1 Appendix

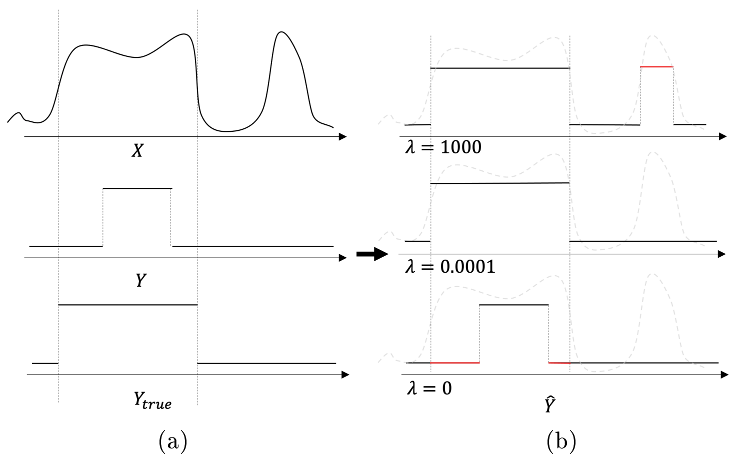

Fig. 1. Using a secondary task to improve segmentations. (a) $\mathbf{X}$ is the input and $\mathbf{Y}_{true}$ is the ground-truth. $\mathbf{Y}$ is the atlas that is roughly correct. (b) When λ is too large, $\mathcal{L}_{mse}$ dominates and the resulting segmentation features a spurious region shown in red that corresponds to image boundaries that are *not* those of the target structure. When λ is zero, only $\mathcal{L}_{ce}$ is minimized and minimizing produces boundaries that are also those of the atlas, which are not at the right place as the denoted by the red lines. For appropriate values of λ, the boundaries are correct and the spurious region is eliminated.

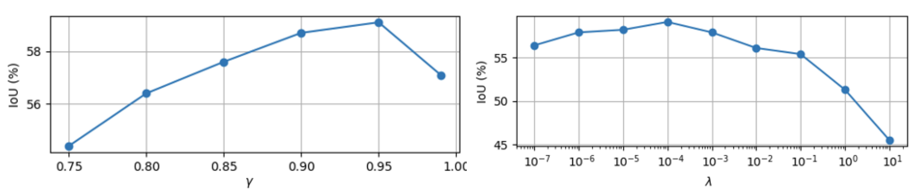

Fig. 2. Influence of λ and γ parameters . IoU (%) as a function of λ in (a), γ in (b) on the Synaptic Junction dataset with $N = 25$.

1.1 Sampling Algorithm

Simulated annotations are generated using the **Improved selection** strategy which is based on **Random selection** strategy.

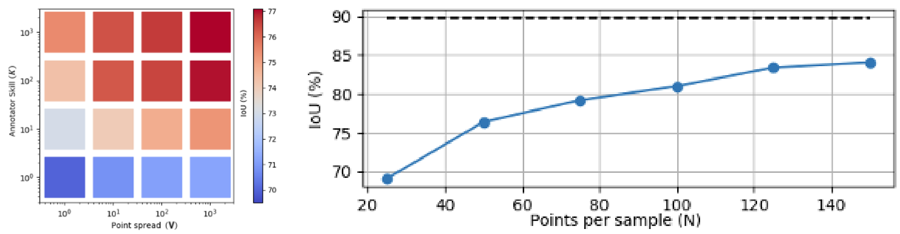

Fig. 3. Annotation simulation on the Liver dataset (a) Reconstruction accuracy (IoU) variation for different values of K and V. (b) Reconstruction accuracy (IoU) variation as a function of the number of annotated points. The black-dashed line indicates the accuracy that would be achieve by annotating all points in each sample, that is 3661 points per sample on average for the liver dataset.

1. **Random selection.** N points are randomly selected across the 3D surface. Ideally, they should be uniformly distributed across the surface but there is no guarantee of that. To emulate the behavior of a conscientious annotator trying to achieve this, we repeat the operation V times and select the set of N points that exhibits the largest intra-point variance. As we increase V, so does the probability that the selected points will indeed be uniformly distributed. The influence of variables N and V is demonstrated in Fig 3.
2. **Improved selection.** We simulate the fact that a skilled annotator will provide the most informative points possible by performing K random annotations as described above, using each one to deform the template, and selecting the one that yields the highest IoU with the ground truth. As K increases, so does the probability that the deformed template will match the ground truth well.

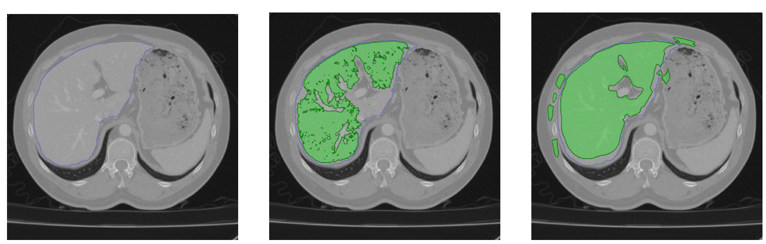

Fig. 4. Use of Fast Marching algorithm from MITK to annotate a liver (a) Image with ground truth contour (in blue) (b) Fast Marching algorithm with small σ (c) Fast Marching algorithm with large σ. In both instances, after the initial segmentation, we have to fix false positive and false negative regions.