Statistical Atlas of the Knee

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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

Paper Relevance: Remember Basic Atlas Construction Process

1. Model representation
2. Model alignment
3. Statistical analysis
4. Bootstrapping

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

Image from Yezzi, A. et al. A variational framework for integrating segmentation and registration through active contours.
3D MR/CT Head Experiment

Image from Yezzi, A. et al. A variational framework for integrating segmentation and registration through active contours.
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.
\[ \hat{x} = g(x) \]
\[ \hat{C} = g(C) \]
\[ g(x) = RMx + D. \]

\[ E(g, C) = E_1(C) + E_2(g(C)) = \int_{\hat{C}_{in}} f_{in}(x) \, dx + \int_{\hat{C}_{out}} f_{out}(x) \, dx \]
\[ + \int_{\hat{C}_{in}} \hat{f}_{in}(x) \, dx + \int_{\hat{C}_{out}} \hat{f}_{out}(x) \, dx. \]
Calculations

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

\[
\begin{align*}
  f_{\text{in}} &= (I - u)^2, & f_{\text{out}} &= (I - v)^2, \\
  \hat{f}_{\text{in}} &= (\hat{I} - \hat{u})^2 & \text{and} & \hat{f}_{\text{out}} &= (\hat{I} - \hat{v})^2
\end{align*}
\]

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:

\[
E(g, C) = \int_{C_{in}}^{C_{out}} (f_{in} + |g'| \hat{f}_{in} \circ g)(x) \, dx \\
+ \int_{C_{out}} (f_{out} + |g'| \hat{f}_{out} \circ g)(x) \, dx
\]
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:

\[
\frac{\partial C}{\partial t} = (f(\mathbf{x}) + m\hat{f}(g(\mathbf{x})))N - \kappa N,
\]
\[
\frac{dg_i}{dt} = \int_{C} \hat{f}(g(\mathbf{x})) \left( \frac{\partial g(\mathbf{x})}{\partial g_i}, mR M^{-1}N \right) d\mathbf{s}
\]
Illustrating How the Contour is Updated

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

- \( f_{in} > 0 \)
- \( f_{out} = 0 \)
- \( (f_{in} - f_{out}) \cdot > 0 \) points inward
- Contour shrinks

- \( f_{in} = 0 \)
- \( f_{out} > 0 \)
- \( (f_{in} - f_{out}) \cdot < 0 \)
- \( (f_{in} - f_{out}) N \) points outward
- Contour expands
Evaluation

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

Image from Yezzi, A. et al. A variational framework for integrating segmentation and registration through active contours.
Evaluation cont.

• Robust against noise in the data
  – Assumes Gaussian distribution

Image from Yezzi, A. et al. A variational framework for integrating segmentation and registration through active contours.
Something Suspicious..

Exp 1: Only segmentation

Exp 2: Developed Algorithm

Image from Yezzi, A. et al. A variational framework for integrating segmentation and registration through active contours.
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

Questions?