NVIDIA

ENHANCING FOREGROUND BOUNDARIES FOR MEDICAL IMAGE SEGMENTATION

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MEDICAL IMAGE SEGMENTATION

Motivation

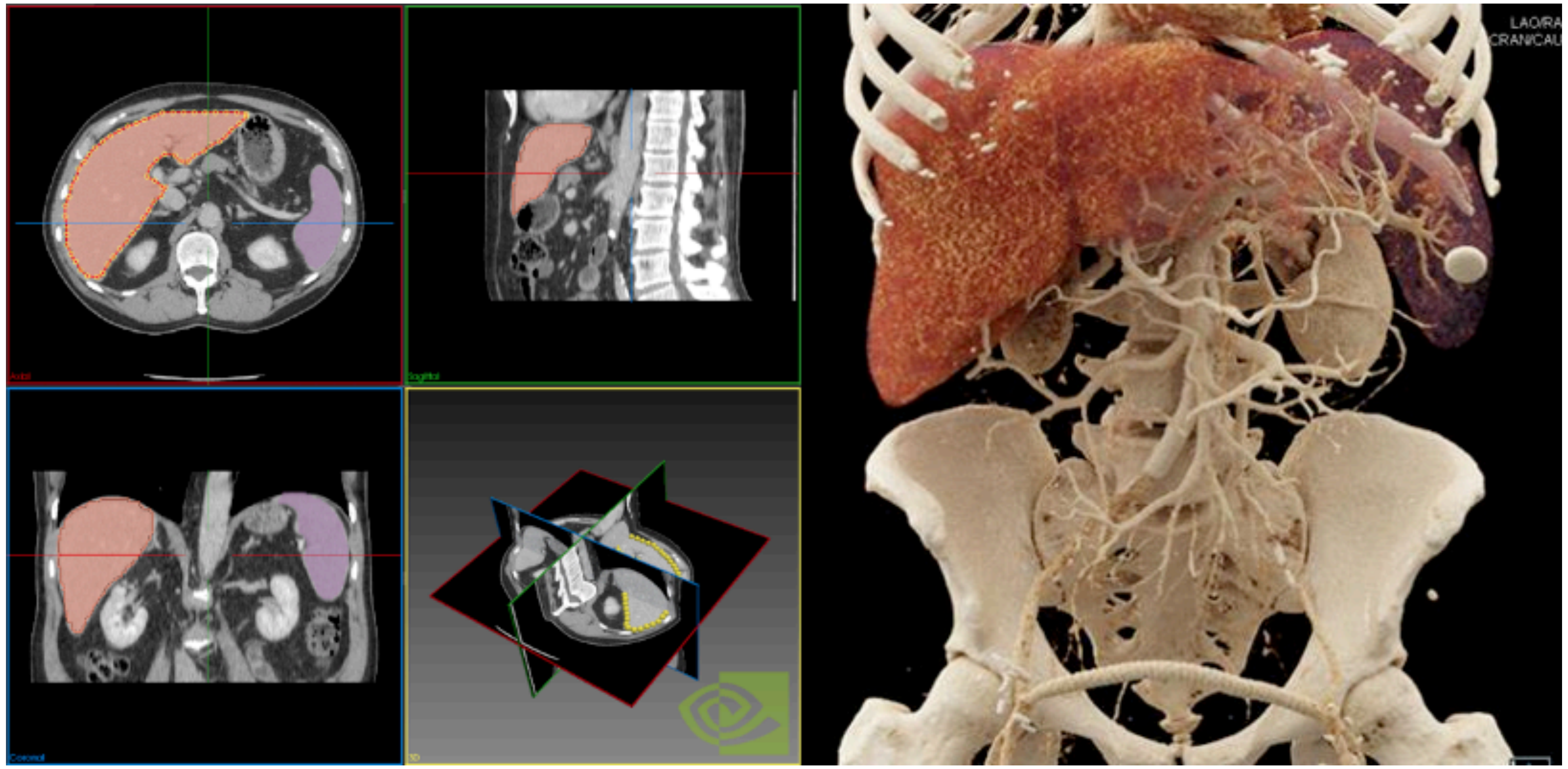
- What?
  - **Pixel-wise classification** in 2D / 3D / 4D medical images
  - Gaining high-level understanding from high-dimensional medical images
- Why?
  - Potentially helpful for disease diagnosis, treatment planning, and surgery planning
- How?
  - **Deep learning (deep neural networks)** with large-scale labeled datasets

CASE STUDY

3D Medical Image Segmentation

Given 3D volumes (e.g. CT, MRI) as input, extracting 3D anatomical structures of organs or tumors

- Challenge – fine-grained details (boundaries)
  - Caused by fuzzy imaging quality, motion blurring, etc.



