Prostate Detection and Segmentation based on Convolutional Neural Network and Topological Derivative

C. Cho, PhD[1]; Y. H. Lee, PhD[2]; S. Lee, PhD[1,2]

[1]AI Research Center, KETI, [2]Chung-Ang Univ.

ABSTRACT

The topological derivative (TD) for shape analysis has been employed in image segmentation, and machine learning schemes based on convol-utional neural network (CNN) provide the high performance in the image processing.

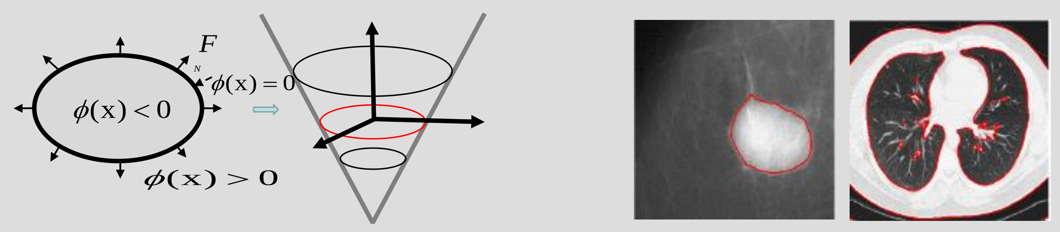
The supervised and unsupervised approaches have different roles and advantages according to their concepts. To maximize the benefits of two approaches, we propose CNN-TD based segmentation approach.

A CNN-based segmentation scheme is employed to faithfully consider the characteristics of an object to be segmented in a given image, and we refine the CNN results using a TD-based scheme. Experimental results show that the proposed scheme produces better performance for the prostate segmentation than the refined results by level set-based schemes.

INTRODUCTION

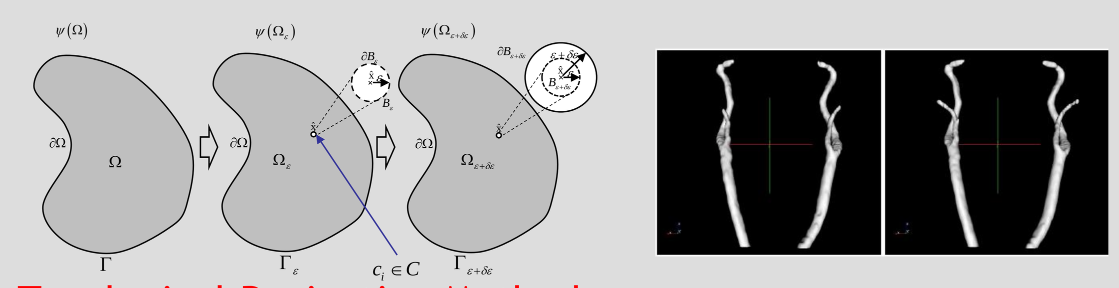
In medical imaging research, segmentation is an essential step for disease diagnosis and estimation, cancer detection and treatment, surgical planning and monitoring, and the identification of arteries.

In the unsupervised image segmentation, several approaches have been proposed with level set (LS) approaches



Level Set Method

The topological derivative (TD) approach



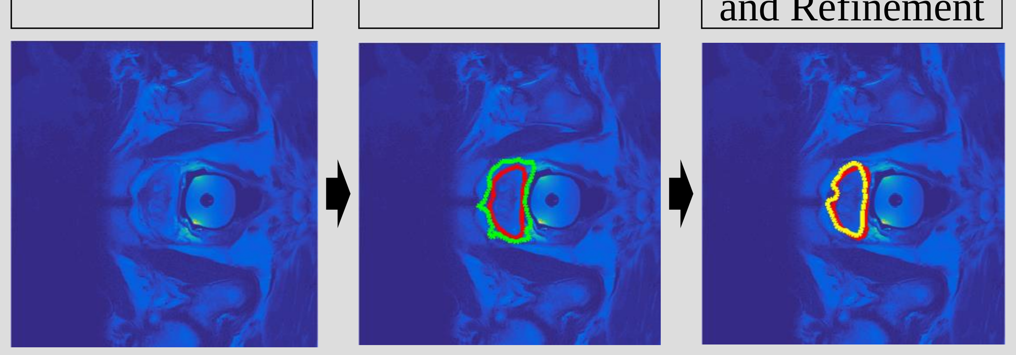
Topological Derivative Method

- Computes the shape sensitivity by the topological derivative
- The optimization is computed by using finite element method (FEM)

