PROSTATE ZONAL SEGMENTATION USING DEEP LEARNING

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ABSTRACT

Prostate cancer is the second most common cancer among men and segmenting the Transition Zone (TZ) and Peripheral Zone (PZ) of the prostate is clinically essential as the frequency and severity of tumors can differ in these zones; however, the boundary of them are unclear. Therefore, we automatically segment those zones on T2-weighted Magnetic Resonance (MR) images using deep learning. Here, we use two different prostate datasets to confirm the influence of concatenating different datasets towards better clinical diagnosis.

1. INTRODUCTION

Prostate cancer is the second most common cancer among men; to localize and diagnose it, radiologists often score and interpret multi-parametric prostate Magnetic Resonance Imaging (MRI) by first dividing the prostate into the Transition Zone (TZ) and Peripheral Zone (PZ) manually [1]. However, this is difficult and laborious as their boundary is unclear. To ease this process, several computer-assisted methods [2], including the one using Convolutional Neural Networks (CNNs) [3], have been proposed.

However, those methods are dataset-dependant as they only use a single dataset, which makes clinical applications hard; thus, cross-dataset generalization using multiple datasets is essential. Also, the previous CNN work [3] uses a Diffusion Weighted Image (DWI) sequence instead of a T2-weighted sequence, which is the most commonly used sequence for prostate zonal segmentation.

So, how can we divide TZ and PZ from the whole prostate gland on diffrent datasets? Our aim is to segment TZ and PZ on two different prostate MR datasets using deep learning for better clinical diagnosis. However, this is challenging—differnt datasets have different contrasts, visual consistencies, and image resolutions. Therefore, we first annotate prostate zones manually on T2-weighted MR images for supervised learning and segment them with a mixed dataset trained on both datasets and with individual datasets trained on each dataset, using SegNet [4].

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2. MATERIALS AND METHODS

Towards better diagnosis in a clinical environment, we segment prostate zones on MR images from the whole gland using a CNN called SegNet.

2.1. The Datasets

This paper exploits two datasets of multi-parametric prostate 2D MR images, the Cannizzaro Hospital (Catania, Italy) dataset with 21 patients/193 images and I2CVB dataset [5] with 19 patients/503 images, to train a CNN and accomplish cross-dataset generalization. In particular, we use a T2-weighted sequence among several sequences as it is most commonly used for prostate zonal segmentation. We crop the images of the I2CVB dataset with a centered square to resize them to 288×288 to fit the image resolution of it to the Cannizzaro dataset, as the I2CVB dataset has a larger image resolution. Furthermore, the images of these datasets are masked by a prostate gland to omit background and only focus on segmenting TZ and PZ from the whole gland. We conduct three experiments to confirm the influence of concatenating different datasets as follows:

- Mixed dataset, training on Cannizzaro (16 patients) & I2CVB (15 patients) together, testing on Cannizzaro (5 patients) & I2CVB (4 patients) separately;
- Individual dataset (Cannizzaro), training on Cannizzaro (16 patients) alone, testing on Cannizzaro (5 patients) & I2CVB (19 patients) separately;
- Individual dataset (I2CVB), training on I2CVB (15 patients) alone, testing on Cannizzaro (21 patients) & I2CVB (4 patients) separately.

2.2. Proposed CNN-based Segmentation Approach

SegNet. SegNet is a CNN architecture for semantic pixel-wise segmentation. It consists of an encoder network and a corresponding decoder network followed by a pixel-wise classification layer.

3. RESULTS

This section shows how SegNet segment prostate zones on MR images. The results include instances of segmented images and their mean Dice Similarity Score (DSC).

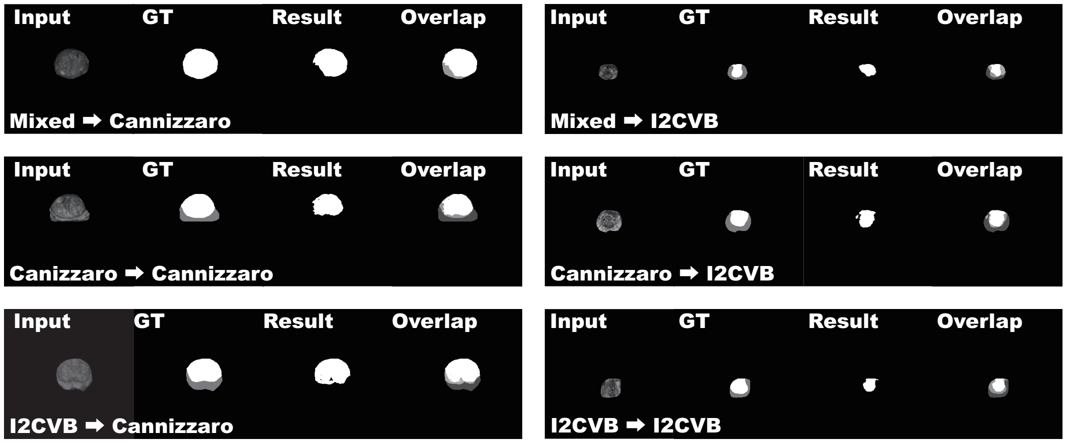

Fig. 1. TZ segmentation example yield by SegNet. (a) input prostate images; (b) ground truth, White: TZ and Gray: PZ; (c) segmentation results; (d) overlap.

Table 1. Prostate gland segmentation accuracy (DSC).

	Cannizzaro	**I2CVB**	**Average**
SegNet (Mixed)	0.74	0.72	0.73
SegNet (Individual, Cannizzaro)	0.74	0.48	0.50
SegNet (Individual, I2CVB)	0.71	0.83	0.75

3.1. Segmentation Results

SegNet. Fig. 1 illustrates examples of segmented TZ images by SegNet. The images look similar to the ground truth.

Table 1 shows the confusion matrix concerning the prostate gland segmentation accuracy with Dice Similarity Coefficient (DSC). Segmentation works best when trained and tested only on the same dataset, while it works worst when trained and tested only on the different datasets. Tests on the Cannizzaro dataset works well when trained only on the I2CVB dataset, while the opposite does not work well. We believe that it is mainly because the I2CVB dataset contains much more data. As the mixed dataset with larger data performs worse than individual datasets, domain adaptation between the datasets, such as transfer learning with GANs and VAEs, is needed for better cross-dataset generalization.

4. CONCLUSION

Our preliminary results show that deep learning, especially SegNet, can segment the TZ and PZ of the prostate MR images on two different datasets to some extent, leading to valuable clinical diagnosis. However, we can improve the results by post-processing the predicted images for better smoothness and continuity without distant segments; furthermore, we can refine the predicted images considering spatial information among slices. As we only use SegNet this time, we need to compare it with other networks, such as U-Net and image-to-image GANs. For better cross-dataset generalization, further domain adaptation using transfer learning with GANs and VAEs is needed.

5. REFERENCES

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