METHODOLOGY

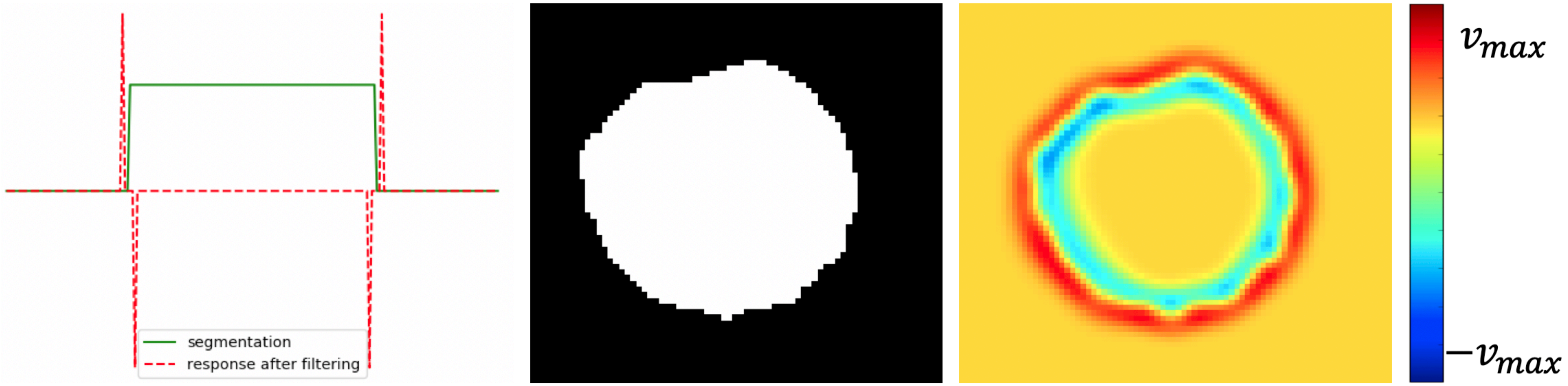
A Novel Boundary Regularization in Optimization

a) Laplacian filtering on 1D cross-section of binary mask (red curve indicates filtered response)

$$\mathcal{L}(x,y,z) = \frac{\partial^2 S}{\partial x^2} + \frac{\partial^2 S}{\partial y^2} + \frac{\partial^2 S}{\partial z^2}$$

b) Ground truth label (binary mask)

c) Filtered result of ground truth label



(a) (b) (c)

Advantage

Laplacian filtering can be fully implemented as non-trainable convolutional operations

METHODOLOGY

A Novel Boundary Regularization in Optimization

Optimization objectives

1) Distance between prediction and ground truth label – focusing on global structure
2) Distance between filtered prediction and filtered ground truth label – focusing on boundary details

$$l_{\text{overall}} = \lambda_1 \cdot l_{\text{dice}} + \lambda_2 \cdot l_{\text{BE}}$$

$$l_{BE} = \|\mathcal{L}(\mathcal{F}(X)) - \mathcal{L}(Y)\|_2 = \left\| \frac{\partial^2 (\mathcal{F}(X) - Y)}{\partial x^2} + \frac{\partial^2 (\mathcal{F}(X) - Y)}{\partial y^2} + \frac{\partial^2 (\mathcal{F}(X) - Y)}{\partial z^2} \right\|_2$$

EXPERIMENTS

Datasets and Performance

Datasets – Medical Segmentation Decathlon (MSD)

Task 01 – brain tumor segmentation in 3D MRI

Task 09 – spleen (body) segmentation in 3D CT

Baseline model – 3D SegResNet (Myronenko, 2018)