METHODS AND MATERIALS

A segmentation method consisting of deep-learning and unsupervised methods is proposed to robustly detect and accurately segment the lesion or organ region

Medical Image → CNN-based Detection → TD-based Segmentation and Refinement



- The proposed CNN-based detection network for a prostate segmentation

Layers	Activation	Size
Convolutional (2D)	RELU	(8, 3, 3)
Convolutional (2D)	RELU	(32, 3, 3)
Max pooling		(2, 2)
Convolutional (2D)	RELU	(16, 3, 3)
Convolutional (2D)	RELU	(64, 3, 3)
Max pooling		(2, 2)
Fully connected	RELU	4469
Fully connected	Softmax	2

METHODS AND MATERIALS

- To segment and refine the detected region using the TD-based scheme, the minimum and maximum indexes of x and y coordinates are computed from the CNN-based result in which a region involving the prostate is obtained as.

$$(x_{\min}, y_{\min}) = \arg\min_{(x,y)} \left(L(x,y) == 1 \right), \forall (x,y),$$

$$(x_{\max}, y_{\max}) = \arg\max_{(x,y)} \left(L(x,y) == 1 \right), \forall (x,y),$$

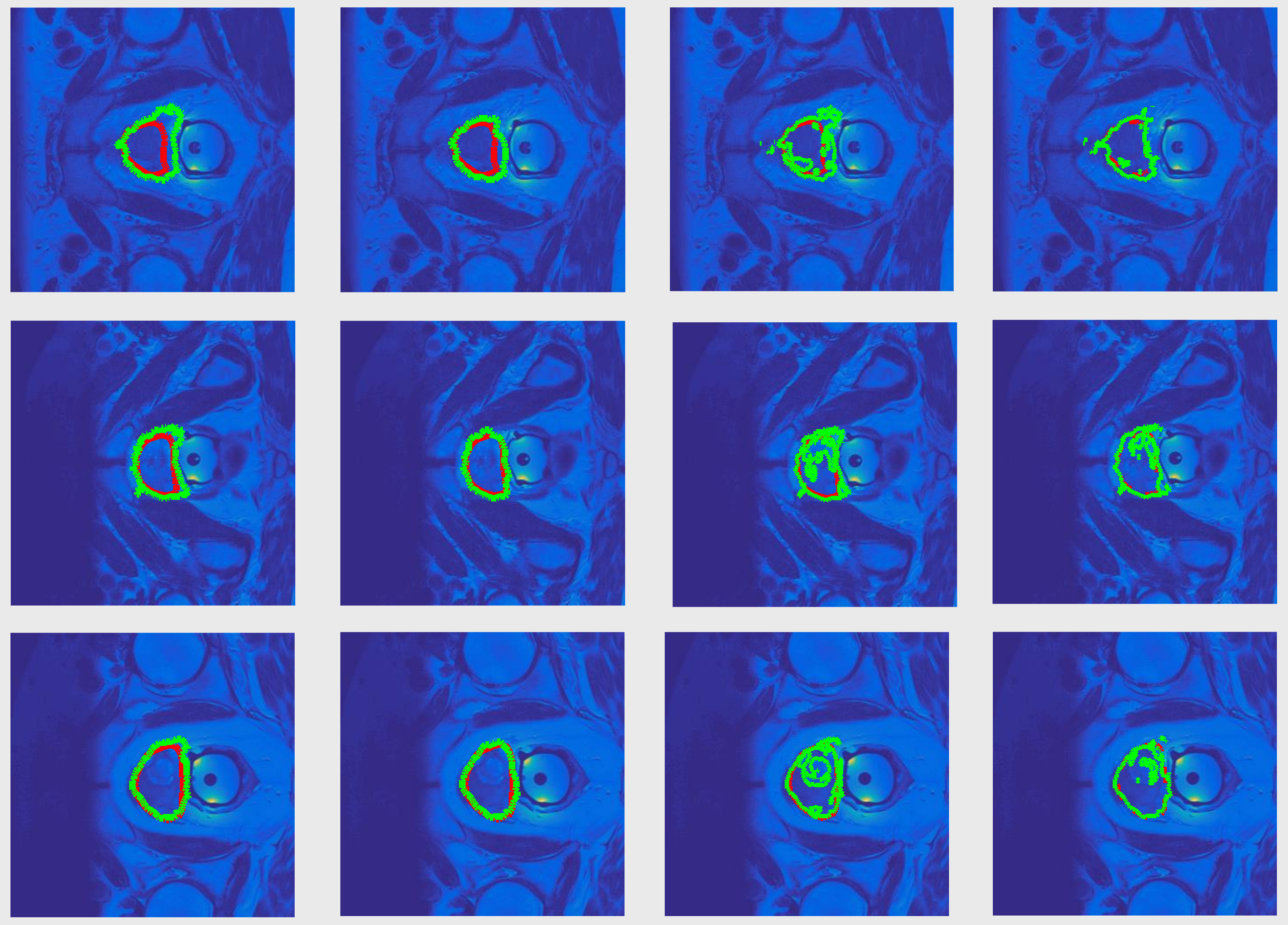
$$\text{and} \quad v = I(x_{\min} : x_{\max}, y_{\min} : y_{\max})$$

