Automatic Segmentation of Musculoskeletal Tumors in Diffusion Weighted Magnetic Resonance Images Using U-Net

Background: Automatic segmentation of medical images using deep learning models has been successfully applied to acute ischemic lesions [1], brain tumors [2], breast [3] and prostate cancer [4], but no attempt has been made to detect and segment musculoskeletal tumors using diffusion-weighted magnetic resonance images (DWI).

Purpose: We propose a fully automatic segmentation of musculoskeletal tumors in DWI using U-Net: Convolutional Networks for Biomedical Image Segmentation [5].

Materials and Methods: This retrospective study included axial DWI acquired from 15 subjects with various types of musculoskeletal tumors. The tumor regions of each subject were manually segmented on DWI with *b*-value of 800s/mm^2 by a radiologist with 11 years of experience in musculoskeletal MRI to be used as a “ground-truth” for training. The 2D implementation of U-Net was designed to receive the images in size of 128 x 128 x 35 pixels per subject and was trained on Radeon Pro Vega 64X GPU with 16GBs RAM, using ADAM as an optimizer and a learning rate of 1x10^{-2} during 200 epochs. The images from 9 subjects were used for training, and those from 6 subjects were used for validation. The training was separately performed for DWI with *b*-value of 800s/mm^2 and for apparent diffusion coefficient (ADC) maps, which was calculated using two DWIs with *b*-values of 0 and 800s/mm^2.

Results: Figure 1 displays the representative slices of the (a) original DWI with *b*-value of 800s/mm^2 (top) and ADC map (down), (b) ground-truth for manually segmented tumor region, (c) U-Net prediction probability map and (d) overlay of the original image with the U-Net segmented region. The Dice coefficient of DWI with *b*-value of 800s/mm^2 was 0.396 and of ADC map was 0.530.

Conclusion: The use of U-net demonstrated good performance on tumor segmentation using DWI.

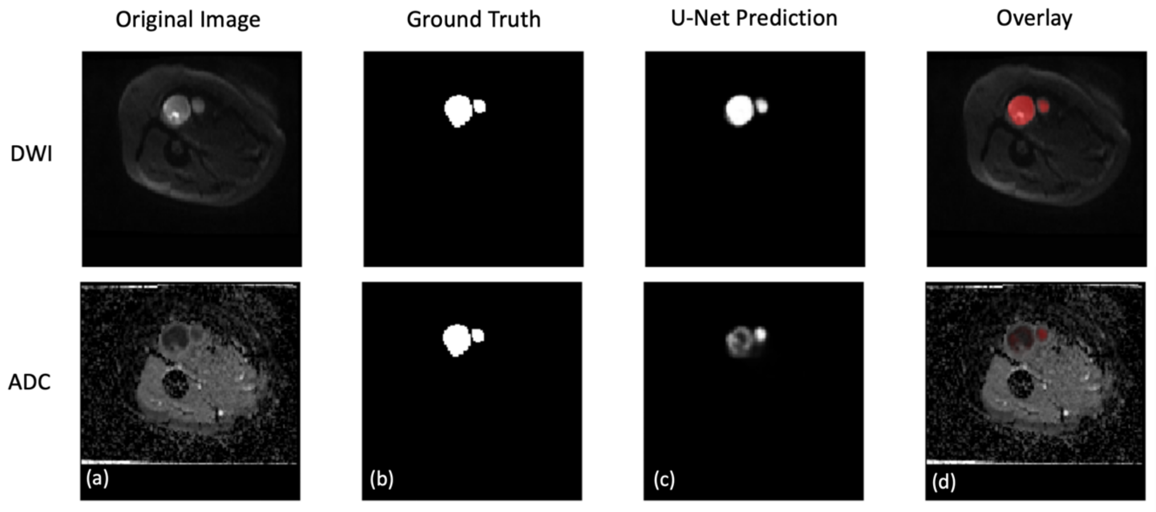

Figure 1: Representative slices of the (a) original image, (b) ground-truth for manually segmented tumor region, (c) U-Net prediction probability map and (d) overlay of the original image with the U-Net prediction on DWI (top) and ADC map (down).

References

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