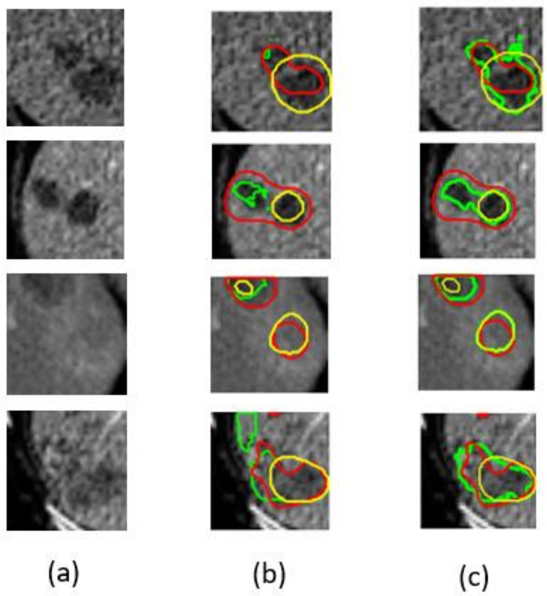

Figure 3 Comparison of boundary optimization segmentation network with and without mask patch.

effectively shrink or expand the rough segmentation results to approach the real results. Figure 4 shows the effect of the mask patch on the optimization algorithm. Column (a) are initial CT images, column (b) are segmentation results without mask patch, column (c) are segmentation results with mask patch. Red, yellow, and green line present ground truth, coarse segmentation, and refined segmentation boundary respectively. When the model remains unchanged, the prediction results without the participation of the mask patch become very unreliable. For some small tumors, the model cannot obtain accurate prediction results or even completely wrong predictions, which are not as good as the results before optimization. The existence of the mask patch allows the network to focus more on the pixels near the area to be optimized, so that the optimization result is closer to the real value which can be clearly seen from Figure 4.

4. CONCLUSION

In this paper, we presented a new method to optimize liver tumors segmentation results from CT scans, which can achieve end-to-end refinement for liver tumor segmentation. We extract the image patches and mask patches according to the coarse segmentation results. We also designed a specialized boundary refinement network for patch size images segmentation. Use mask patch to strengthen the network's attention to the boundary area to improve segmentation performance. Compared to traditional U-shape deep neural networks, our proposed network uses more feature extraction block to replace the skip connection to obtain more information in the case of limited input information. We obtained an average dice score of 0.805 and volume overlap error of 0.325 on the liver tumour segmentation challenge. Due to the reduced input image size, the problem of class imbalance is improved.

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