New advances in the U-net architecture

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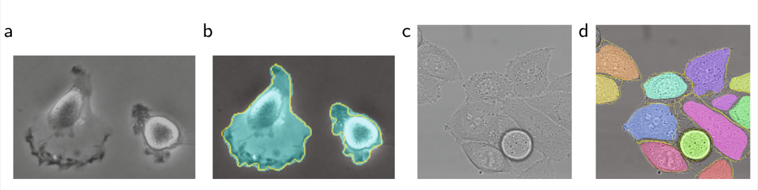
20. 5. 2022

Contents

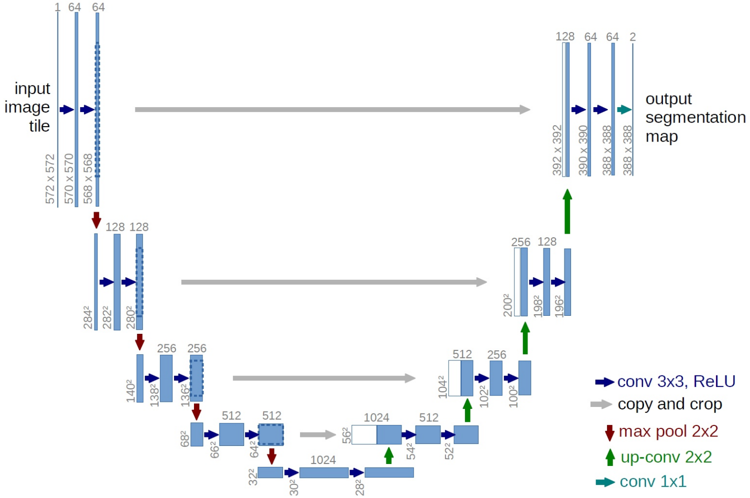
U-net review

- First described 2015 in “Ronneberger & al: U-Net: Convolutional Networks for Biomedical Image Segmentation”
- Segmentation network

Segmentation examples – from the original paper



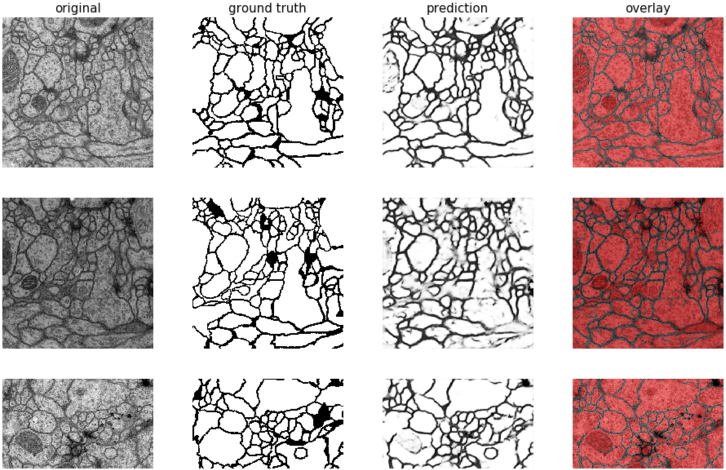
U-net configuration



U-net

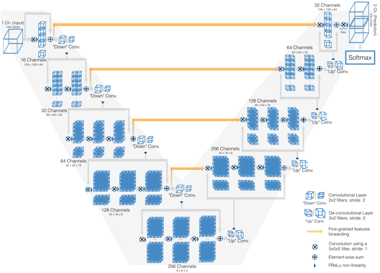
- contracting path
  - reducing resolution
  - doubling the number of features
  - from fine, low-level to high-level features
- expansive path
  - reconstruction of image
  - novelty: shortcut connections to improve localization
- Original implemenation: caffe language
- “Reference implementation”: Karol Zak
  `https://github.com/karolzak/keras-unet`

ISBI 2015 Winner



Applications: medical imaging, bioimaging

Example:
V-net: 3D Net for Volumetric Segmentation, Milletari & al, 2016
PROMISE12 MICCAI MRI prostate segmentation challenge



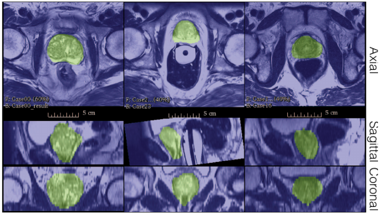


Figure 5. Qualitative results on the PROMISE 2012 dataset [10].

