An U-Net - based regression model incorporating a parametric description of the prostate

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Abstract. Accurate prostate segmentation in the CT data remains a challenging task due to organ variation, typically unclear boarder between neighbouring structures and low signal-to-noise ratio of the CT data. We propose an U-Net based algorithm, which combines its encoder part with the parametric shape model of prostate. The presented algorithm acts as a regression model, has a linear activation function of the output layer and could be directly optimized by minimization of the MSE distance to ground-truth parameters. Segmentation accuracy of the proposed method was measured using Dice Similarity Coefficient (DSC) and was equal 0.73 with STD equal 0.18.

Keywords: prostate segmentation · CT · U-NET· CNN · semantic segmentation.

1 Introduction

A prostate cancer remains one of the most common cancer among the men population [1]. Often practised treatment strategy is the radiotherapy which needs a several of CT volumes with precise manual delineation of the radiated structures. Since such task is time consuming, an automatic (semiautomatic) image segmentation techniques is desired. It is, however, not a trivial task due to organ variation, typically unclear boarder between neighbouring structures and low signal-to-noise ratio in the CT data.

To overcome these problems, a several segmentation algorithms (operating in CT or other modalities) has been developed. Part of them can be described as a conventional [2], while other are based on convolutional neural networks (CNNs). The latter group have gained a significant attention in the field of medical image segmentation, including CT images of the pelvis area [3, 6].

2 Methods and Data

Available image database was consisted of 42 real-patient CT volumes without contrast enhancement, each having 512×512 pixels in axial plane with the in-slice resolution ranged from 0.9678 to 1.225 mm. Number of slices in one volume

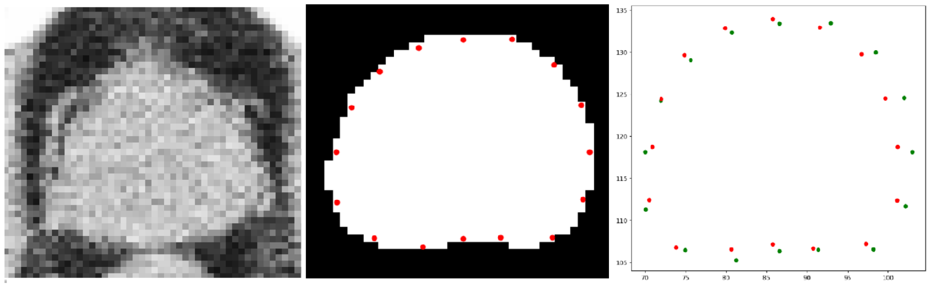

Fig. 1. Segmentation stages of the proposed method. Left image: original CT slice; central image: ground truth - manually delineated by the doctor (white contour), parametric model calculated from ground truth (red dots); right image: parametric model calculated from ground truth (red dots), parametric model inferred by CNN from the original CT slice (green dots).

was varied from 63 to 116 across the set (84 at average), number of delineated slices varied from 6 to 18 (9.1 at average), while their slice thickness was always equal 5 mm. Each volume came from a different patient and was delineated manually by a medical doctor (see Fig. 1).

Along with other researchers [4, 5], in our ongoing work we state, that U-Net architecture is suitable for prostate segmentation. It means, that latent space in that model is capable enough to describe the shape of the prostate from a single CT slice. This observation is explored in the proposed model.

The original U-Net architecture is the so-called fully-convolutional network and consists of the encoder and the decoder. Since the information is located mostly in the latent space (the layer between the encoder and the decoder) the proposed model ends on this layer.

In order to recover the shape of the prostate slice, a simple parametric model was proposed. It consists of 18 parameters. The first two parameters (a_1 and a_2) correspond to the "x" and "y" coordinate of the prostate center and the remaining 16 corresponds to the uniformly spaced radius which spans the shape of the prostate contour (see Fig. 2). This model is justified by the observation of the typical shape of the prostate slice. It is a continuous round shape with a lack or a single small cavity. It could be well described by this parametric model. Another justification of that prostate model is the possibility to minimize parameters by the MSE algorithm.

Finally, the proposed model is shown in the Fig. 3. It consists of the encoder part of the original U-Net. The layer corresponding to the latent space is followed by three fully-connected layers. The output layer corresponds to the parametric model of the prostate shape. In this example, the size of the output layer is set to 18.

