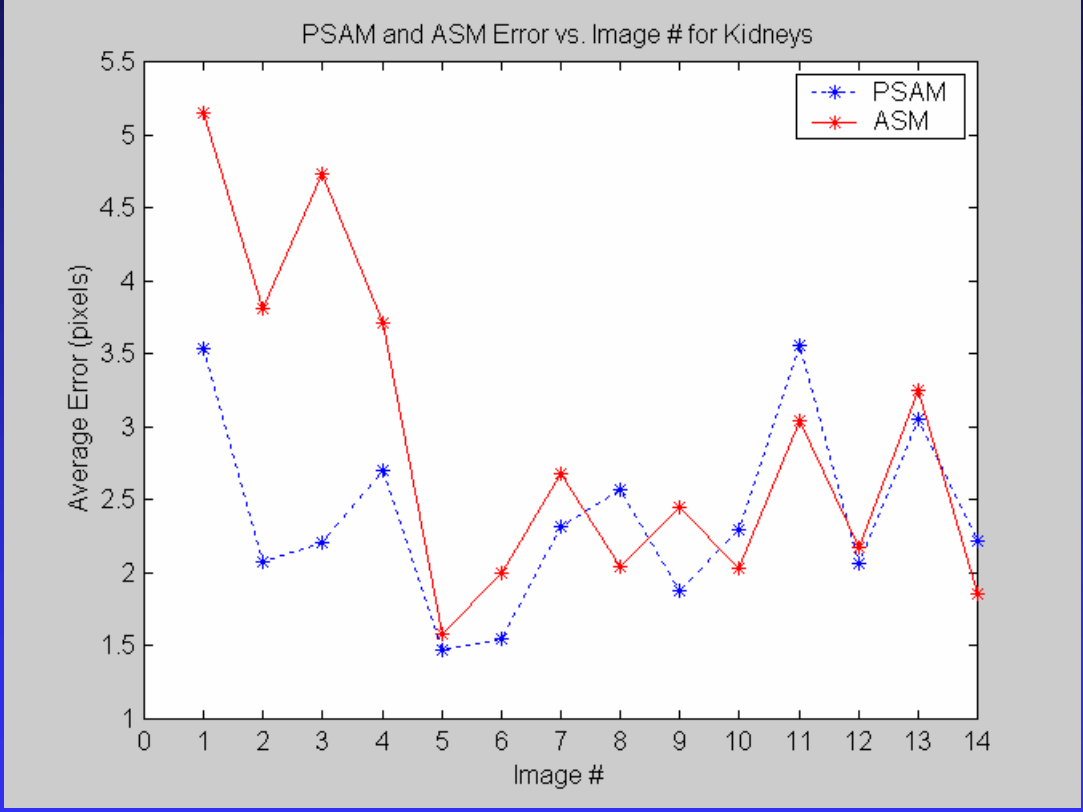


Results: Kidneys (PKD)





