Deep Active Learning for Interactive 3D Segmentation Of Medical Images

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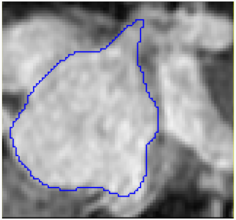

Figure 1: Segmentation of the left atrium

Main Problem: Laborious, particularly in 3D

Medical Image Segmentation

3D Medical Image Segmentation

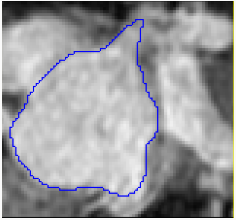

Figure 1: Segmentation of the left atrium

Main Problem: Laborious, particularly in 3D

How can we automate this?

Conditional Random Fields

Aim: Separate the set of *background* pixels ($\mathbf{B}$) from the set of *object* pixels ($\mathbf{O}$)

Define a cost function to be minimized over image $\mathbf{X}$

Conditional Random Fields

$$E(\mathbf{X}) = \sum_i R_i + \lambda \sum_i \sum_j B_{ij} \tag{1}$$

- R_i - **Regional Penalty Term** - penalty for assigning pixel i to either the background ($\mathbf{B}$) or object ($\mathbf{O}$)
- B_{ij} - **Boundary Penalty Term** - penalty depending on properties of pixels i and j
- $\lambda > 0$ - a relative weighting

Conditional Random Fields

R_i - **Regional Penalty Term**

Map (0,1) probabilities to (∞, 0) penalties with negative log

Conditional Random Fields

R_i - **Regional Penalty Term**

Map (0,1) probabilities to (∞, 0) penalties with negative log

$$R_i = \begin{cases} -\log P(i \in O) & i \in \mathbf{O} \\ -\log P(i \in B) & i \in \mathbf{B} \end{cases} \tag{2}$$

Conditional Random Fields

B_{ij} - **Boundary Penalty Term**

Want to encourage boundaries at discontinuities in intensity

Penalize boundaries that are placed between similar pixels

Conditional Random Fields

B_{ij} - **Boundary Penalty Term**

Want to encourage boundaries at discontinuities in intensity

Penalize boundaries that are placed between similar pixels

$$B_{ij} = \begin{cases} 0 & y_i \neq y_j \\ \frac{1}{r_{ij}} e^{\frac{-(x_i - x_j)^2}{2\sigma^2}} & y_i \neq y_j \end{cases} \tag{3}$$

- X_i - grayscale value at pixel i
- y_i - binary label for pixel i (0 means $i \in \mathbf{B}$)
- r_{ij} - euclidean distance between pixels i and j

Conditional Random Fields

How do we solve it?

Represent the image as a graph with

- One node per pixel
- One source node (object)
- One sink (background)

Conditional Random Fields

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Represent the image as a graph with

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and

- Edges between pixels have a cost $\lambda \frac{1}{r_{ij}} e^{\frac{-(x_i - x_j)^2}{2\sigma^2}}$
- Edges between pixels and the source terminal cost $-\log P(i \in B)$
- Edges between pixels and the sink terminal cost $-\log P(i \in O)$

A minimum cost cut which severs the source from the sink will now minimize the cost function

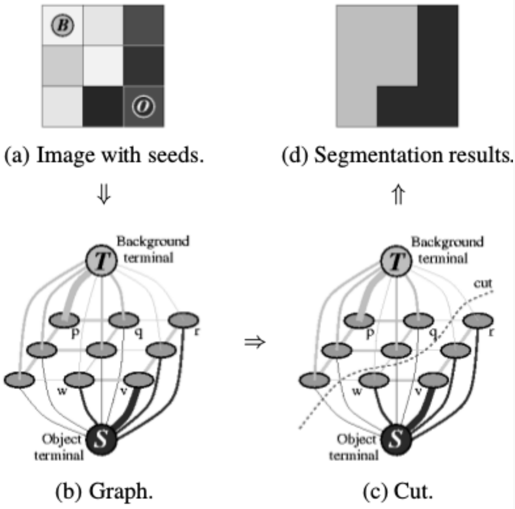

Figure 2: Minimum cost cut

Conditional Random Fields

Maxflow: Finding the maximal flow from source to sink

The edges that are saturated in maxflow are those in the minimal cost cut.

