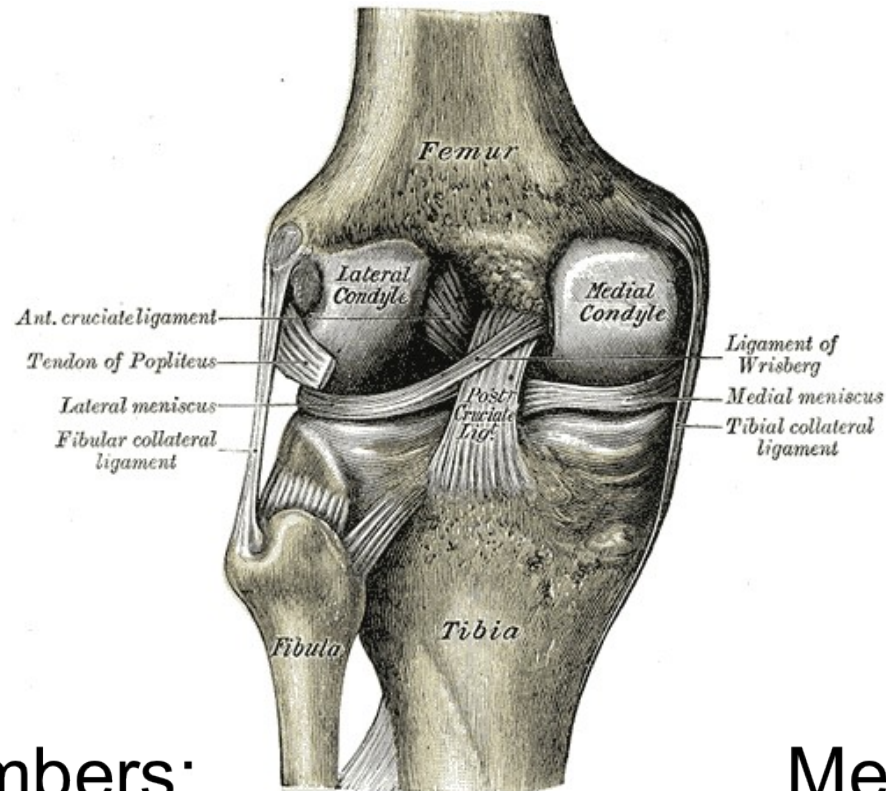


Statistical Atlas of the Knee



Team Members:

Murat Bilgel

Ceylan Tanes

Mentors:

Dr. Russell Taylor

Xin Kang (Ben)

Outline

- Project Update
- Paper Selection
- Summary
- Significance
- Relevance
- Algorithm Details
- Paper Evaluation
- Possible Improvements