- To segment the section ν into N_C disjoint regions υ by the TD-based scheme, the cost function in the unperturbed domain is computed as

$$\psi_i(\Omega) = \frac{1}{2}\int_{\Omega} \mathrm{K}\nabla\varphi_i \bullet \nabla\varphi_i d\Omega + \frac{1}{2}\int_{\Omega} \left[\varphi_i - (v-u)\right]^2 d\Omega,$$

- To keep the labels that have many elements close to the center position of a detected region, the elements are evaluated by the average distance

$$Rf_i = \frac{C(L(i))}{\max(C(L))} + \left[1 - \frac{D_c(L(i))}{\max(D_c(L))}\right], \; i = 1, \cdots, l_n$$



(a) (b) (c) (d)

Figure 1. Prostate segmentation performance comparison for a MR image. From top to bottom: (a) result by CNN-based method, (b) by the proposed), (c) refined by the bias-correction; and (d) refined by the nonparametric approach

RESULTS

In order to evaluate the segmentation performance, the proposed scheme is compared with CNN and LS-based approaches to refine the deep-learning results for the same purpose of using TD-based scheme.

- The CNN-based scheme consists of 8 layers and was implemented by using Theano and Keras frameworks.

- For the model of CNN-based deep-learning, the 45 sets of 50 prostate MRI sets [11] were used to generate the train and validation data, and the remaining sets were used for the test.

Table 1. Objective evaluation results for prostate segmentation.

Methods	Precision	Recall	Dice score
CNN-based scheme	0.62	0.96	0.74
Proposed scheme	0.78	0.81	0.78
CNN+Bias-correction	0.70	0.64	0.65
CNN+Nonparametric	0.70	0.65	0.65

CONCLUSIONS

In this work, we proposed a CNN and TD-based prostate segmentation scheme. Specifically, the prostate region was detected by a CNN-based method, and the result was adjusted by the connected-component labeling for removing the small regions.

- The CNN-results were improved by the TD-based segmentation and refinement methods.

- The contours of the proposed method were much closer to the ground truth than those by the compared approaches

REFERENCES

1. Lequan Yu, Xin Yang, Hao Chen, Jing Qin, and Pheng-Ann Heng, "Volumetric convnets with mixed residual connections for automated prostate segmentation from 3d mr images," in Thirty-First AAAI Conference on Artificial Intelligence (AAAI), 2017.
2. Chunming Li, Rui Huang, Zhaohua Ding, J Chris Gatenby, Dimitris N Metaxas, and John C Gore, "A level set method for image segmentation in the presence of intensity inhomogeneities with application to mri," IEEE Transactions on Image Processing, vol. 20, no. 7, pp. 2007–2016, 2011.
3. Marcelo Pereyra, Hadj Batatia, and Steve McLaughlin, "Exploiting information geometry to improve the convergence of nonparametric active contours," IEEE Transactions on Image Processing, vol. 24, no. 3, pp. 836–845, 2015.
4. Choong Sang Cho and Sangkeun Lee, "Low-complexity topological derivative-based segmentation," IEEE Transactions on Image Processing, vol. 24, no. 2, pp. 734–741, 2015.

CONTACT

<Choongsang Cho>
<AI Research Center, Korea Electronics Technology Institute>
Email: ideafisher.cho@gmail.com
Phone: +82-31-739-7457