Clustering Propagation for Universal Medical Image Segmentation
Supplemental Material

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https://github.com/dyh127/S2VNet

This document provides additional qualitative results and discussions of S2VNet, which are organized as follows:

- Additional Details (§A)
- Discussion (§B)

A. Additional Details

Image Preprocessing Following nnUnet [1], we firstly clip intensity of CT images into a range of -175 to 250. For MRI images, the clipping is performed using the 0.5 and 99.5 percentiles of the intensity values within each image. Then, we rescale images into the range of 0 to 255.

Qualitative Results We provide additional visual comparison results on three datasets, including WORD [5] `test` in Fig. S1, BTCV [3] in Fig. S2, and AMOS [2] `val` in Fig. S3.

Failure Cases We provide failure cases in Fig. S4. As seen, our method faces challenges in statementing small objects or targets with indistinct boundaries, which is commonly observed in previous method [6].

B. Discussion

Limitation In comparison to state-of-the-art methods, S2VNet stands out by seamlessly integrating both automatic and interactive medical segmentation, showing notable computational efficiency, and achieving better accuracy in multi-class segmentation. However, S2VNet only addresses predefined classes during automatic segmentation, remaining unable to handle undefined classes. We will explore this direction to improve S2VNet in the future work.

Broader Impact This paper introduces S2VNet, a method with potential applications in various medical contexts, such as the early detection of diseases and the development of personalized treatment plans. Furthermore, the speed and user-friendly nature of S2VNet can not only alleviate the workload of experts but also seek to mitigate the increasing burden faced by the healthcare system as a whole.

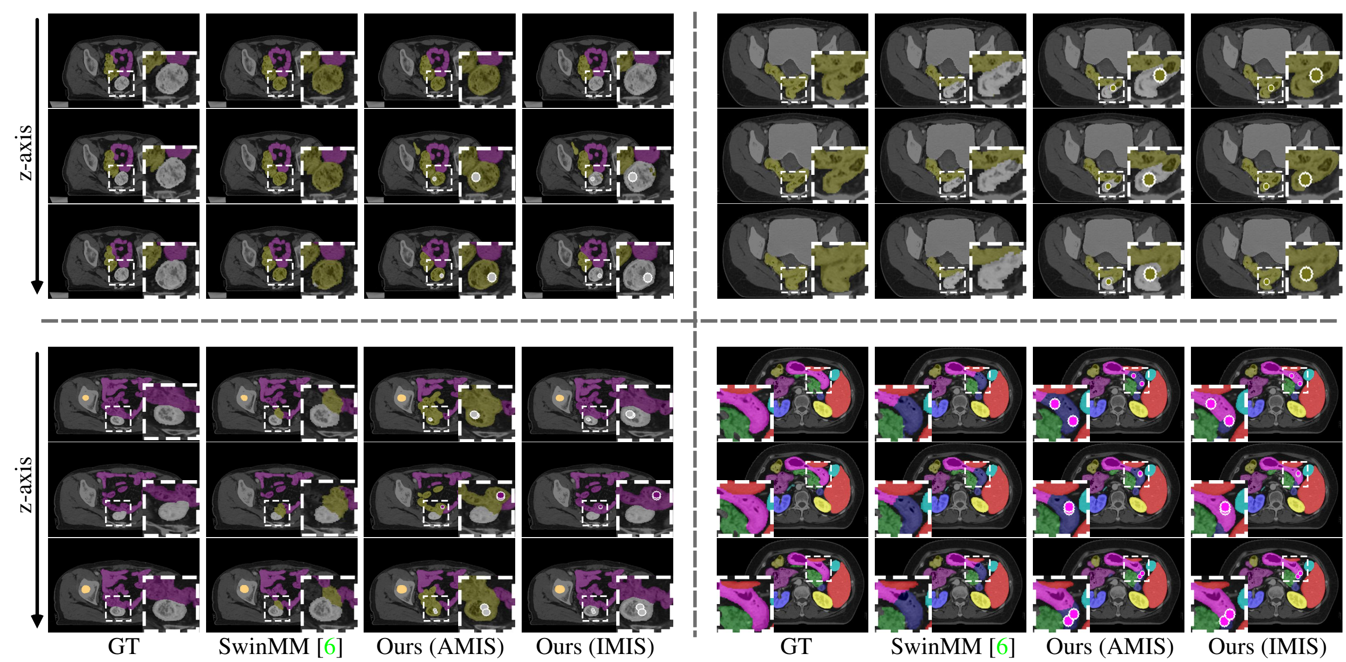

Figure S1. **Visual comparison results** on WORD [5] `test`.