What we have done so far

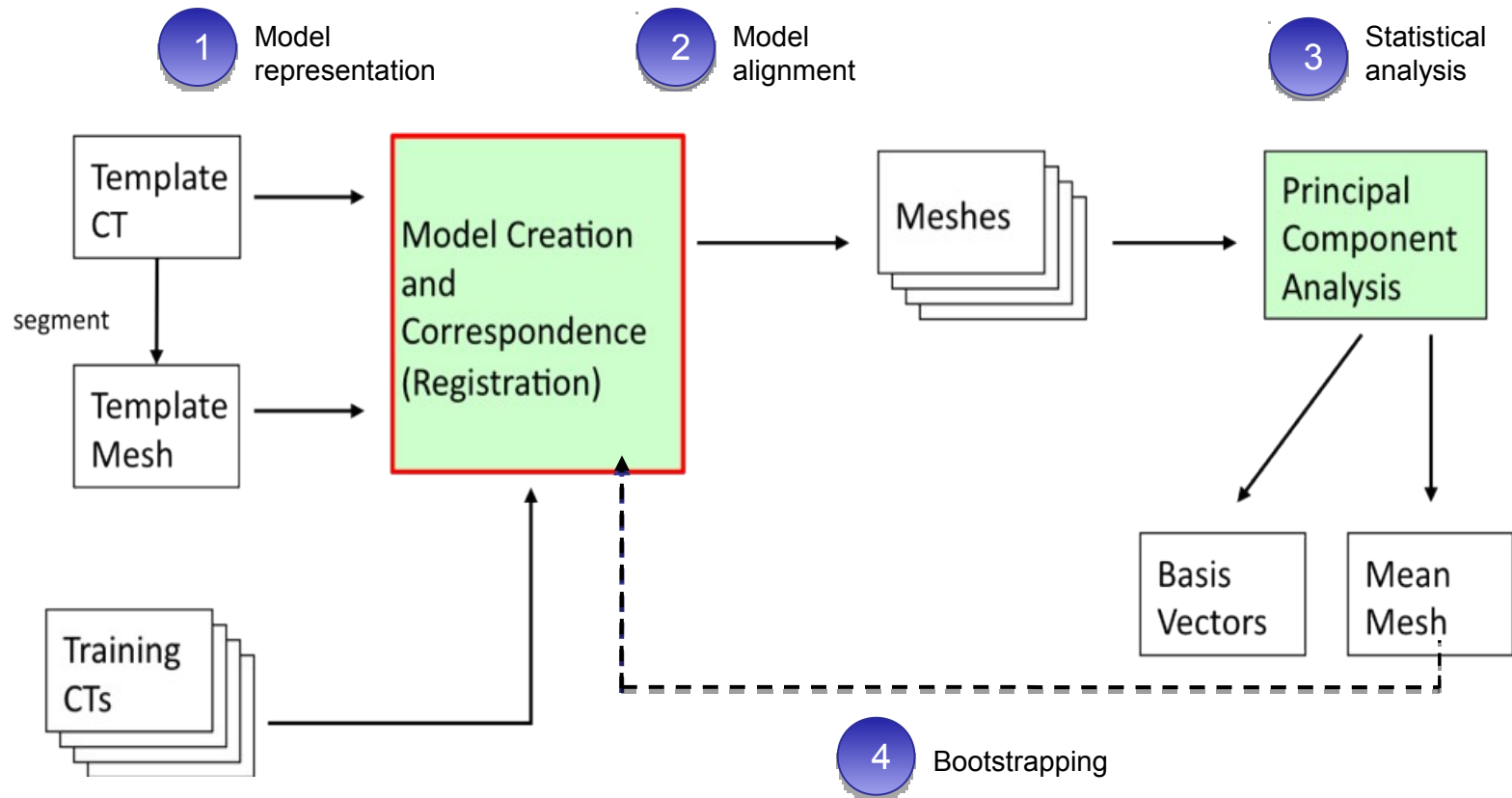
- Obtain preliminary atlas using the current pipeline and existing pelvis data
 - by February 25 **Done!**
- Create a tetrahedral mesh of femur and tibia using the Hong Kong dataset
 - by March 27 (Ceylan)
- Automate the pipeline
 - by March 27 (Murat)

Paper Selection

- Yezzi, A. Zollei, L. Kapur, T. *A variational framework for integrating segmentation and registration through active contours.* Medical Image Analysis 7 (2003) 171 – 185.

Paper Relevance:

