A comparison of image segmentation methods

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Goal : Image segmentation with limited data

In the last decade, the traditional method of PDE-based image segmentation has been replaced by techniques using deep convolutional neural networks (DCNN). However, DCNN methods require large amounts of labeled training data; in many industrial problems, such training data is difficult and costly to obtain. This contrasts the previous PDE methods, which required little or no training data.

DCNN methods $\Longleftrightarrow$ PDE methods $\Longleftrightarrow$ Training with less data

Three methods

Level Sets

- First-order hyperbolic PDE

$$\phi_t + F^T \nabla \phi = 0$$

- Segmentation is level set of solution $\phi = 0$
- F forces ϕ outward based on image, curvature

UNet

- Type of DCNN developed for biomedical images
- Edge + feature detection at increasing scales

UNet + Skip

- Improvement on standard UNet architecture
- Adds skip connections across layers of 'U'

Metric of comparison

Using data from the MICCAI 2017 LiTS challenge, we compare the performance of the PDE-based level set equation to a standard deep convolutional UNet, with and without skip connections. Models are scored by the Dice similarity coefficient (DSC):

$$DSC(S_{true}, S_{pred}) = \frac{2\,|S_{true} \cap S_{pred}|}{|S_{true}| + |S_{pred}|}$$

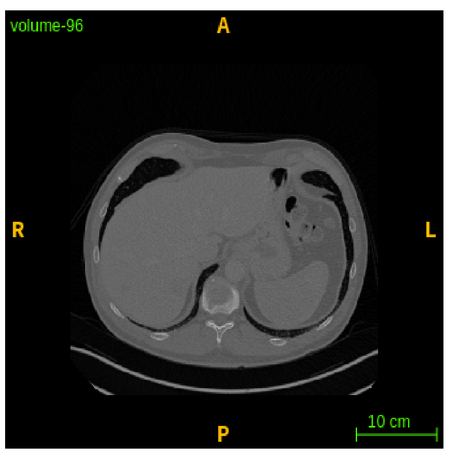
Implementation

	Level Set	UNet	UNet+Skip
Framework	ITK-SNAP	TF + Keras	TF + Keras
Training time	—	78h	78h
Prediction time	600s	70s	73s
# Parameters	3	32M	32M