PSAM vs. ASM Boundary Error: Kidney Data

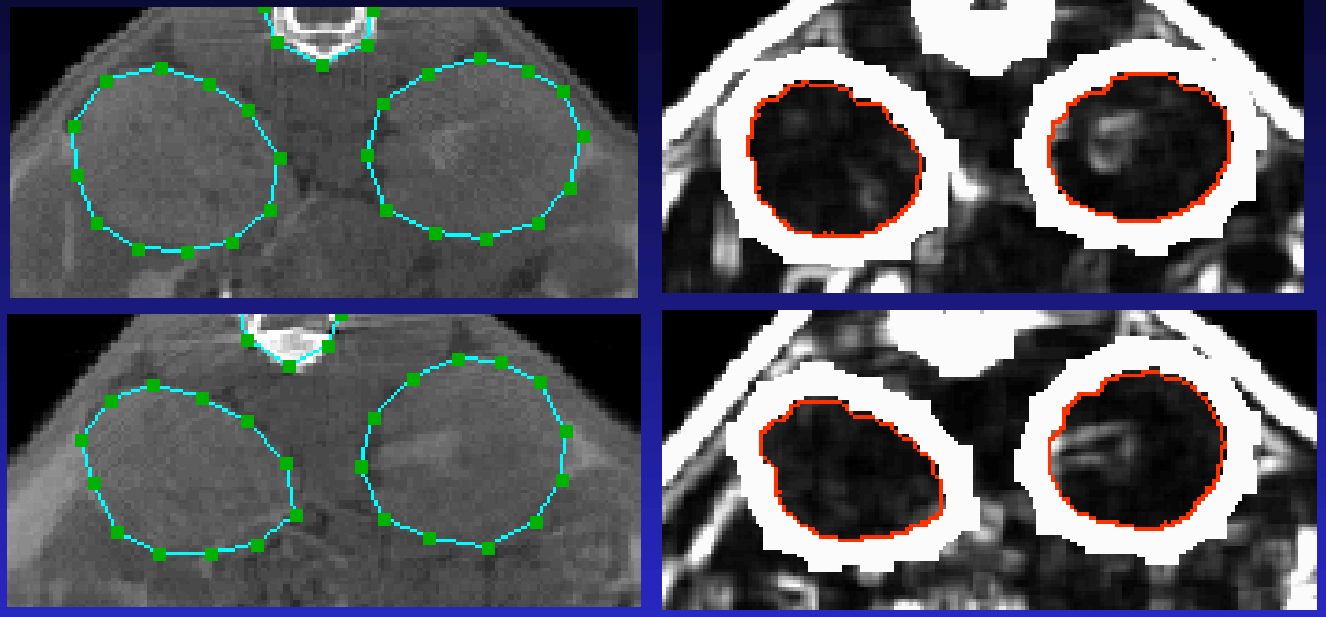


Total boundary error for ASM was on average 21% higher on the 14 kidney images

Normal Kidneys

Texture Measure

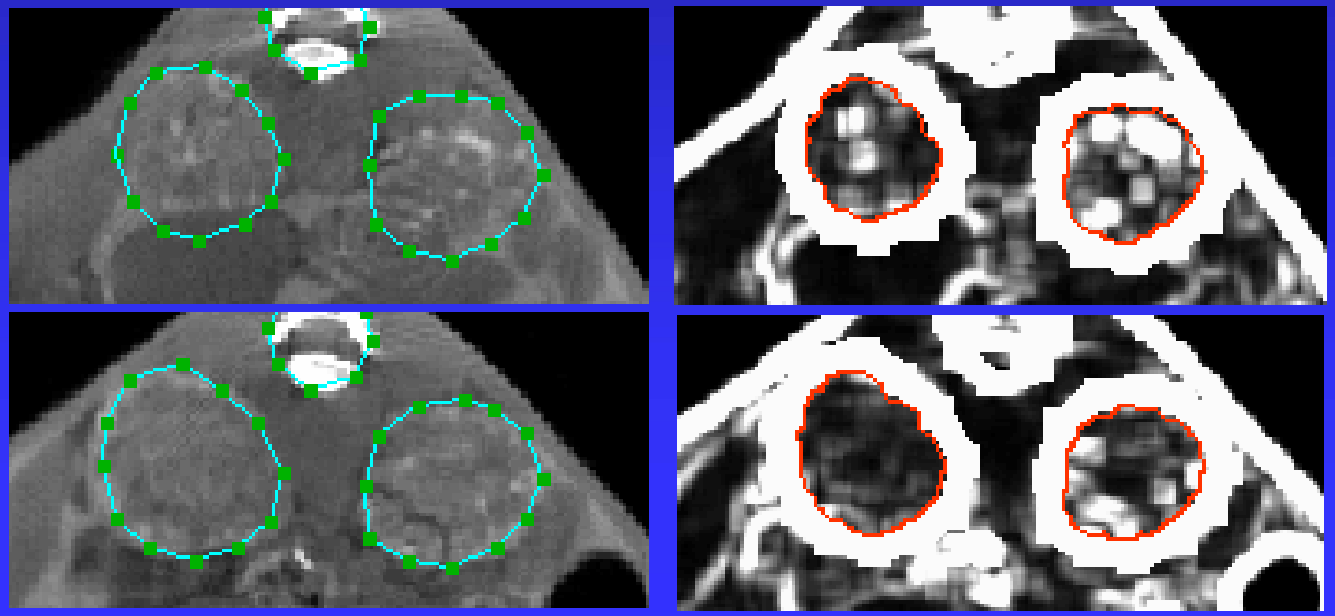
Left	Right
27.8	37.9
29.9	34.2



PKD Kidneys

Texture Measure

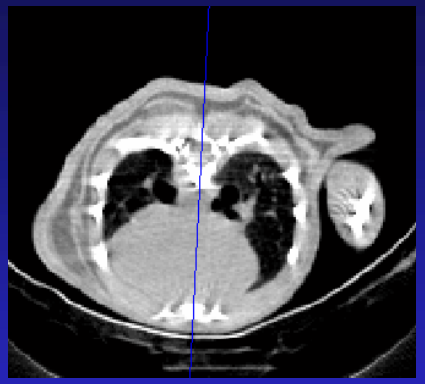
Left	Right
104.0	215.2
65.17	130.7



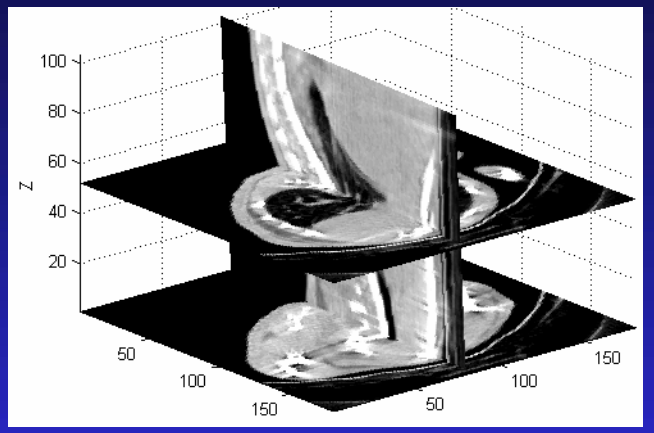
3D PSAM Development…

Extend Training Process to 3D…

Step 1:

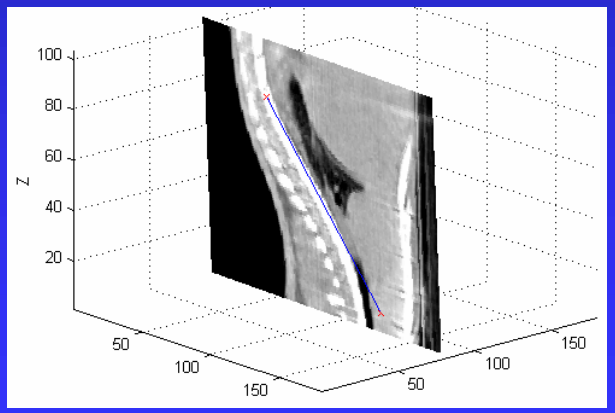


Step 2:



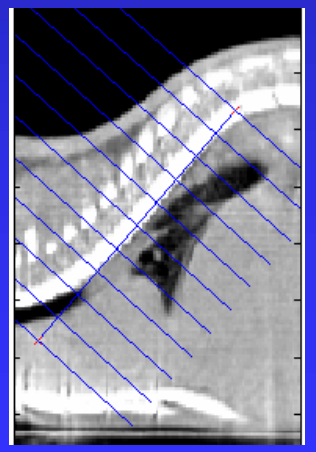
Define plane for new coordinate system