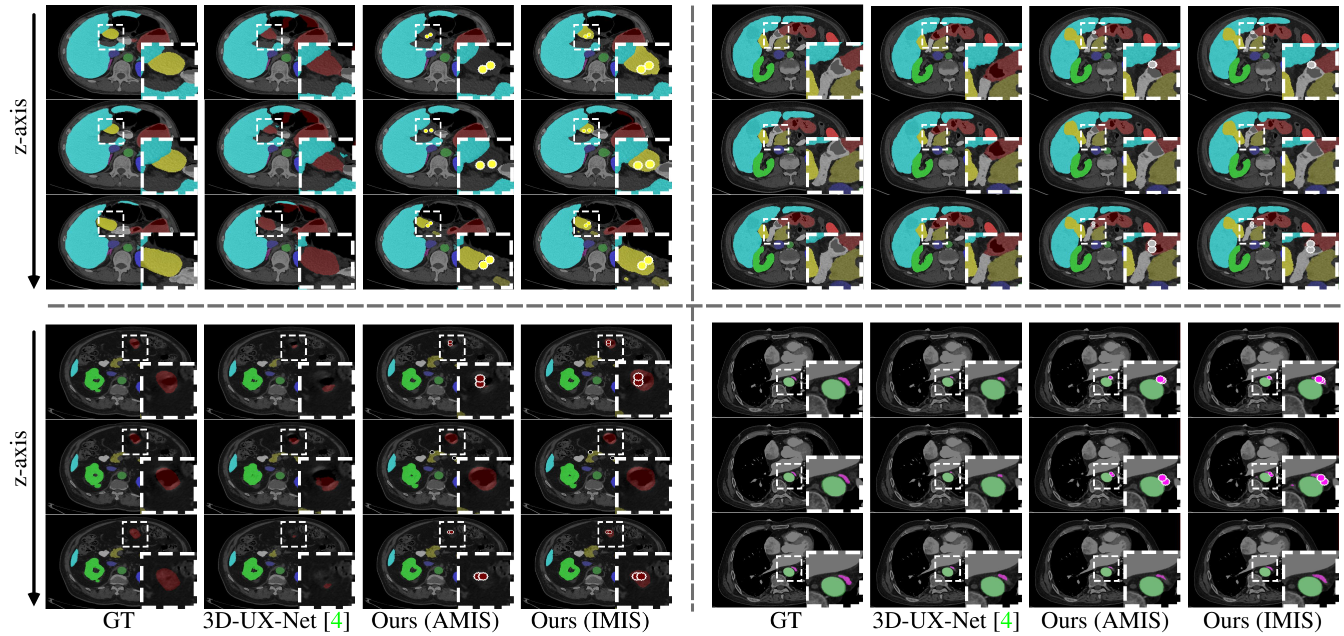

Figure S2. **Visual comparison results** on BTCV[3].