Conditional Random Fields

Maxflow: Finding the maximal flow from source to sink

The edges that are saturated in maxflow are those in the minimal cost cut.

Solve with **Breadth First Search**, by gradually saturating edges

Graph Cuts

How do we get $P(i \in B)$ and $P(i \in O)$?

User interaction

- User gives seed points
- Probability distribution produced from seed points
- Probabilities of other pixels inferred from distribution

Works well, but...

Graph Cuts

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Graph Cuts

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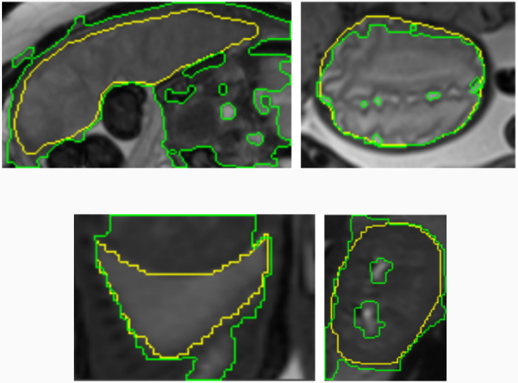

Figure 3: Grabcut algorithm in difficult cases

Graph Cuts

Requires object and background pixels to have distinct intensity values

This is the case for most traditional segmentation methods

Convolutional Neural Networks

Convolutional Neural Networks

Advantages

- Spatial operations
- Learning
- Performance

Disadvantages

- Computationally expensive
- Poor generalisation to unseen types
- Need large datasets - expensive for medical imagery

Convolutional Neural Networks

Classification CNNs - gradually extract larger features from smaller ones

Convolutional Neural Networks

Classification CNNs - gradually extract larger features from smaller ones

U-Net - gradually re-combine those features to produce a segmentation map

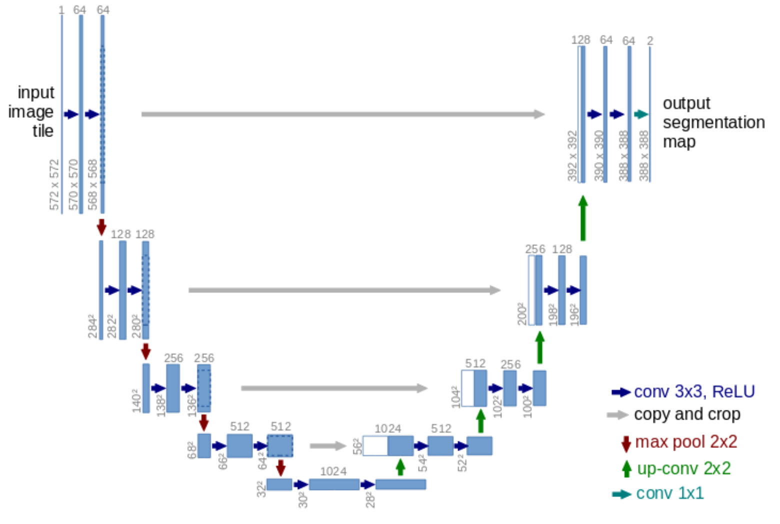

Figure 4: The U-Net architecture

Segmentation CNNs

Improvements since original U-Net:

- Residual blocks
- Spatial Dropout
- Segmentation Layers

Segmentation CNNs

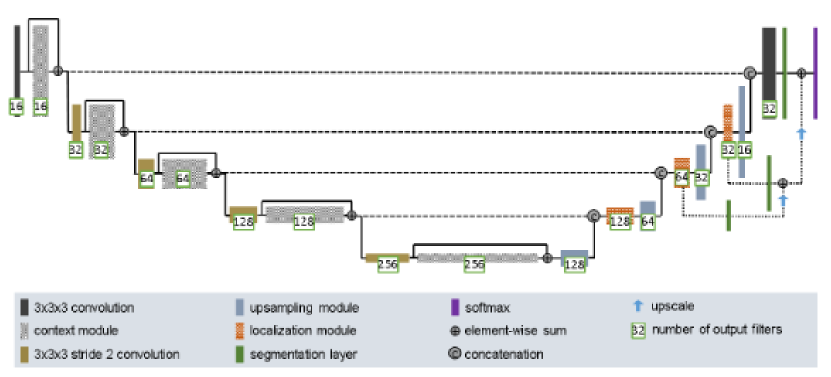

Figure 5: The Isensee et al. architecture

Segmentation Layers encourage earlier layers to produce segmentations

Aims and Design

Aims

Aims:

Minimize the disadvantages of CNNs so that they can be used for 3D image segmentation

Disadvantages

1. Computationally expensive
2. Poor generalisation to unseen types
3. Need large datasets - expensive for medical imagery

BIFSeg

Bounding-box Image-specific Fine-Tuning Segmentations (BIFSeg)
Combines CNN and CRF

Leverages user corrections

1. Draw bounding box around area of interest
2. CNN and CRF give initial guess
3. User provides correction scribbles
4. CNN fine-tunes using corrections and gives corrected result

BIFSeg

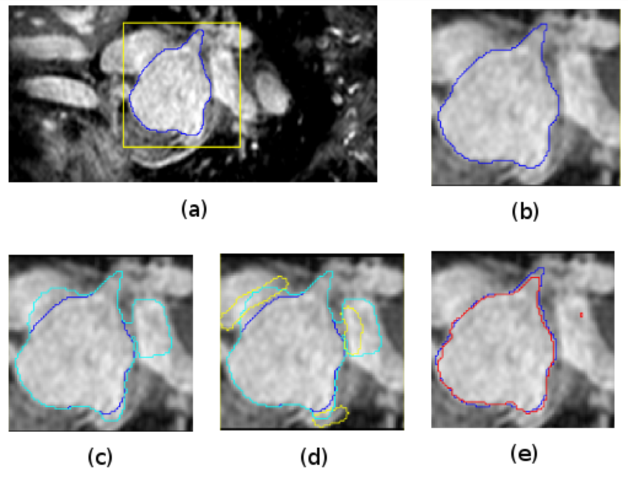

Figure 6: The steps in the BIFSeg framework. In *blue* is the ground truth, in *cyan* the initial guess, in *yellow* pixels relabelled as background and in *red* is the final result

BIFSeg

Two things going on:

- **Combining CNN and CRF**
  CNN softmax output used as probability values for calculating R_i

Two things going on:

- **Combining CNN and CRF**
  CNN softmax output used as probability values for calculating R_i
- **Fine-Tuning CNN using CRF**
  1. CNN, CRF and scribbles produce segmentation
  2. CNN trained to match segmentation
  3. Repeat steps 1 and 2 n times

Fine-Tuning CNN using CRF

CNN loss function is **weighted** on a per-pixel basis during fine-tuning, such that the weight for pixel i is

$$w_i = \begin{cases} 0 & i \in \mathbf{U} \\ w & i \in \mathbf{S} \\ 1 & \text{otherwise} \end{cases} \tag{4}$$

- **U** - set of pixels for which the current segmentation is uncertain
- **S** - set of user scribbles

BIFSeg

Fine-Tuning CNN using CRF

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Pixels in **U** are either **geodesically** near a scribble of opposite label or have P_i near 0.5

Design

BIFSeg works on unseen object types - though it needs a CNN that has learned **generalisable features**

Performs better and with less user interaction on seen object types

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Transfer learning

1. Start by using a CNN trained in generalised segmentation
2. After *n* images have been segmented, add them to a dataset
3. Load a new CNN with the generalised CNN weights and train it on the dataset
4. Repeat steps 2 and 3 until all images have been segmented

Results

Seen objects

Evaluate performance on **seen** objects

Train and test on left atrium images

Dice Scores

- Initial Prediction - 0.872 ± 0.025
- After User Interaction - 0.9112 ± 0.018

Seen objects

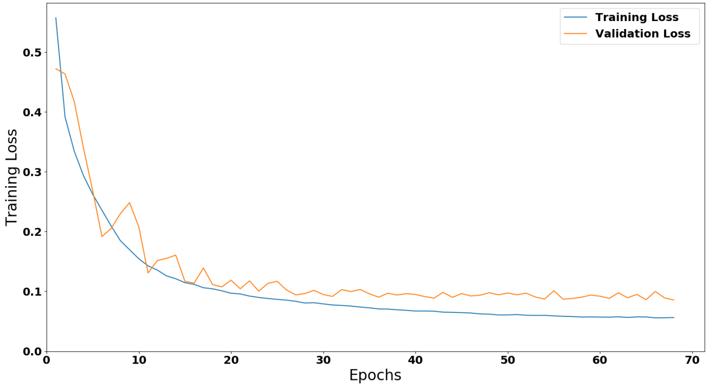

Figure 7: Loss plot for weighted dice coefficient loss on left atrium data

Seen objects

Evaluate performance on **seen** objects

First train a generalised CNN

Organ Type	Dice Score
Left Atrium	0.616 ± 0.025
Prostate	0.873 ± 0.054
Hippocampus	0.487 ± 0.125
All	0.617 ± 0.054