Remember Basic Atlas Construction Process



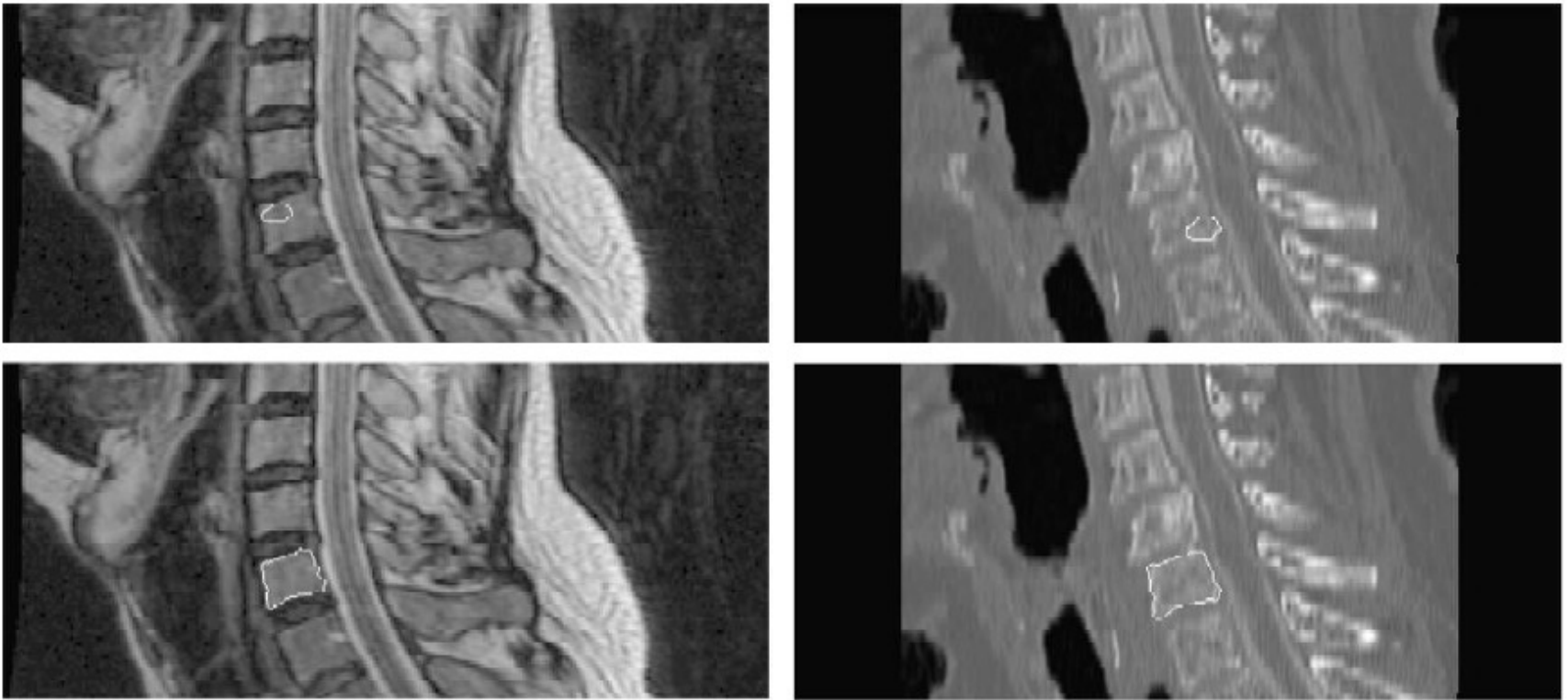
Shamelessly stolen from Dr. G. Chintalapani's PhD dissertation

Paper Summary

- Use feature based energy constraints to simultaneously segment and register multiple images with active contours
- They tested this algorithm on
 - 2D MR-CT head images
 - 3D MR-CT spine, head and ventricle images
 - Synthetic validation images

