HDU-CN

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Platform: Linux (tested on Ubuntu 18.04 LTS)

Prerequisites: Python 3.7 with PyTorch

HDU-CN: SUMMARY

This algorithm uses U-Net [1] to segment cell morphology and nucleus semantically, and then uses watershed algorithm [2, 3] to deal with adhesion region, so that each cell region becomes a separate region. Finally, it realizes instance segmentation. Due to the limitation of participation time, it only tests and submits on **BF-C2DL-MuSC**.

HDU-CN: PREPROCESSING

U-Net requires the input of 32 integer times of the image size, so the first preprocessing of the image is to randomly cut it to 640 $\times$ 640, and then input it into the network. Before watershed, the original image is processed by a Sobel operator.

HDU-CN: SEGMENTATION

U-Net can only complete semantic segmentation. In order to complete the instance segmentation, each cell region should be an independent region. So this algorithm is divided into two steps. The first step is to input the image into two different U-Net to predict the nuclear region mask and cell morphology mask. In order to train two different U-Net， we use the gold segmentation and tracking truths, and binarize all masks. The gold segmentation truth is used to train the U-Net of cell morphology segmentation, the gold tracking truth is used to train the U-Net of cell nucleus segmentation. In the second step, the watershed mask is generated according to the nucleus region and cell morphology region generated in the first step. At this time, the watershed mask can separate the cells in the adhesion region, but the cell region generated by the watershed result is generally smaller than the real region. So the next operation is to combine the watershed result and cell morphology to generate the final instance segmentation result. After this, the cell area size is consistent with the cell cell morphology and the cells in the adhesion area have been separated. Before training, random flip, non rigid transformation, random brightness, contrast and other operations are adopted for the case of less samples. During the training, the backbone of U-Net adopts ResNet-34, and the loss adopts the Dice loss.

In general, training ends at *N* epochs, and the initial learning rate is R, reducing the learning rate after 200 and 700 epochs. The maximum inhibition method is used to save the parameter model with the best evaluation index.

HDU-CN: POST-PROCESSING

After obtaining the final segmentation result of the instance, we can also remove the redundant cell morphology mask area according to the nuclear mask, that is, we can remove those cells with edges that generally appear on the four corners, because it can be observed that U-Net sometimes mistakenly predicts the cell like area of the image boundary, but in fact, the boundary of the image is outside the culture dish, so there is no cell at all.

REFERENCES

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3. Chien SY, Huang YW, Chen LG. Predictive watershed: A fast watershed algorithm for video segmentation. *IEEE Transactions on Circuits and Systems for Video Technology* **13**, 453-461 (2003).