Good overview (2019)

Hesamian, M.H., Jia, W., He, X. et al.
Deep Learning Techniques for Medical Image Segmentation: Achievements and Challenges
Journal of Digital Imaging 32, 582–596 (2019)
https://doi.org/10.1007/s10278-019-00227-x

Other applications

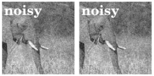
Denoising

attempts to avoid clean reference

- often difficult to obtain
  (medical X-ray, confocal time-lapse microscopy, etc.)
- Several approaches:
  - Noise2noise: compare with noisy image
  - Noise2Void: compare with void image

Clever construction of targets

Noise2Noise



Standard training task:

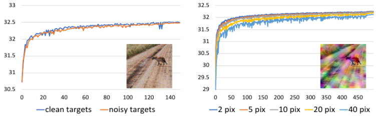
$$\arg\min_{\Theta} \mathbb{E}_x\{\mathbb{E}_{y|x}\{L(f_\Theta(x), y)\}\}$$

Replace distribution $p(y|x)$ with distributions with the same expected values:

$$\arg\min_{\Theta} \sum_i L(f_\Theta(\hat{x}_i), \hat{y}_i)$$

`https://github.com/NVlabs/noise2noise`

Noise2Noise - performance



(a) White Gaussian, $\sigma = 25$ **(b) Brown Gaussian,** $\sigma = 25$

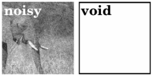
Performance for white and coloured noise

Text removal

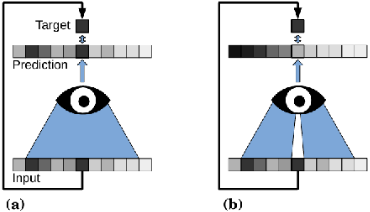
Disadvantage

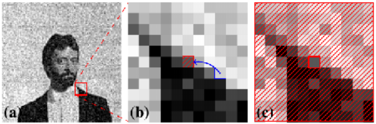
Two independent images with the same contents not always available – especially in bioimaging

Noise2void



Target patches from the input image





Blind-spot network

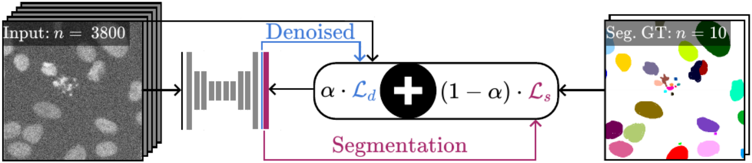
Construction of patches

`https://github.com/juglab/n2v`

DenoiSeg

Joint denoising & segmentation

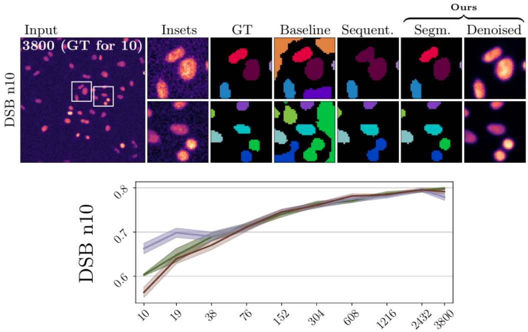
- Annotations for segmentation are often costly (time-consuming manual preparation)
- (Much) more images than annotations
- This method combines Noise2Void training with segmentation training



$$\mathcal{L} = \frac{1}{m} \sum_{i=1}^{m} \alpha \cdot \mathcal{L}_d(\mathbf{x}_i, f(\mathbf{x}_i)) + (1-\alpha) \cdot \mathcal{L}_s(\mathbf{y}_i, f(\mathbf{x}_i))$$

