Learning tissue differentiation based on polarimetric imaging

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Introduction

Gliomas are among the most common types of brain cancer. Their infiltrative growth into neighboring tissue complicates the distinction between tumor and non-tumor tissue during surgery. The application of polarimetric imaging in combination with segmentation models has been widely investigated. A domain gap between different wavelengths and between ex vivo and in vivo data, combined with time-intensive annotation processes, motivates the need to investigate methods for closing this domain gap.

Materials and Methods

Three experiments were defined: two investigating domain shift between wavelengths and one evaluating application to in-vivo tissue. All experiments were conducted using U-Net models. Two fully supervised models were trained on the NPP dataset at 550 nm and 600 nm, respectively, with the 550 nm model serving as the baseline. A third model employed a self-learning, pseudo-label–based domain adaptation approach, where pseudo-labels were generated using transform-invariant features. This model was trained with 550 nm data as the source domain and 600 nm data as the target domain, using Gaussian blurring, random brightness adjustment, and color jittering for extracting transform-invariant pseudo-labels.

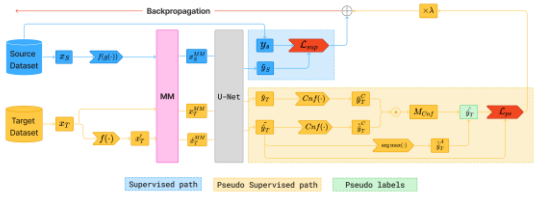

Fig. 1 Self-learning architecture investigated to close domain shift.

Experimental results were evaluated using Dice score, IoU, accuracy, AUC, as well as qualitative analysis of segmented images and Lu–Chipman features.

Results

In the first experiment, the self-learning approach improved Dice score by 0.064 (8.8% realtive to baseline) and AUC by 0.024 (2.7%). The second experiment showed no significant quantitative improvements. However, segmented images from both experiments suggested better alignment with the target domain.

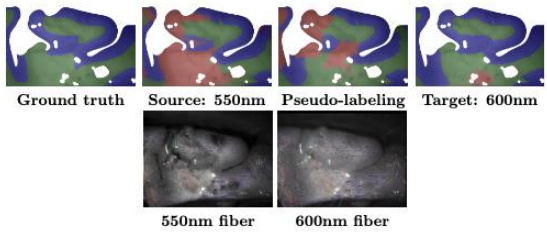

Fig. 2 Segmentation results for a non-tumor sample at 600nm. Domain gap closure is visible at the pseudo-labeling model. Fiber images illustrate differences in 550nm and 600nm. Labels: blue = gray matter, red = tumor, green=non-tumor.

Discussion

Since data augmentation primarily drives pseudo-label generation, it remains an open question whether alternative augmentations or other pseudo-labeling strategies could further improve segmentation performance. Both wavelength and in vivo experiments relied on relatively sparse datasets biased toward tumor tissue; larger, more balanced datasets could enhance performance, particularly in the in vivo experiments. Overall, results from the wavelength experiments, both quantitative and qualitative, indicate promising directions.

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