

U-Net: Convolutional Networks for Biomedical Image Segmentation

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Content

- Previous work
- About U-net
- Architecture
- U-net strategy
- Data augmentation
- Experiment
- Conclusion

Previous work

The winner ISBI 2012

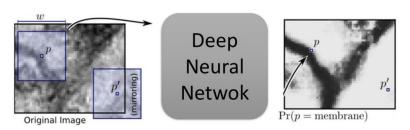
- Trained a network in a slidding window (local region (patch) around a pixel)

Advantage

- The network can localize
- Training data in term of patches is much larger than the number of training images

Disadvantages

- Slow because the network run separetly for each patch
- Having redondancy



About U-net

- U-Net is a convolutional neural network that was developed for biomedical image segmentation
- Works with very few training sample (30 images approximately)
- Gets his name from the U shape of the architecture

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Figure 2: Biomedical image segmentation with U-net

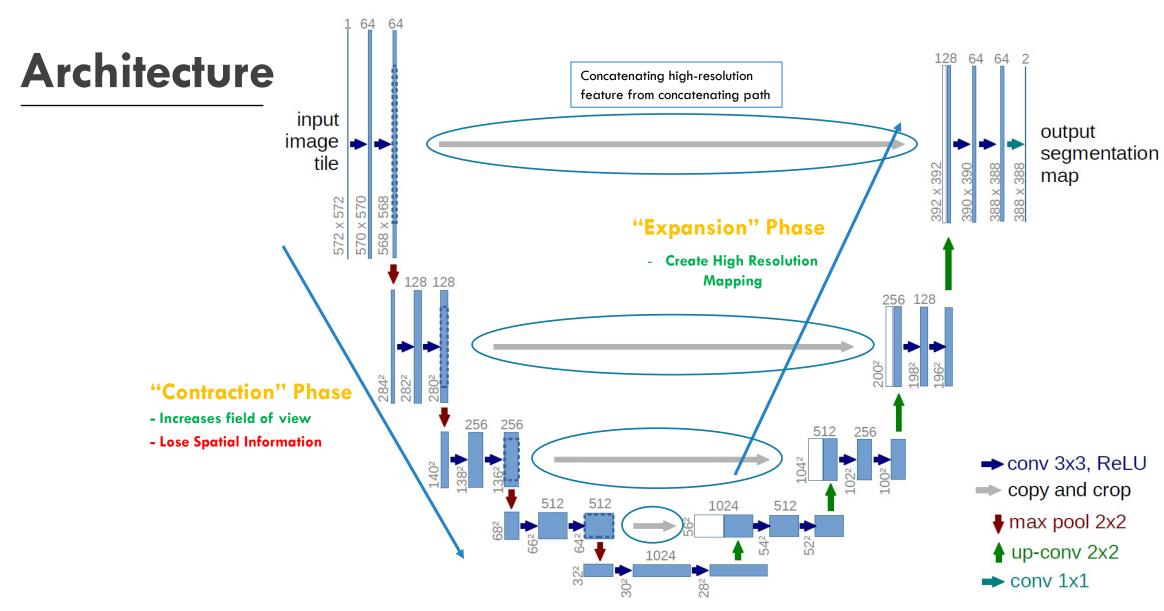


Figure 3: U-net Architecture, Ronneberger et al. (2015)

U-net strategy

- To the yellow part a padding from the blue region is added as padding
- Raw data extrapolated by mirroring

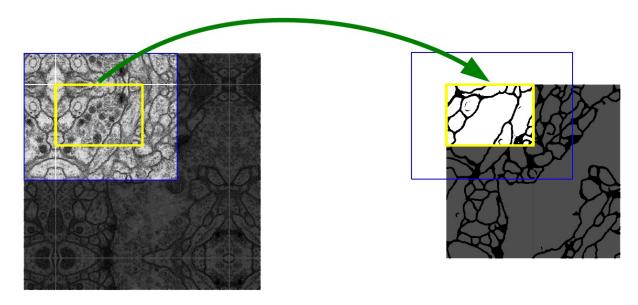


Figure 4: Overlap-tile strategy for seamless segmentation of arbitrary large images

Data augmentation

- Few images provided
- Elastic deformation
- Shift and rotation invariance of the training Sample
- Random displacement vectors on 3 by 3 grid

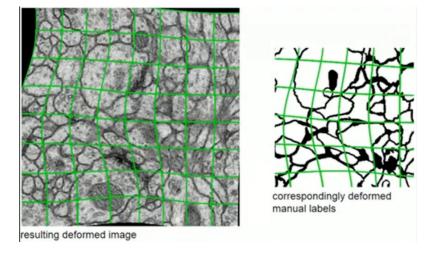


Figure 5: Augmented training data using deformation

Experiment

- Winner of the ISBI challenge in 2015
- Better than slidding window

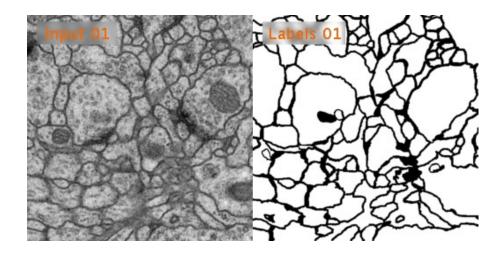


Figure 6: EM (Electron microscopic) images segmentated

Rank		Group name	Warping Error	Rand Error	Pixel Error
		** human values **	0.000005	0.0021	0.0010
	1.	u-net	0.000353	0.0382	0.0611
	2.	DIVE-SCI	0.000355	0.0305	0.0584
	3.	IDSIA [1]	0.000420	0.0504	0.0613
	4.	DIVE	0.000430	0.0545	$\boldsymbol{0.0582}$
	:				
	10.	IDSIA-SCI	0.000653	0.0189	0.1027

Table 1: Ranking on the EM segmentatation challenge

Conclusion

- very good performance on very different biomed-medical segmentation applications
- Faster than the slidding window (1 sec per image)
- Works with limited amount of data
- succeeds to achieve very good performance on different biomedical segmentation applications
- Reasonable time to train (10 hours on a NVidia Titan GPU (6 GB))

