DiffRect: Latent Diffusion Label Rectification for Semi-supervised Medical Image Segmentation (Supplementary Materials)

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A Evaluation of Different Noise Schedules and Denoising Steps

The noise schedule and denoising step are critical factors for training a DDPM model [2]. To find the optimal choices in the proposed LFR, we ablate the (1) cosine schedule and (2) linear schedule. Notably, the cosine schedule reduces the $\overline{\alpha}$ value more slowly, which adds noise to the input with a milder pattern. The effect of the denoising step is also investigated by varying it to 2, 5, 10, 20, 50, and 100. As observed in Fig. 1, the cosine schedule continuously outperforms the linear schedule, demonstrating that the milder pattern of noise addition could benefit the learning of the denoising U-Net. When varying the denoising step from 2 to 10, the Dice improves from 78.56% to 82.40% progressively, while further increasing it does not bring significant performance gain. The phenomenon suggests that LFR learns the distribution transportation with low computational cost ($\leq$10 steps), indicating the efficiency of our framework design.

B Qualitative Results

Fig. 2 shows qualitative results on three different cases [6,3,1,4,5,7]. DiffRect shows the best overall segmentation performance, with smooth boundaries and accurate locations. Especially, although the foreground area is small in prostate segmentation, our method demonstrates significantly fewer false negative predictions. This could be attributed to the ability to rectifying noise in pseudo labels and provide more precise supervision, resulting in improved accuracy.

C Limitations and Future Works

Although DiffRect is efficient, it may be slow for extremely large inputs. It is also designed only for modeling data within the same domain. Future directions include exploring faster ODE solvers to improve sampling speed and investigating its robustness to out-of-distribution data.

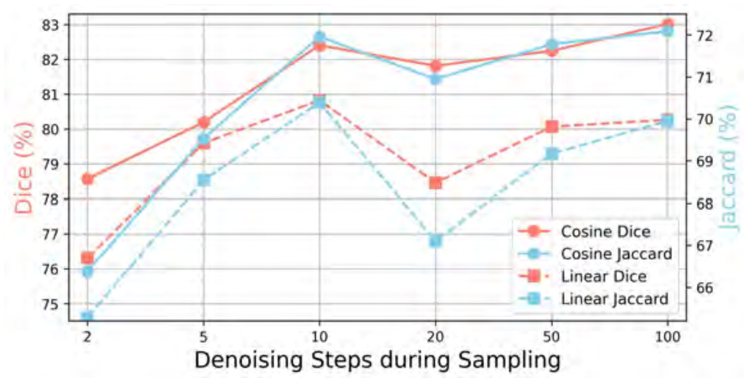

Fig. 1. Performance with different noise schedules and denoising steps.

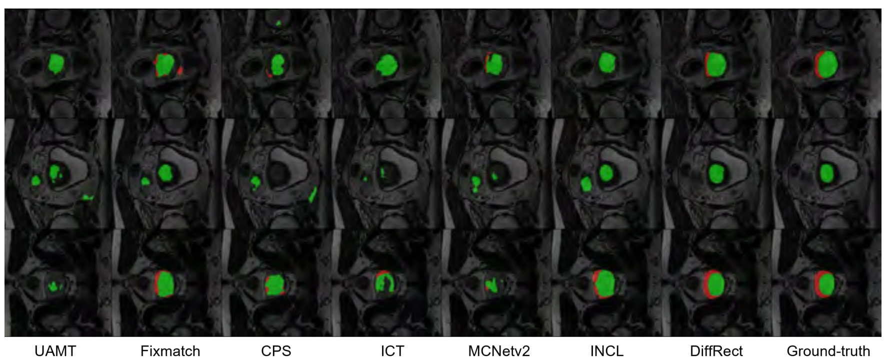

Fig. 2. Typical examples of segmentation results on the Decathlon Prostate dataset.

References

1. Chen, X., Yuan, Y., Zeng, G., Wang, J.: Semi-supervised semantic segmentation with cross pseudo supervision. In: CVPR. pp. 2613–2622 (2021)
2. Nichol, A.Q., Dhariwal, P.: Improved denoising diffusion probabilistic models. In: ICML. pp. 8162–8171. PMLR (2021)
3. Sohn, K., Berthelot, D., Carlini, N., Zhang, Z., Zhang, H., Raffel, C.A., Cubuk, E.D., Kurakin, A., Li, C.L.: Fixmatch: Simplifying semi-supervised learning with consistency and confidence. NeurIPS **33** (2020)
4. Verma, V., Kawaguchi, K., Lamb, A., Kannala, J., Solin, A., Bengio, Y., Lopez-Paz, D.: Interpolation consistency training for semi-supervised learning. Neural Netw. **145**, 90–106 (2022)
5. Wu, Y., Ge, Z., Zhang, D., Xu, M., Zhang, L., Xia, Y., Cai, J.: Mutual consistency learning for semi-supervised medical image segmentation. MIA **81**, 102530 (2022)
6. Yu, L., Wang, S., Li, X., Fu, C.W., Heng, P.A.: Uncertainty-aware self-ensembling model for semi-supervised 3d left atrium segmentation. In: MICCAI. pp. 605–613. Springer (2019)
7. Zhu, Y., Yang, J., Liu, S., Zhang, R.: Inherent consistent learning for accurate semi-supervised medical image segmentation. In: MIDL (2023)