DenoiSeg

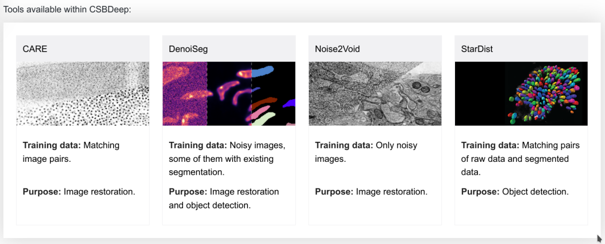
https://github.com/juglab/DenoiSeg



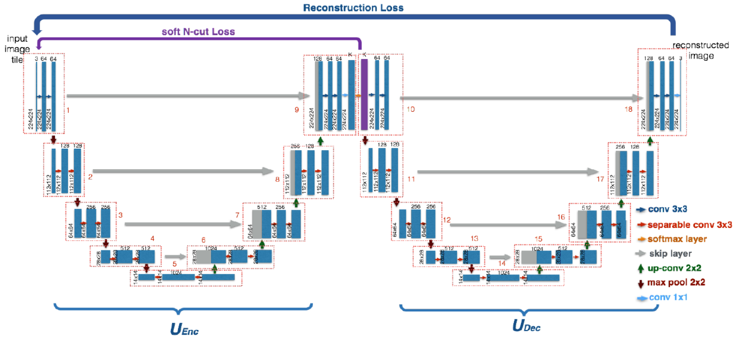
CSBDeep toolbox

Noise2Void + DenoiSeg + CARE + StarDist = CSBDeep

Jug Lab Center for Systems Biology Dresden
Max Planck Institute of Molecular Cell Biology and Genetics
Florian Jug



W-net



Xia, Kulis, Boston University, 2017

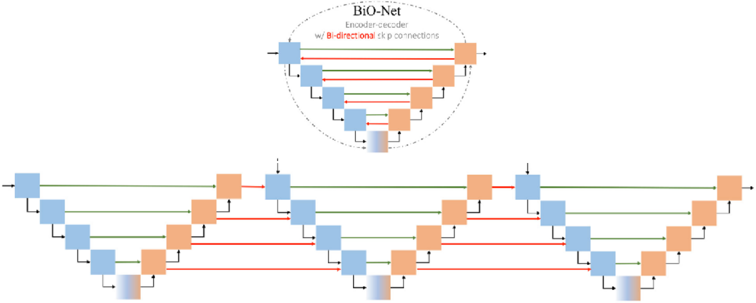
- Fully unsupervised segmentation
- Two cascaded U-nets: segmentation/image reconstruction
- Segmentation: encoding U-net output
- K features, postprocessing (CRF + merging of segments)

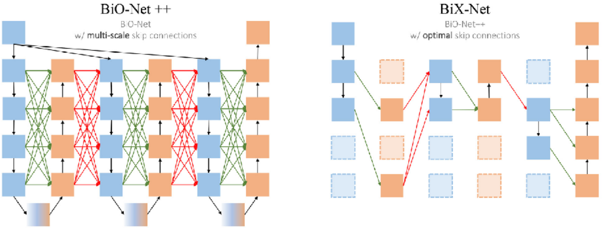
W-net

Some segmentation examples

Bi-directional U-net

Xiang, Zhang, & al: *Towards bi-directional skip connections in encoder-decoder architectures and beyond*
Medical Image Analysis, Vol. 78, 2022
https://doi.org/10.1016/j.media.2022.102420





Bix-Net: connections optimized by Neural Architecture Search

	MoNuSeg		TNBC					
Methods	IoU (%)	DICE (%)	IoU (%)	DICE (%)	#Params	Overhead[1]	MACs	Overhead[1]
BiO-Net	69.9±0.2	82.0±0.2	62.2±0.4	75.8±0.5	14.99 M	3845%	115.67 G	313%
BiO-Net++	**70.0±0.3**	**82.2±0.3**	67.5±0.4	80.4±0.5	0.43 M	13%	34.36 G	23%
Phase1 searched	69.8±0.2	82.1±0.2	66.8±0.6	80.1±0.4	0.43 M	13%	31.41 G	12%
BiX-Net	69.9±0.3	**82.2±0.2**	**68.0±0.4**	**80.8±0.3**	**0.38 M**	0%	**28.00 G**	0%

[1] Overhead compared to BiX-Net.

Conclusions

- Introduction to U-net
- U-net in denoising applications
- New architectures for segmentation