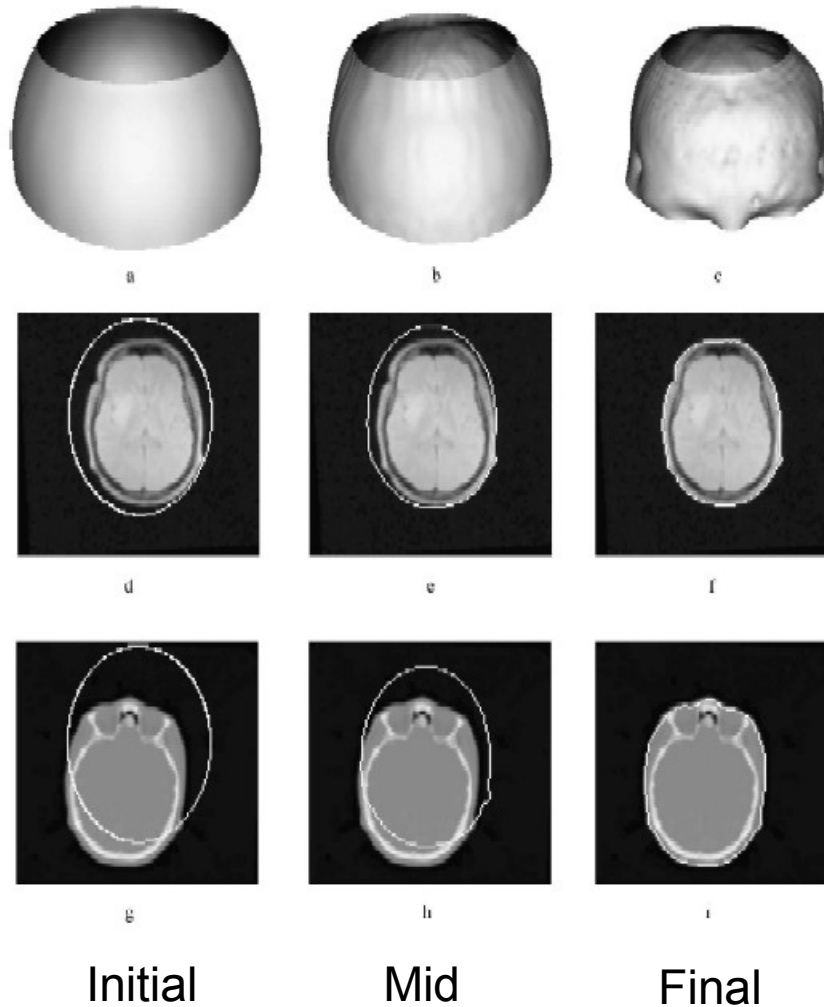
MR / CT Spine Experiment

Top images: Initial step



bottom images: final step

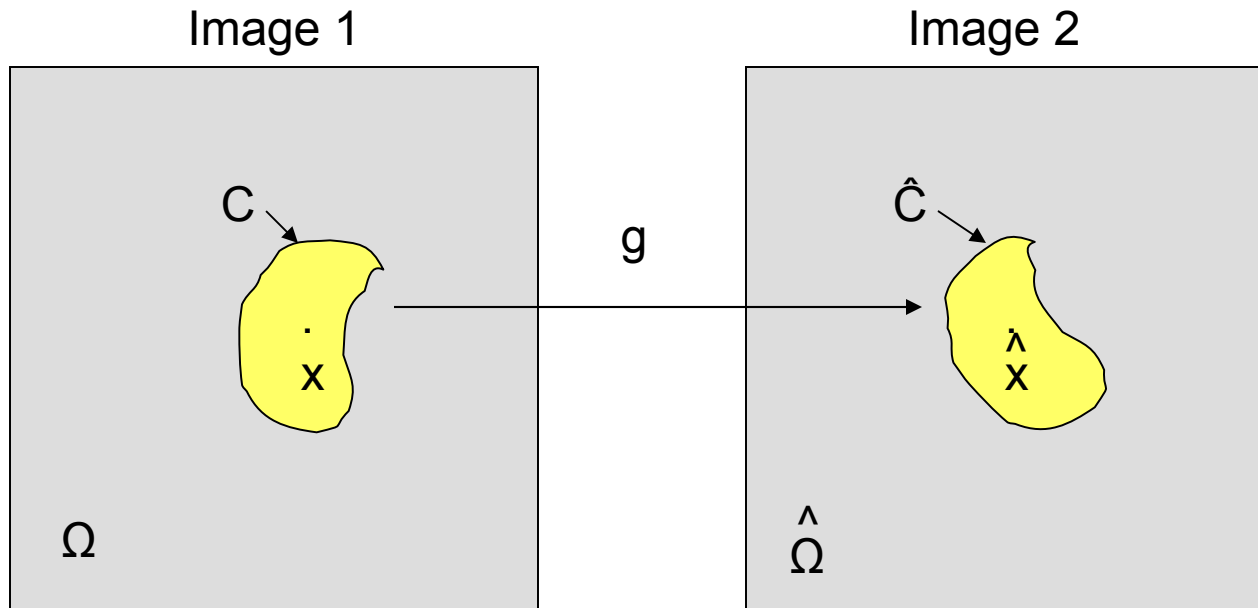
3D MR/CT Head Experiment



Significance

- Registration depends on segmentation
 - Rigid and non-rigid transformations depend on segmentation results
- Segmentation may depend on registration
 - Higher level model-based segmentation methods require registering images on a model
- This method eliminates the dependency of one method's result on the other.

