Active Learning for Interactive 3D Image Segmentation

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How Can the Interactive 3D Image Segmentation Process Be Improved?

Frustrating, time consuming and error-prone

Standard 3D image segmentation flow

Initial Segmentation \rightarrow User chooses new input location \rightarrow User gives new input \rightarrow Somewhat improved segmentation results

Painless, quick and accurate

Our method

Improved 3D image segmentation flow

Initial Segmentation \rightarrow Our method chooses new input location \rightarrow User gives new input \rightarrow Much improved segmentation results

Active Learning in Segmentation

Formulate segmentation as a supervised learning classification problem. Labeled voxels represent training data.

- **Query**: A voxel chosen by the algorithm for the user to label.
- **Query strategy**: The method for choosing a query.

Given an intermediate segmentation, use a query strategy to produce a query that the user labels to improve the segmentation.

Method Summary

Given an intermediate 3D segmentation and the segmentation algorithm’s uncertainty of the labeling, what is the best query strategy?

We examine variations of Uncertainty Sampling query strategy:

- **Single query**
  - Most uncertain voxel
  - Inefficient: Must re-segment after each voxel is labeled. Unrealistic.

- **Naïve batch query**
  - n-most uncertain voxels
  - Inefficient in 3D: Difficult to visualize image data at arbitrary query voxels simultaneously.

Proposed method: Plane batch query

- The plane that passes through the highest uncertainty
- Efficient: User can label query voxels simultaneously by labeling the 2D plane.

Segmentation Uncertainty

Segmentation uncertainty $U(x)$ is calculated as:

\[
U(x) = \lambda_B U_B(x) + \lambda_R U_R(x) + \lambda_S U_S(x)
\]

- **Entropy** $U_B(x) = \delta(D_s(x, y(x))) \frac{1}{1 + |y(x)|}$
- **Boundary** $U_E(x) = -p_1(x) \log_2 p_1(x) - (1 - p_1(x)) \log_2 (1 - p_1(x))$
- **Regional** $U_R(x) = p(Y = y(x) | I(x)) = \frac{p(f(x) | Y = y(x))}{p(f(x) | Y = 0) + p(f(x) | Y = 1)}$
- **Smoothness** $U_S(x) = \iint_{N_x} \delta(D_s(x, y)) dV$

- $p_1(x)$: The probability voxel $x$ is labeled foreground.
- $y(x)$: The label (either 0 or 1) assigned to voxel $x$.
- $D_s(x, y)$: The shortest distance from voxel $x$ to the segmentation surface.
- $\delta(x)$: The delta function, gives 1 when $x = 0$, and 0 otherwise.

Plane Suggestion

- We wish to find the plane, $P^*$, that slices through the most uncertainty in the uncertainty field, $U$:
  \[
P^* = \arg \max_P \iint_P U(x) dA
  \]
- Use gradient descent with multiple random initializations to find the plane intersecting with the most uncertainty.

TurtleSeg

TurtleSeg is a full-featured interactive 3D segmentation software with a functional implementation of our Active Learning method.

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Results

Quantitative Results

Learning curves for Active Learning plane suggestion versus random plane suggestion. Notice that the Active Learning method consistently out-performs random plane selection. Experimented on 8 independent data sets, but only 4 are shown here.

User Study

A user study was performed on a radius bone CT image. The graph shows Active Learning versus user intuition. First plane already chosen. The figure shows Active Learning reduced user interaction time by 64%.