THU-Pe-CN

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Platform: Linux

Prerequisites: Python

THU-Pe-CN: SUMMARY

Our hybrid approach combines a fully convolutional network architecture and seeded watershed segmentation for cell instance semantic segmentations. Our previous effort indicated that a traditional SOM network with sophisticated preprocessing procedures can be used to construct markers for watershed segmentation [1]. Due to the development of more convenient convolutional network architecture recent years, the underling hybrid idea is adopted in this watershed on U-net framework. The U-Net architecture can work with very few images and yields more precise segmentations [2]. We use the trained end-to-end network output with morphological operations as the roughly classified inner-cell regions, cell borders and backgrounds. Based on these results, proper foreground and background seeds were constructed for the seeded watershed segmentation and every single cell in a cell cluster can be segmented correctly. The framework for training and testing the networks is available under https://github.com/faithfading.

THU-Pe-CN: PREPROCESSING

As for our tasks there is very little training data available, we use excessive data augmentation by applying elastic deformations to the available training images [3]. This allows the network to learn invariance to such deformations, without the need to see these transformations in the annotated image corpus. This is particularly important in biomedical segmentation, since deformation used to be the most common variation in tissue and realistic deformations can be simulated efficiently. Data augmentation is essential to teach the network the desired invariance and robustness properties, when only few training samples are available. In case of microscopic images, we primarily need shift and rotation invariance as well as robustness to deformations and gray value variations, especially random elastic deformations of the training samples seem to be the key concept to train a segmentation network with very few annotated images. We generated smooth deformations using random displacement vectors on a coarse 3 by 3 grid. The displacements are sampled from a Gaussian distributions with 10 pixels standard deviation. Per-pixel displacements are computed using bi-cubic interpolation. Drop-out layers at the end of the contracting path perform further implicit data augmentation. Another challenge in many cell segmentation tasks is the separation of touching objects of the same class. To this end, we propose the use of a weighted loss, where the separating background labels between touching cells obtain a large weight in the loss function.

THU-Pe-CN: SEGMENTATION

The U-Net network consists of a contracting path and an expansive path. The contracting path follows the typical architecture of a convolution network. It consist of the repeated application of two 3x3 convolutions (unpadded convolutions), each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for downsampling. At each down-sampling step, we double the number of feature channels. Every step in the expansive path consists of an up-sampling of the feature map followed by a 2x2 convolution (“up-convolution”) that halves the number of feature channels, a concatenation with the corresponding cropped feature map from the contracting path, and two 3x3 convolution, each followed by a ReLU. At the final layer a 1x1 convolution is used to map each 64-component feature vector to the desired number of classes. In total the network has 23 convolutional layers. In our experiments, the weights on different categories can be adjusted and we find that, batch normalization layers is not needed.

THU-Pe-CN: POST-PROCESSING

The methods above can be useful to find proper watershed seeds. The foreground seeds were obtained using the inner-cell regions with small contaminations removed by area opening operation. The background seeds were constructed with eroded and small objects removed. These seeds were imposed to be the local minima on the inverse of the original image. The simulated water immersion process started from these local minima and reached the ridges representing the actual cell borders.

REFERENCES

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3. Schaefer S, McPhail T, Warren J. Image deformation using moving least squares. *ACM Transactions on Graphics* **25**, 533-540 (2006).