Table 1: Validation scores for the generalized segmentation CNN on the organs it was trained on

Seen objects

Organ Type	Dice Score (CNN)	Dice Score (CNN+CRF)
Liver	0.516 ± 0.019	0.532 ± 0.022
Spleen	0.417 ± 0.033	0.484 ± 0.037

Table 2: Dice scores by the generalized segmentation CNN on unseen object types with and without the CRF

Organ Type	Dice Score (10 scribbles)	Dice Score (15 scribbles)
Liver	0.873 ± 0.029	0.891 ± 0.021
Spleen	0.892 ± 0.018	0.918 ± 0.016

Table 3: Dice scores by the generalized segmentation CNN on unseen object types, after fine-tuning with user interaction

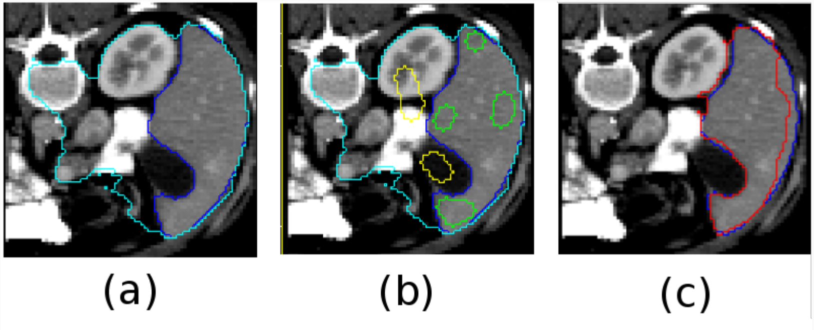

Figure 8: Segmentation of unseen object type (liver) using BIFSeg. In *blue* is the ground truth, in *yellow* are background scribbles, in *green* foreground scribbles and in *red* the final segmentation. Final Dice score over the 3D image was 0.884

Transfer Learning - Liver

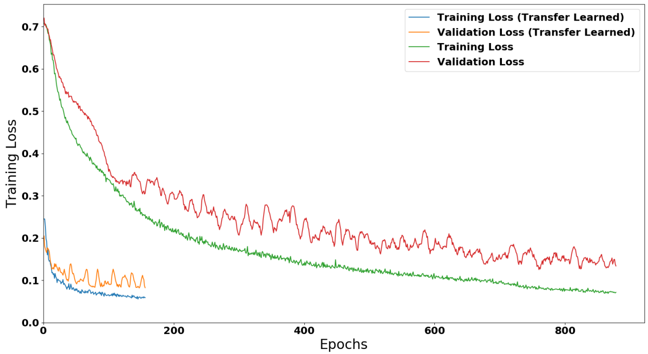

Figure 9: Comparison of transfer learning and learning from scratch learning on the liver with 4 training images and 6 validation images

Transfer Learning - Spleen

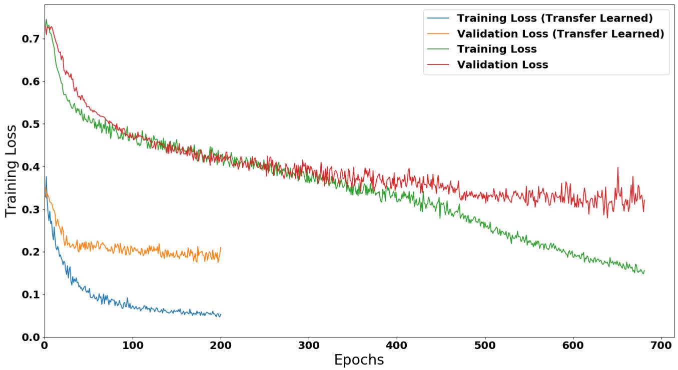

Figure 10: Comparison of transfer learning and learning from scratch learning on the spleen with 4 training images and 6 validation images

Further Work

Conclusion