In contrast to the original U-Net which was the so-called semantic segmentation model, the proposed one acts as a regression model and thus, the activation function of the output layer is a linear one. Since all parameters of the prostate

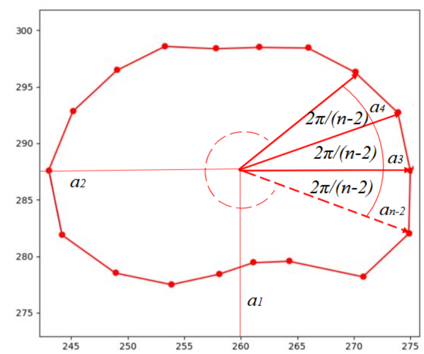

Fig. 2. Parametric model description. The first two parameters correspond to the "x" and "y" coordinate of the prostate center and the remaining *n-2* (in tested implementation 16) corresponds to the uniformly spaced radius which spans the shape of the prostate contour.

model are located on the x-y plane, the model could be optimized by the MSE distance to ground-truth parameters.

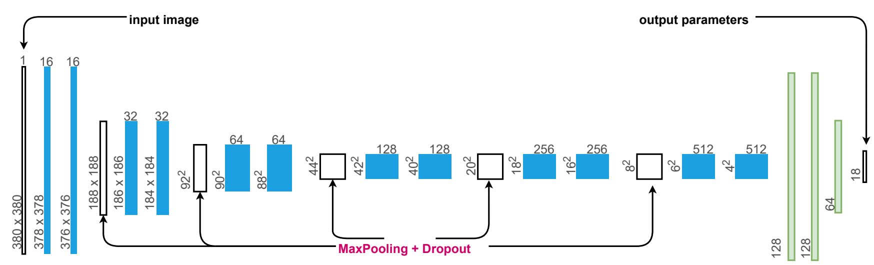

Fig. 3. Network architecture. Data flow is from left to right. Blue boxes correspond to the convolutional layer. The number of filters (channels) is denoted above each box, while the size of the layer - on the left-hand side. The max-pooling operation is stacked with dropout regularization. The Green color denotes the fully connected layer. Size of the output layer corresponds to the number of parameters of the prostate parameters.

The network presented in Fig. 3 was trained and validated only on slices from CT scans on which the prostate intersection was located and delineated by the professional clinics. The training and the validation set consists of 275 and 83 slices respectively. The training procedure was the Adam algorithm with the standard parameters. The loss function was the standard MSE distance to the ground truth. To prevent model overfitting, the dropout layers were added as well as L2 regularization to fully-connected layers. Additionally, the data augmentation procedure was applied to the input data. Input images (DICOM slices) were cropped from 512x512 to 380x380 pixels. Additionally, this window was randomly shifted in the "x" and "y" direction, such as the ground truth region was still located into the output window. Additionally, random Gaussian noise was added to the image. The distribution of Gaussian noise was set to match the distribution of pixels intensity of the prostate. Both augmentations were applied simultaneously to all slices from all batches in all epochs. The proposed computational model is relatively simple and well understood, and thus, the standard training and preprocessing procedures could be applied. It has the potential to be used with other, more sophisticated parametric description of the prostate contour.

3 Results and Discussion

Table 1. Comparison of results obtained from the proposed method and the U-Net

method	Dice
U-Net	0.720+-0.17
Proposed method	0.73+-0.18

The obtained results presented in Table 1 are not superb, however, in our opinion they prove that it is possible to extract the correct shape and location of the prostate slice from the latent space of the U-Net architecture and obtain comparable results with the regular U-net. What is more, this approach could provide the so-called "model explainability" required for application in a real medical case.

References

1. Bray, Freddie, et al. Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA: a cancer journal for clinicians 68.6 (2018): 394-424
2. Soumya Ghose, Arnau Oliver, et al. A survey of prostate segmentation methodologies in ultrasound, magnetic resonance and computed tomography images, Computer Methods and Programs in Biomedicine, Volume 108, Issue 1, 2012
3. Yamashita, Rikiya, et al. Convolutional neural networks: an overview and application in radiology. Insights into imaging 9.4 (2018): 611-629.
4. O. Ronneberger, P. Fischer, T. Brox, U-net: Convolutional networks for biomedical image segmentation, in: International Conference on Medical image computing and computer-assisted intervention, Springer, 2015
5. Balagopal A, Kazemifar S, Nguyen D, Lin MH, Hannan R, Owrangi A, Jiang S. Fully automated organ segmentation in male pelvic CT images. Phys Med Biol. 2018 Dec 14
6. Sultana, Sharmin et al.CNN-based hierarchical coarse-to-fine segmentation of pelvic CT images for prostate cancer radiotherapy. Proceedings of SPIE–the International Society for Optical Engineering vol. 11315 (2020): 113151I.