A New CNN Model for Medical Image Segmentation

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At the beginning of the CNN era, most of the state-of-the-art CNN models for medical image segmentation were 2D. Later, 2.5D models emerged, which fused the segmentation results with three independent 2D models trained on patches from axial, sagittal and coronal imaging planes (Lyksborg, Puonti, Agn, & Larsen, 2015). With computation advanced in hardware and software, 3D models had been proposed and developed since they tend to outperform 2D models (Chen, Dou, Yu, Qin, & Heng, 2018). Intuitively, the performance improvement of 3D or 2.5D models over 2D ones can be attributed to that more spatial contextual information benefits the segmentation. However for some sequences with large slice gaps, this does not hold true (Ghafoorian et al., 2016), as shown in the following figure. In the experiment, the VoxResNet (Chen et al., 2018) is trained on the dataset IBSR[2]. The DICE values of gray matter, white matter and CSF decrease while the slice gap increases. In real applications, the slice gap could be large than 6 mm. Consequently, the performance of the VoxResNet drops significantly when it is applied to those images scanned with large slice gaps. Hence, in this paper a 2D model inspired by U-Net (Ronneberger, Fischer, & Brox, n.d.) is proposed. Furthermore 3D models usually require extensively computation resources at both training and inference stage.

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[2] https://www.nitrc.org/projects/ibsr/

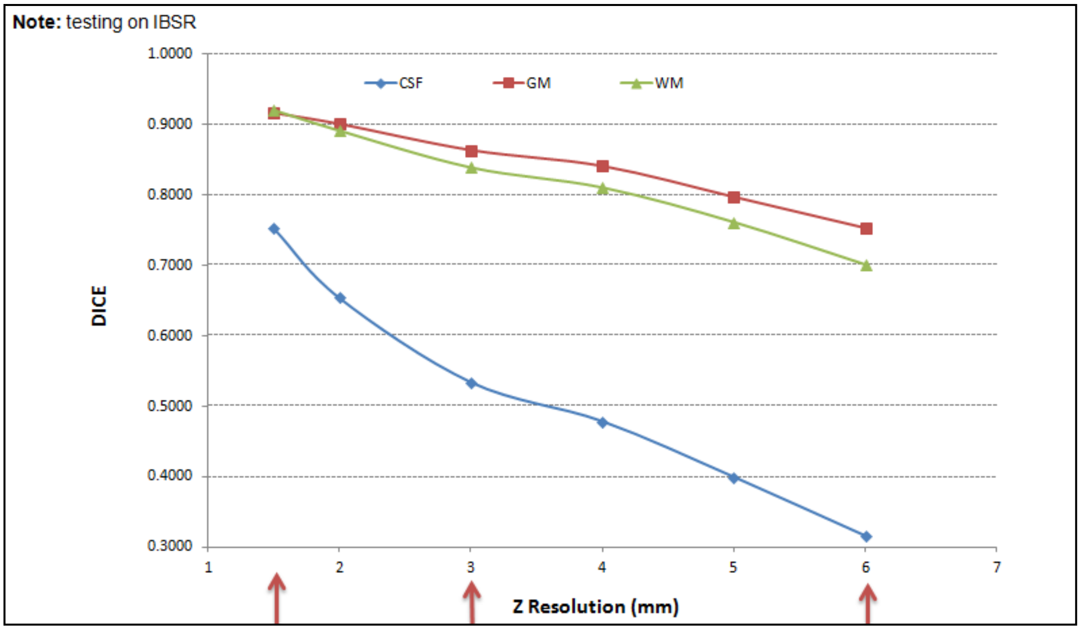

Figure 1. The influence of the third dimension resolution to the 3D model (VoxResNet) performance.

In this paper, a novel 2.5D CNN model is proposed for the segmentation task, which takes advantage of both spatial context information and multi-modalities. Based on this model, a MRI segmentation system is developed, where DICOM[3] images could be viewed via a web browser and sent to a server for segmentation. Once the segmentation is finished, the segmentation results are retrieved from the server. The user can view and make some modifications to the automated results if necessary through viewer tools. Then the model can be re-trained with these revised labels.

References

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