Algorithm Details



$$\hat{\mathbf{x}} = g(\mathbf{x})$$

$$\hat{C} = g(C)$$

$$g(\mathbf{x}) = RM\mathbf{x} + D.$$

$$E(g, C) = E_1(C) + E_2(g(C))$$

$$= \int_{C_{\text{in}}} f_{\text{in}}(\mathbf{x}) \, d\mathbf{x} + \int_{C_{\text{out}}} f_{\text{out}}(\mathbf{x}) \, d\mathbf{x}$$

$$+ \int_{\hat{C}_{\text{in}}} \hat{f}_{\text{in}}(\mathbf{x}) \, d\mathbf{x} + \int_{\hat{C}_{\text{out}}} \hat{f}_{\text{out}}(\mathbf{x}) \, d\mathbf{x}.$$

Calculations

Where the region based energy functionals (f and f^\wedge) are defined as:

$$f_{\text{in}} = (I - u)^2, \quad f_{\text{out}} = (I - v)^2,$$
$$\hat{f}_{\text{in}} = (\hat{I} - \hat{u})^2 \quad \text{and} \quad \hat{f}_{\text{out}} = (\hat{I} - \hat{v})^2$$

Where u and v are the mean intensity values inside and outside the contour respectively.

Note that these functions are a variation of Gaussian Distribution

$$\phi(x; \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x - \mu)^2}{2\sigma^2}\right)$$

Calculations Continued

$$E(g, C) = E_1(C) + E_2(g(C))$$

Rearranging the equation and writing \hat{C} in term of C by using g provides:

$$E(g, C) = \int_{C_{\text{in}}} (f_{\text{in}} + |g'| \hat{f}_{\text{in}} \circ g)(\mathbf{x}) \, d\mathbf{x} \\ + \int_{C_{\text{out}}} (f_{\text{out}} + |g'| \hat{f}_{\text{out}} \circ g)(\mathbf{x}) \, d\mathbf{x}$$

Calculations Continued

To describe how the contour changes with respect to time we can use the energy functionals:

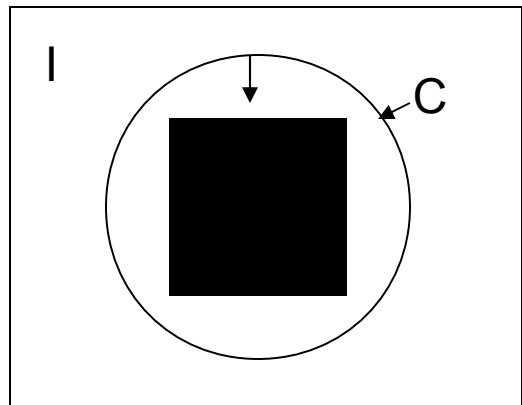
$$\frac{\partial C}{\partial t} = (f_{\text{in}} - f_{\text{out}})N \quad \text{and} \quad \frac{\partial C}{\partial t} = (\hat{f}_{\text{in}} - \hat{f}_{\text{out}})\hat{N}.$$

Combination of all the equations yield the necessary derivatives to calculate the contour line (C) and the affine transformation (g) at each iteration:

$$\frac{\partial C}{\partial t} = (f(\mathbf{x}) + m\hat{f}(g(\mathbf{x})))N - \kappa N,$$
$$\frac{dg_i}{dt} = \int_C \hat{f}(g(\mathbf{x})) \left\langle \frac{\partial g(\mathbf{x})}{\partial g_i}, mRM^{-1}N \right\rangle ds$$

Illustrating How the Contour is Updated

$$\frac{\partial C}{\partial t} = (f_{\text{in}} - f_{\text{out}})N \quad \text{and} \quad \frac{\partial C}{\partial t} = (\hat{f}_{\text{in}} - \hat{f}_{\text{out}})\hat{N}.$$



