

Automatic Target Segmentation and Uncertainty Prediction for Post-Prostatectomy Radiotherapy Planning Using Bayesian U-Net

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INTRODUCTION

Prostate bed (or prostatic fossa) segmentation is an essential prerequisite for the post-prostatectomy radiotherapy planning. In clinical practice, this challenging task is commonly carried out by physicians using manual contouring tools, which is time-consuming and prone to inter-/intra-observer variation. To achieve efficient segmentation of the prostate bed, atlas-based segmentation (ABS) methods are commonly used in clinic. However, due to the high-dependence on image intensity, it shows relatively low accuracy on the prostate bed, whose boundary is mainly defined by neighboring organs and semantic guidelines rather than intensity contrast. Although the deep learning-based methods have potential to provide a faster and more accurate segmentation of the prostate bed, which can be used as a good initial contour for manual modification, it is difficult to know in which part the auto-generated contour needs further modification and in which range the modification should be made.

AIM

To address the above issues, in this work, we propose a **Bayesian U-net** (by adding the Monte Carlo dropout^[1] in the powerful U-net^[2] architecture) to achieve fast and accurate prostate bed segmentation while provide an uncertainty map of the predicted contours to give suggestions on manual modification.

METHOD

This study is carried out in three stages.

• Stage I: Data preparation and augmentation.

186 post-prostatectomy cases from the year 2009 to 2019 are collected. Each case contains one planning CT image and a segmentation mask of the prostate bed. All the CT images have a uniform slice size of 512 × 512. The slice number of each CT image varies from 98 to 270. The slice in-plane spacing ranges from 0.81mm to 1.37mm, while the slice thickness ranges from 1.50mm to 3.00mm. To mitigate overfitting, data augmentation (random translation and rotation) are applied on the training data.

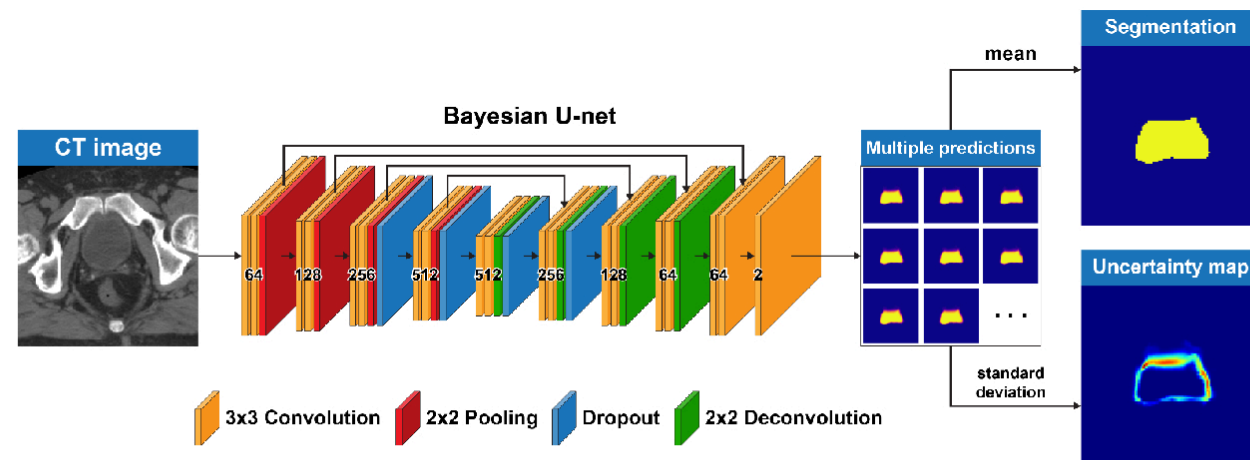
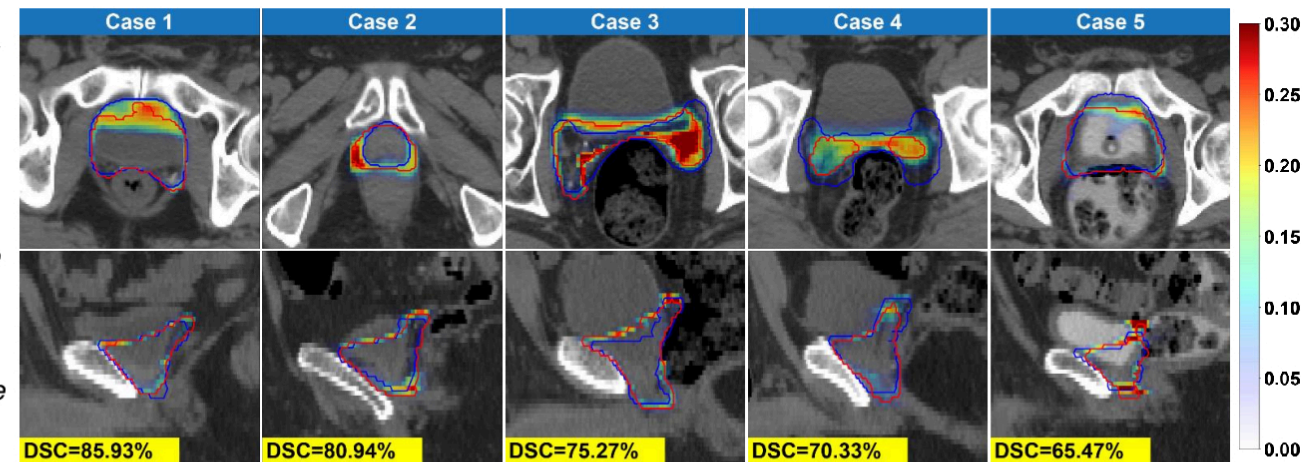