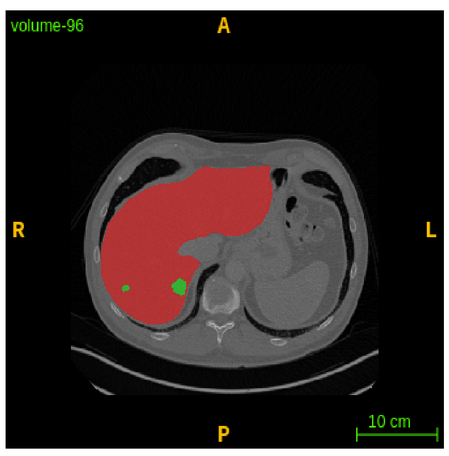
DCNN Hyperparameters

Epochs	40
Layers	8
# Convolutions	32
Activation	ReLu
Optimizer	Adadelta
Loss	DSC

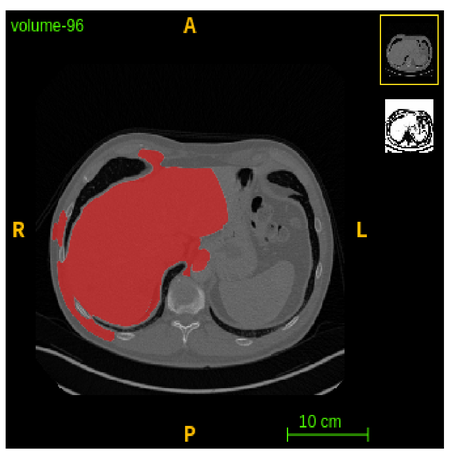
Image



Truth

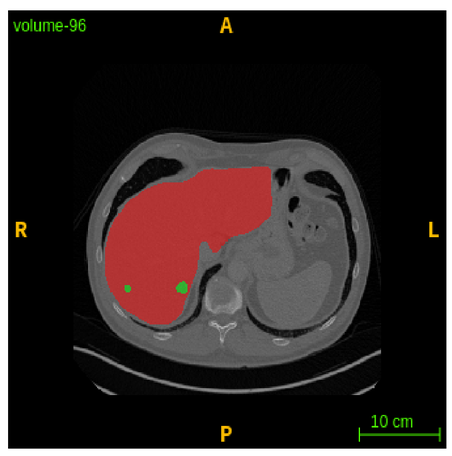


Level Set



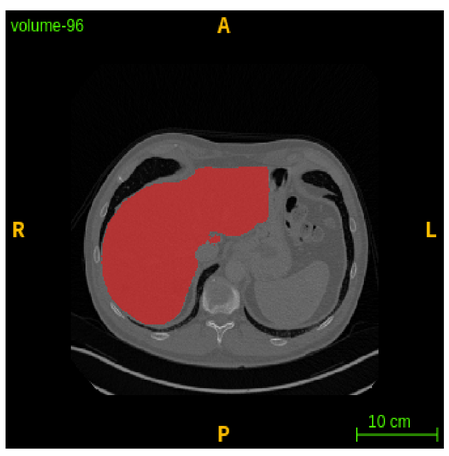
DSC(Liver)=0.745
DSC(Tumor)=0.000

UNet



DSC(Liver)=0.955
DSC(Tumor)=0.339

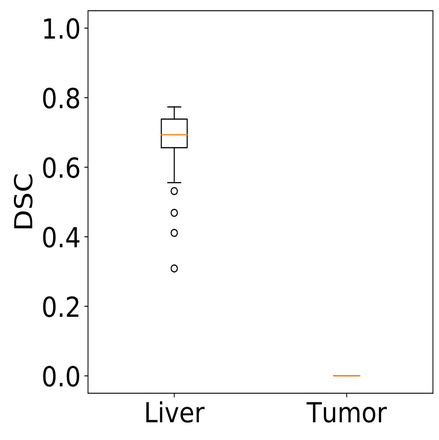
UNet+Skip



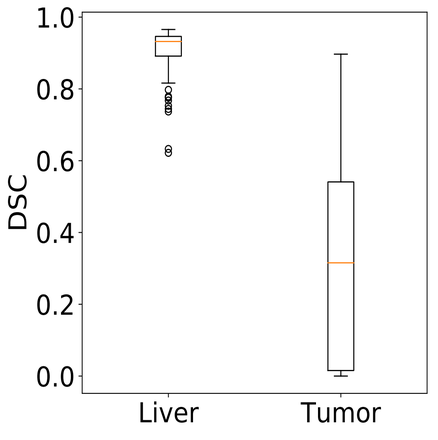
DSC(Liver)=0.953
DSC(Tumor)=0.000

Conclusions

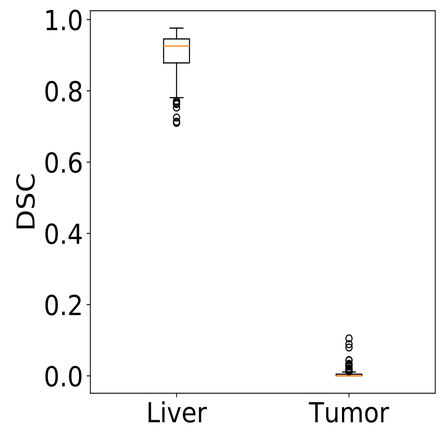
- Level sets require significant tuning **but** no training.
- DCNN provides accurate liver boundary segmentation.
- No method excels at tumor identification.
- **Complicated architectures are not always better!**



Test set DSC scores ($N = 22$)



Test set DSC scores ($N = 131$)



Test set DSC scores ($N = 131$)

Future Work

- Implement 2-stage process for tumor segmentation
- Compare with other DCNN architectures, e.g. ResNet
- Develop optimal control formulation for level set equation

Acknowledgements

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