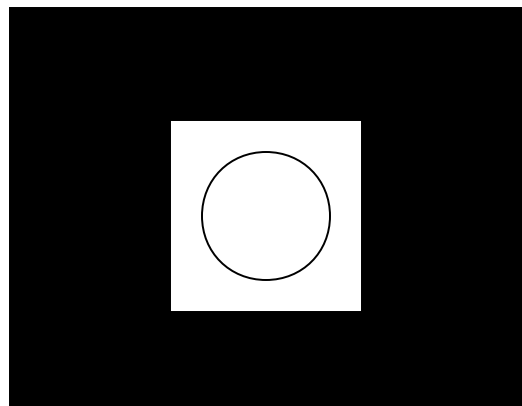
$$f_{\text{in}} > 0$$

$$f_{\text{out}} = 0$$

$$(f_{\text{in}} - f_{\text{out}}) > 0$$

$$(f_{\text{in}} - f_{\text{out}})N \text{ points inward}$$

Contour shrinks



$$f_{\text{in}} = 0$$

$$f_{\text{out}} > 0$$

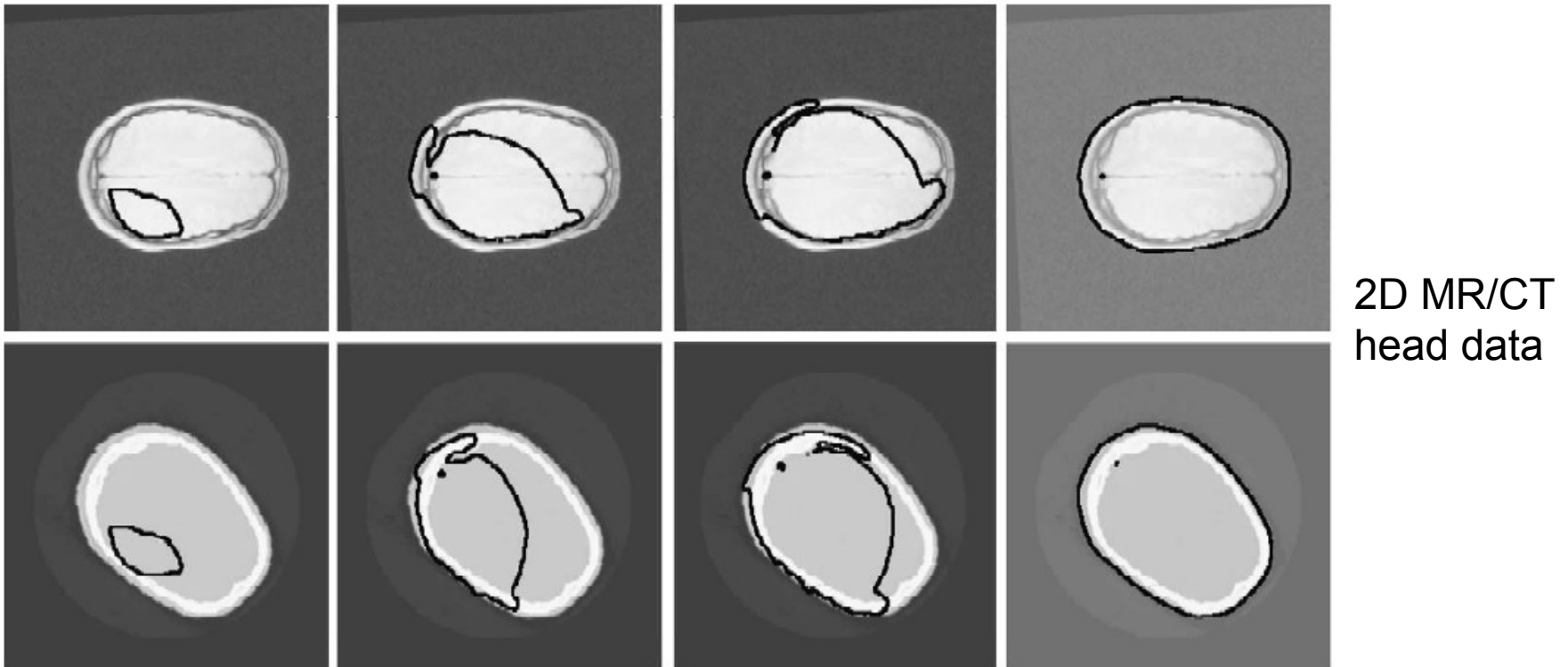
$$(f_{\text{in}} - f_{\text{out}}) < 0$$