Step 3:



Define axis of cylindrical coord. system

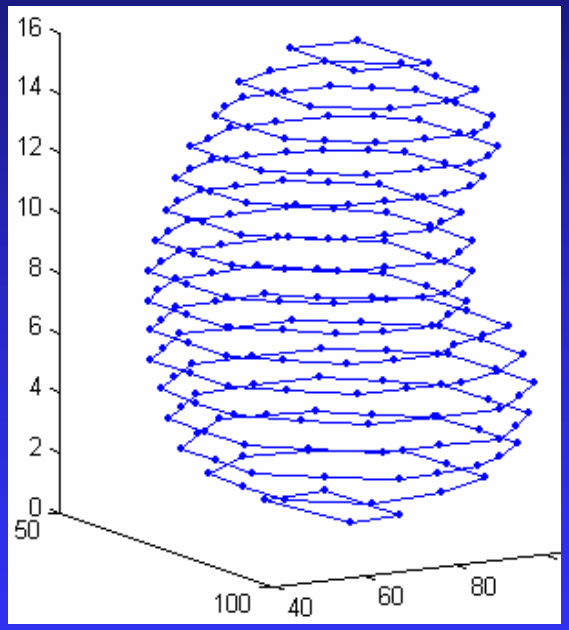
Step 4:



Re-slice volume for PSAM training

Create the 3D PSAM

Synthetic Kidney



Mean Shape After 3D Training

Conclusion: Contributions of new PSAM Algorithm

- Provides a general theoretical framework for previous research into probabilistic shape models.
- Simultaneous optimization with respect to shape and gray-level information
- Optimizes over pose parameters (translation, scale and rotation)
- Incorporation for local shape models around critical LPs to preserve important local shapes