Noise-tolerant Deep Learning for Histopathological Image Segmentation
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Introduction

To assess the progression of disease Duchenne Muscular Dystrophy (DMD), the proportion of fibrosis has been considered an important biomarker to provide prognostic clue [2]. With the histolimages where muscle and fibrosis are stained red and blue, it is hence critical to have accurate segmentation for muscle and fibrosis in histo-images. While the classical K-Means and Otsu are unable to provide satisfactory results, the popular supervised deep learning image segmentation framework u-net is effective in such tasks [3].

In our work, on the one hand we implement original u-net [3] by taking great K-Means segmentations as training set. In our work, on the other hand we innovatively modify the u-net [3] to a noise-tolerant u-net (NTUN) so that the training with noisy segmentations such as those from Otsu is possible. Both of methods show better performance than the K-Means and Otsu.

Objectives

- Apply deep learning in histo-image segmentation with noisy training sets.
- Relieve doctor from manual segmentation.

Innovation

Motivated by the work [4], we innovate a noise-tolerant layer (Figure 1) to the output layer of a deep learning image segmentation framework u-net (Figure 2), which alleviates the requirement of accurately segmented training images and enables “unsupervised” histo-image segmentation by taking noisy segmentation results of traditional image segmentation algorithms as the training outputs.

Model

![Model Diagram](image)

Figure 2: Schematic illustrations of u-net (without the extra linear layer in the red box) and our noise-tolerant u-net (with the extra layer). The sizes of input images or feature maps with the corresponding numbers of features are denoted under each box.

Given u training images \( X = \{X_1, \ldots, X_n\} \) and the corresponding noisy segmentation \( Y_n \), we aim to recover clean segmentations \( Y_n \). With the probabilistic model \( Pr(Y_n) = \left[ \sum_{i} Pr(Y_n|Y_i) Pr(Y_i|X) \right] \), we can construct the loss function:

\[
L = \frac{1}{K} \sum_{i=1}^{K} \log \left[ \sum_{j} Pr(Y_n = j|Y_i, X) \right] = -\frac{1}{K} \sum_{i=1}^{K} \log \left[ \sum_{j} s_i Pr(Y_n = j|X) \right],
\]

where \( K \) is the total number of pixels in \( X \) and \( i \) and \( j \) are label class.

Segmentation Results

![Segmentation Results](image)

Figure 3: Segmentation results. u-net: u-net trained with ten “clean” segmented images. u-net: u-net trained with one “clean” segmented image. u-net: u-net trained with one “noisy” segmented image. NTUN: Noise-tolerant u-net trained with one “noisy” segmented image.

Both of u-net and NTUN perform better than K-Means and Otsu’s method, moreover NTUN outperforming the u-net without the noise-tolerant layer, especially at the places marked in green boxes. The segmentation results by NTUN, when trained with “noisy” segmentation, are in fact consistent with the results by the u-net trained with “clean” segmentation.

Statistical Results

We quantitatively evaluate segmentation results based on the uniformity within clustered regions and disparity across regions in L*a*b* color space following [1, 5] since we do not have the ground-truth.

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Table 1: Performance comparison by \( E \) for five groups. KM: K-Means; OS: Otsu; UN: u-net trained with K-Means segmentation; UN*: u-net trained with Otsu segmentations; and NTUN: NTUN trained with Otsu segmentation.

Conclusion

We have proposed a noise-tolerant version of the u-net, which enables “unsupervised” deep learning for reliable segmentation of histo-images. Our preliminary experimental results show clear advantages of NTUN over the u-net and other traditional histo-image segmentation algorithms.

Acknowledgment

The authors would like to thank Dr. Joe Korngay, Dr. Jay Griffin, Mr. Stephen McConnell, Dr. Sharla Birch and Dr. Yoonsuck Choe for helpful discussions.

References