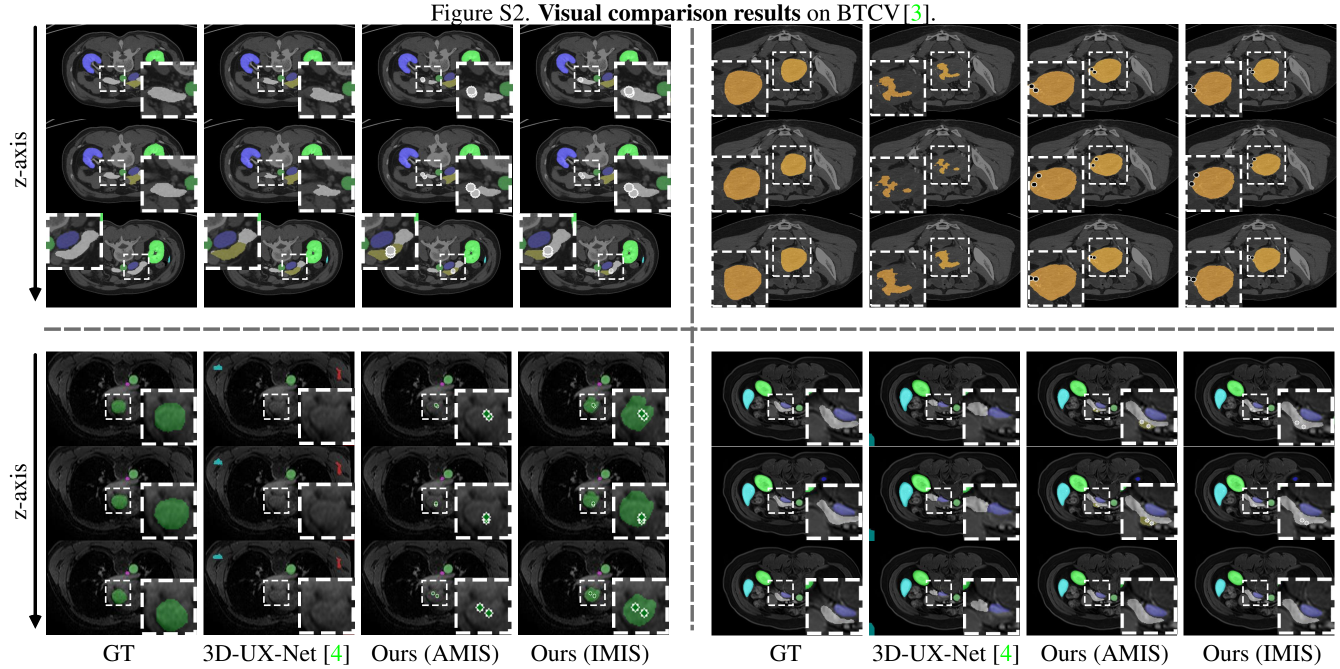

Figure S3. **Visual comparison results** on AMOS[2] `val`. *Top*: AMOS CT samples. *Bottom*: AMOS MR samples.

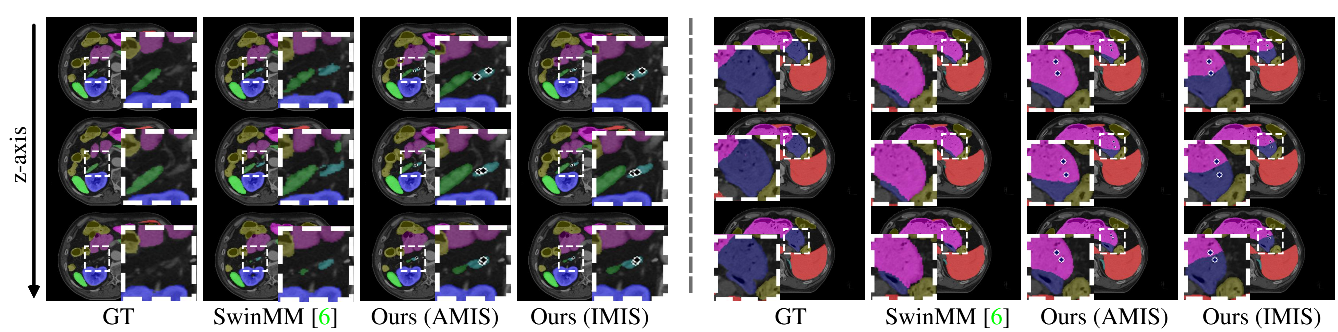

Figure S4. **Failure cases** on WORD[5] `test`.

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