BFR-GE (2)

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Platform: Windows, Linux

Prerequisites: Python 3

BFR-GE (2): SUMMARY

Our approach utilizes the Microscopic Image Analyzer (MIA) software for image segmentation [1]. MIA is custom written software application allowing image labeling, neural network training, model predictions and post-processing.

BFR-GE (2): PREPROCESSING

All training input images were normalized to the range of [-1, 1].

BFR-GE (2): SEGMENTATION

First, MIA was used to train a small model on the given gold-truth reference segmentation annotations. That trained model was used to predict the missing labels of the training set. The predicted labels were manually curated using MIA to create an extended training set. Additionally, the extended and curated gold-truth reference segmentation annotations were extended by one more class consisting of 3-pixel-wide borders of individual cells. Next, a U-Net [3] with an Inception-v4 [4] backbone with pre-trained weights was trained with a batch size of 8 for 500 epochs using the extended and curated gold-truth reference segmentation annotations. The model was trained with 512 × 512 image patches that are randomly sampled from the training images. The CTC labels were converted to MIA compatible labels. Since MIA counts touching objects as one, touching objects were separated by introducing a zero-valued boundary between them. The cell border class was weighted with 1, the center cell class with 0.1, and background with 0.05. The Adam optimizer [2] with an initial learning rate of 0.0005, halved every 50 epochs, was used to optimize the cross entropy cost function. The augmentation strategy used for training involved image flipping, rotation, up to 10 % shearing, 90-110 % scaling and a 15 % probability of image blurring, piecewise affine image transformation or image dropout.

The model predictions were done with test time augmentation, meaning that the input image was flipped and rotated by +-90 degree to generate a total of six input images. The model predictions of these transformed images were averaged to the final prediction.

BFR-GE (2): POST-PROCESSING

The detected objects were split based on morphological image operations. Upon conversion to the CTC labels, the detected objects were extended to neighboring objects to expand the objects into the cell border class.

REFERENCES

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