Fig. 1 Schematic representation of the proposed method.

RESULTS

The global DSC and ASD of the proposed method on the prostate bed are $74.23 \pm 7.39\%$ and $2.61 \pm 1.27\text{mm}$, respectively, outperforming the atlas-based segmentation (ABS) tool in MIM (DSC=64.21 ± 11.88%, ASD=4.81 ± 11.40mm) by a large margin. The average processing time of the proposed method is **10.8 seconds** per CT image, significantly faster than that of the MIM ABS tool (approximately 3 minutes per CT image). These experimental results demonstrate a superior performance of the deep learning-based method for prostate bed segmentation in comparison to the conventional atlas-based method. Moreover, the proposed method can output an uncertainty map of the predicted segmentation, which can be used as a reference for the clinicians to tell them where the contour needs further modification. As visualized in Figure 2, the predicted prostate bed masks generally get high uncertainty in the superior and inferior surface and the region overlapped with bladder, which is also ambiguous to human observers.

Fig. 2 Visualization of some case results with the DSC varies from 65% to 85%. Red lines indicate the predicted contours. Blue lines indicate the ground-truth. The overlapped heatmap indicates the uncertainty map of the predicted contours.



• Stage II: Model designing.

The schematic representation of the proposed method is shown in Figure 1. We exploit a standard **U-net**^[2], which is mainly composed of an encoding path and a decoding path with several skip connections, as the backbone network to predict the segmentation of the prostate bed. To estimate the uncertainty map of the predicted segmentation, we further derive a Bayesian network^[1], called **Bayesian U-net**, from the backbone U-net. Specifically, we add four **Monte Carlo (MC) dropout**^[1] layers to the middle four convolutional blocks of the backbone U-net. These MC dropout layers work in both training and testing phase, randomly blocking half nodes in forwarding propagation. By performing T times forward passes through the Bayesian U-net, we can get T different predictions from the same input image. The final predicted segmentation can be calculated by averaging the T predictions while the uncertainty map of the predicted segmentation can be represented by the standard deviation of the T predictions. In this work, T is set to 10.

• Stage III: Model training and evaluation.

To perform a comprehensive evaluation, a **five-fold cross-validation** strategy is used in this study. Specifically, the collected cases are randomly divided into five folds (with the size of 37/37/37/37/38 cases, respectively). Each fold will be used for testing alternatively, while the rest four folds are used for training and validation (three for training and one for validation). The experimental results are evaluated by calculating the dice similarity coefficient (**DSC**) and average symmetric surface distance (**ASD**) on all the cases. Five cases with severe metal artifacts caused by artificial femoral heads are excluded when testing. We use **MIM Maestro 6.9.6** (**MIM software**) to generate the ABS contours to compete with our method.

Method	DCS [%]	ASD [mm]	Time
ABS	64.21±11.88	4.81±11.40	3 min
Ours	74.23±7.39	2.61±1.27	10.8 sec

Table 1 Quantitative comparison between ABS method and our method on prostate bed segmentation

CONCLUSIONS

We developed a deep learning-based method, called Bayesian U-net, for automatic prostate bed segmentation and uncertainty prediction in CT image. Extensive experiments on an in-house dataset that consists of 186 post-prostatectomy cases show that the proposed method achieves efficient and accurate prostate bed segmentation, **significantly outperforming the conventional ABS method**. Moreover, the proposed method can generate an uncertainty map with the output segmentation mask, **indicating a confidence level for each part of the predicted contours**, thus provide more reference information to the clinicians for manual modification.

ACKNOWLEDGEMENTS

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