A Surprisingly Effective Perimeter-based Loss for Medical Image Segmentation

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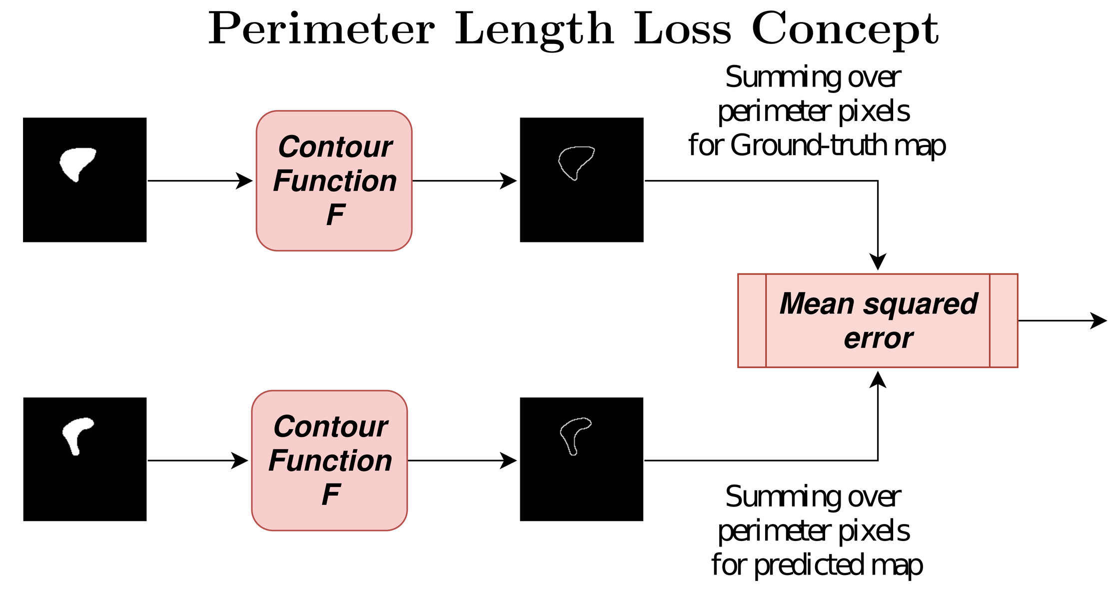
Abstract

Deep convolutional networks recently made many breakthroughs in medical image segmentation. Still, they may produce aberrant errors with holes or inaccuracies near the object boundaries. To address these issues, contour-based losses that incorporate spatial and location constraints have been introduced. However, these losses may be computationally expensive or susceptible to trivial local solutions. Moreover, they depend on distance maps that, tend to underestimate the contour-to-contour distances. We propose a novel loss that constrains the perimeter length of the segmented object. The novelty lies in computing the perimeter with a soft approximation of the contour of the probability map via specialized non-trainable layers. Furthermore, we optimize the mean squared error between the predicted perimeter length and ground-truth perimeter length. Experiments on 3 public datasets show the ability of the proposed loss to accommodate border irregularities in organs while still being efficient.

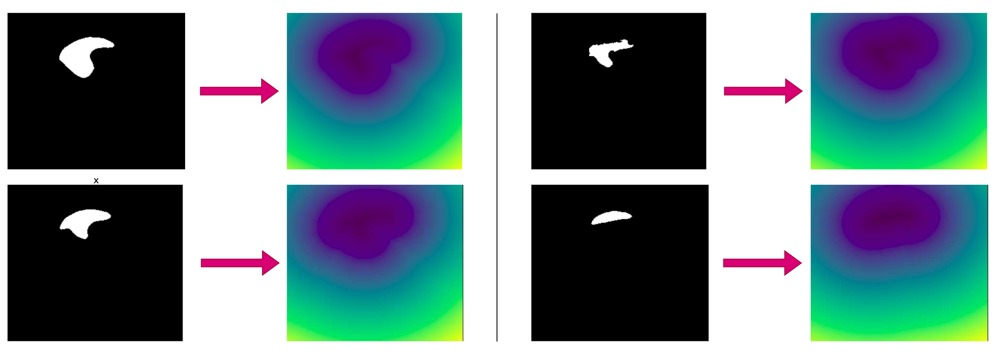
Perimeter Length Loss Concept



Motivation

State-of-the-art Contour-based Losses

- minimize the one-to-one correspondence between points on the predicted and label contour;
- exploit distance maps to represent the change between predicted and ground-truth boundaries;
- are Complex in nature due to hard gradients and high computational cost;



- tend to underestimate contour-to-contour distances since the closest point is chosen systematically in distance maps.

Contribution:

We propose a novel contour-based loss, that targets constraining the perimeter length of the organ.