$$(f_{\text{in}} - f_{\text{out}})N \text{ points outward}$$

Contour expands

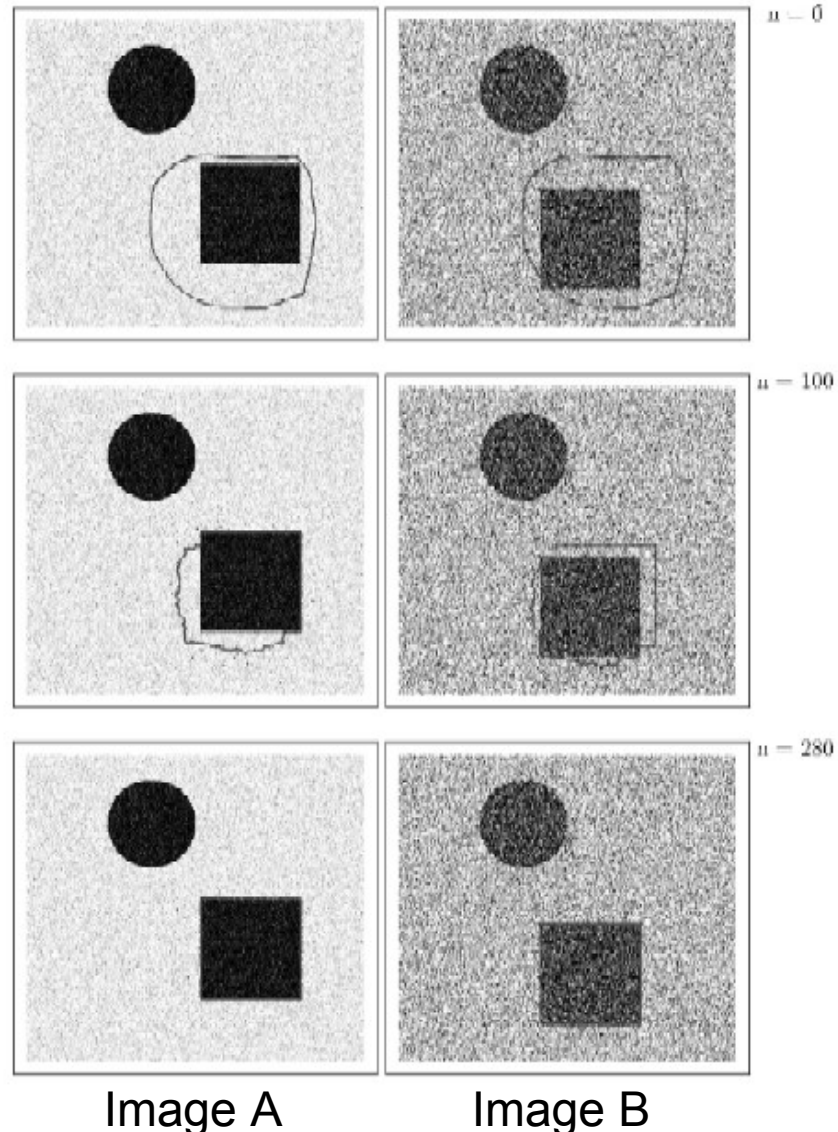
Evaluation

- Solves segmentation and registration problems at the same time
 - Decreases the effect of error propagation

