HD-Wol-GE

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Platform: Linux

Prerequisites: Python

HD-Wol-GE: SUMMARY

Our method for cell segmentation combines a convolutional neural network (CNN) and a recurrent neural network (RNN). Features are extracted at multiple scales using a neural network based on a Deconvolution Network [1] with Densely Connected layers [2]. The extracted features are combined iteratively using an RNN. We used LReLU [3] as activation function and instace normalization [4].

HD-Wol-GE: PREPROCESSING

We pre-process the images with Contrast Limited Adaptive Histogram Equalization (CLAHE) [5] and convert them to 8-bit.

HD-Wol-GE: SEGMENTATION

In the first stage, we pre-trained our network on all annotated images of the challenge. The AdamW [6] optimizer was used (learning rate: 0.001; weight decay: 0.0001; β_1: 0.9; and β_2: 0.999) with cross-validation (90% training, 10% validation) and early stopping. In the second stage, we fine-tuned the network for 25 epochs on the manually annotated images of each training dataset. We used random cropping (256×256 patches), flipping, and rotation for data augmentation. Only patches that include objects with available ground truth were considered. Segmentation is performed independently for each time step of the videos. For 3D videos, the network is applied slice-wise.

HD-Wol-GE: POST-PROCESSING

Objects with a too large or too small major axis are discarded, and holes in the segmentation masks are closed using morphological operators. For 3D images, objects spanning less than five slices are discarded. The provided field of views and ground truth trajectories are used to filter the segmentation masks. The thresholds for the major axis were determined from the training datasets. The upper threshold is set to 125% of the maximum in the training datasets. The lower threshold is set to 0.25% of the mean in the training datasets.

REFERENCES

1. Noh H, Hong S, Han B. Learning deconvolution network for semantic segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 1520-1528 (2015).
2. Huang G, Liu Z, Van Der Maaten L, Weinberger KQ. Densely connected convolutional networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 4700-4708 (2017).
3. Maas AL, Hannun AY, Ng AY. Rectifier nonlinearities improve neural network acoustic models. In *Proceedings of the 30th International Conference on Machine Learning*, 192 (2013).
4. Ulyanov D, Vedaldi A, Lempitsky V. Instance normalization: The missing ingredient for fast stylization. arXiv:1607.08022 (2016).
5. Van der Walt S, Schönberger JL, Nunez-Iglesias J, Boulogne F, Warner JD, Yager N, Gouillart E, Yu T. Scikit-image: Image processing in Python. *PeerJ* **2**, e453 (2014).
6. Loshchilov I, Hutter F. Fixing weight decay regularization in Adam. arXiv:1711.05101 (2017).