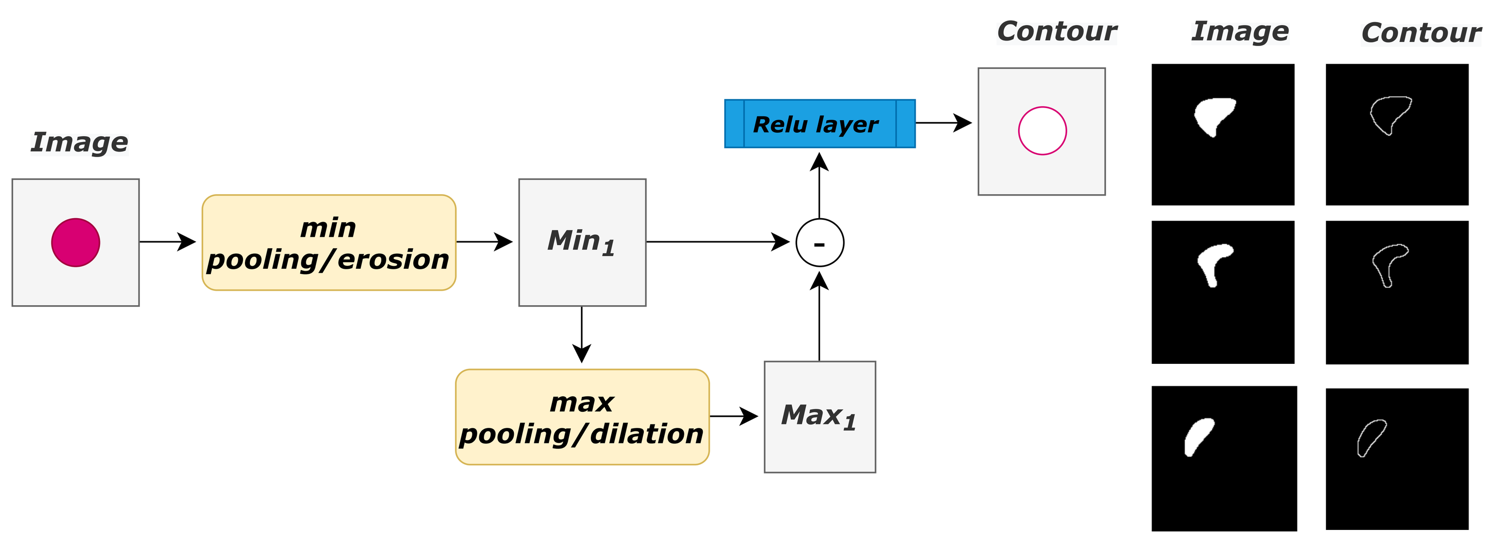
Novelty:

- Propose a contour function $\mathcal{F}$ inspired by [1].
- Constrain perimeter-length of organs instead of exact boundary matching.

[1] S. Shit, J. C. Paetzold, A. Sekuboyina, A. Zhylka, I. Ezhov, A. Unger, J. P. W. Pluim, G. Tetteh, and B. H. Menze,âclDice - a topology-preserving loss function for tubular structure segmentation,âArXiv, vol. abs/2003.07311, 2020

Proposed Method

Principle of the Contour Function $\mathcal{F}$



– Contour maps are produced by subtracting the erosion segmentations from the dilation of the eroded map.

– Dilation and erosion are conducted via max pooling, min pooling and ReLu layer.

Loss Formulation

The proposed loss is defined as a combination of the Dice loss and the perimeter-based loss weighted by λ (finetuned dynamically) as follows:

$$\mathcal{L} = (1-\lambda)\mathcal{L}_{Dice} + \lambda\mathcal{L}_{perim} \quad with \quad \mathcal{L}_{perim} = \Big(\sum_{p\in\Omega} \widehat{y_p^{\mathcal{F}}} - \sum_{p\in\Omega} y_p^{\mathcal{F}}\Big)^2 \qquad (1)$$

where $\Omega \subset \mathbb{R}^2$ is the spatial image domain, $y_p^{\mathcal{F}}$ (resp. $\widehat{y_p^{\mathcal{F}}}$) is the value of pixel p in the map $\mathcal{F}(\mathbf{y})$ (resp.. $\mathcal{F}(\hat{\mathbf{y}})$), equal to y_p (resp.. $\widehat{y_p}$), if p belongs to the contour, 0 otherwise. From both predicted and ground-truth segmentations:

1. contour maps are extracted via $\mathcal{F}$.
2. perimeter lengths are produced by summation over the pixels of the contour maps.
3. minimization of the mean squared error between the two entities is conducted.