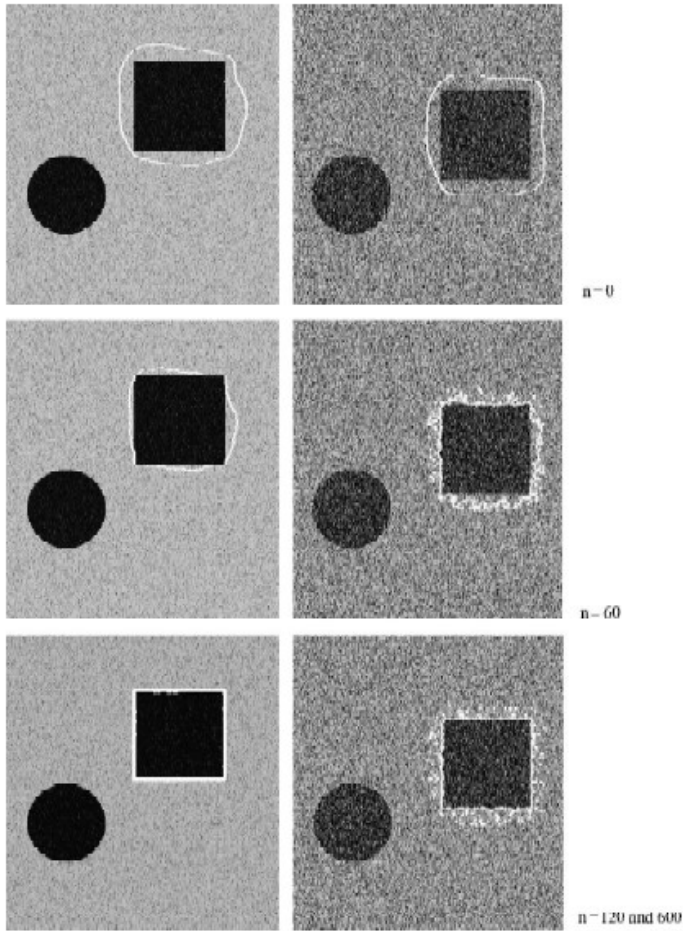


Evaluation cont.

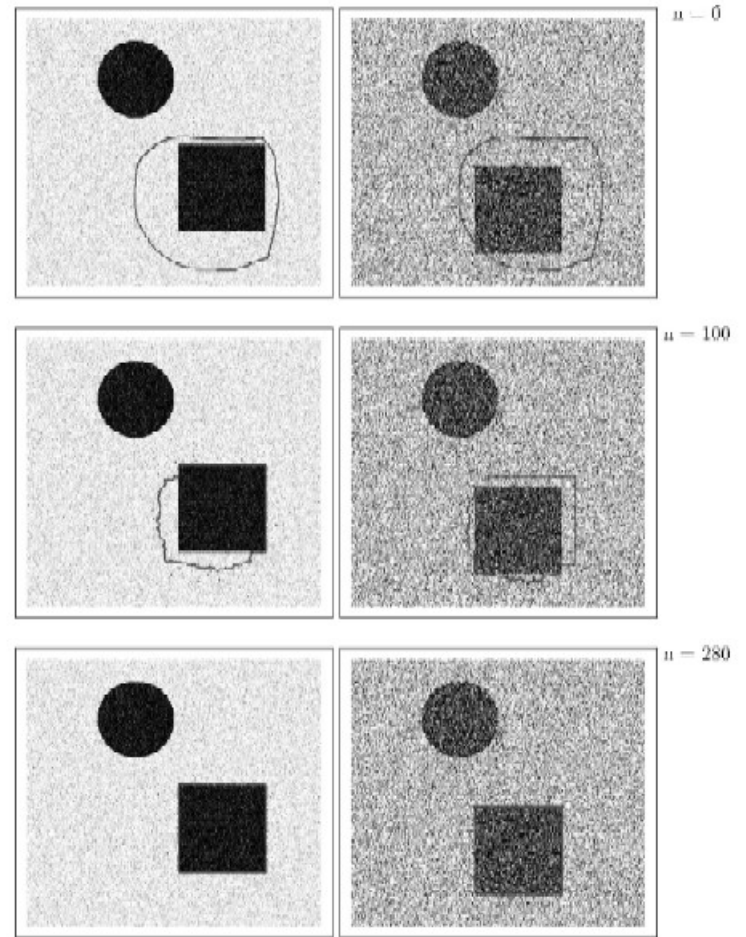
- Robust against noise in the data
 - Assumes Gaussian distribution



Something Suspicious..



Exp 1: Only segmentation



Exp 2: Developed Algorithm

Evaluation cont.

- Uses region based energy functionals
 - More applicable to medical data
- Can be generalized to work with multiple images
- Works with images from different imaging modalities

How can we implement this in our project?

Pros

- We can use it in the second step: model alignment
- Use segmented cadaver study to aid the segmentation of patient data
- Improve the knee atlas by using images from different modalities

Cons

- Algorithm assumes Gaussian distribution
 - The segmented volume has $\sigma=0$
- We would be using the algorithm for different patients

Possible Improvements

- Generalize the algorithm for multiple images
- Use a weighted combination of E_1 and E_2 where one image would be easier to segment than the other

Bibliography

- Yezzi, A. Zollei, L. Kapur, T. A variational framework for integrating segmentation and registration through active contours. *Medical Image Analysis* 7 (2003) 171 – 185.

Questions?