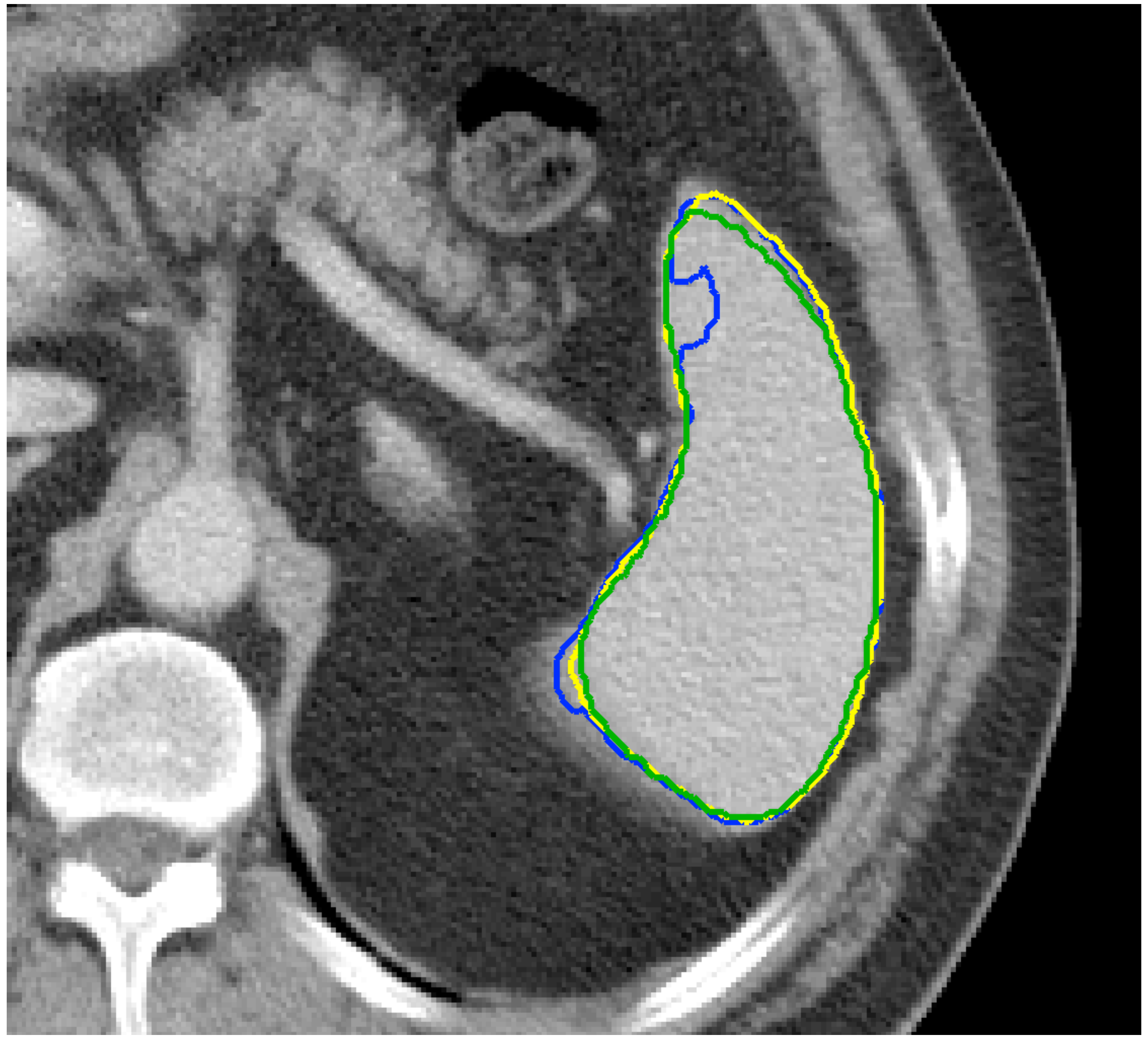
Table 1: Validation Dice comparison with baseline approaches and proposed approach.

Method	Task01	Task09
U-Net (Ronneberger et al., 2015)	0.72	0.94
AH-Net (Liu et al., 2018)	0.81	0.95
SegResNet (Myronenko, 2018)	0.83	0.95
(Myronenko, 2018)+Boundary Loss (Kervadec et al., 2018)	**0.85**	0.94
(Myronenko, 2018)+Focal Loss (Zhu et al., 2019)	0.85	0.95
(Myronenko, 2018)+Proposed BE Loss	**0.85**	**0.96**

EXPERIMENTS

Visual Comparison of Spleen Segmentation

- Green contour is ground truth label
- Blue contour is the result applying (Myronenko, 2018)
- Yellow contour is from the proposed work



CONCLUSIONS

Discussion and Findings

- Boundary enhancement enhanced overall quality of segmentation;
- Enhancement helps for segmentation of both structural and non-structural anatomy (e.g. organ, tumor);
- Boundary regularization in objective is light-weight with minimal increase of computing resource.

THANK YOU!

QUESTIONS?