Single Organ Segmentation

Qualitative Results

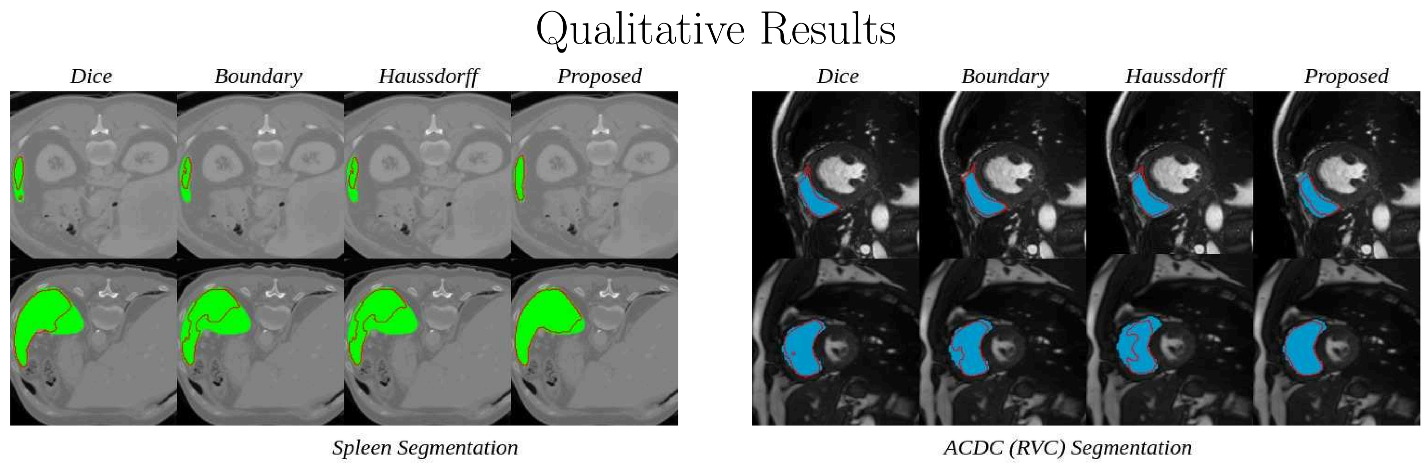


Table: Dice accuracy and Hausdorff distance results

Loss	*Spleen Dataset* Dice index	Hausdorff	*ACDC Dataset (RVC)* Dice index	Hausdorff
$\mathcal{L}_{Dice}$	76.80 ± 7.59	1.33 ± 0.28	81.22 ± 1.05	2.47 ± 0.04
$\mathcal{L}_{perim}$	58.98 ± 11.42	1.89 ± 0.35	29.34 ± 11.83	4.21 ± 0.49
$\mathcal{L}_{Dice} + \mathcal{L}_{Boundary}$	80.38 ± 5.46	1.34 ± 0.21	81.73 ± 0.81	2.35 ± 0.01
$\mathcal{L}_{Dice} + \mathcal{L}_{HD}$	91.79 ± 2.67	0.92 ± 0.15	81.47 ± 1.01	2.42 ± 0.05
$\mathcal{L}_{Dice} + \mathcal{L}_{perim}$	**95.39 ± 1.26**	**0.71 ± 0.07**	**85.67 ± 0.50**	**2.21 ± 0.09**

- Significant improvement in performance is realized over Dice baseline and state-of-the-art peer contour losses for the spleen and RVC organs.
- Ability of the proposed loss in accounting for curvature and shape irregularities

Multi-Organ Segmentation

Evolution Curves on all **ACDC** structures

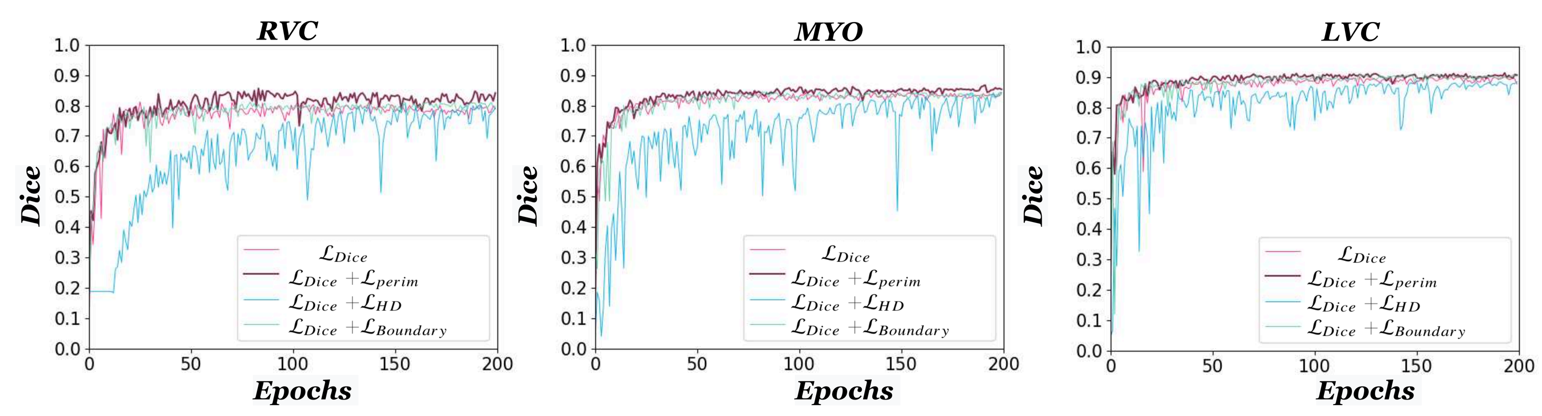


Table: Results for the **Hippocampus** Dataset. H1: tissue 1, H2: tissue 2

Loss	Dice index H1	Dice index H2	Hausdorff Distance H1	Hausdorff Distance H2
$\mathcal{L}_{Dice}$	49.37 ± 1.76	66.85 ± 3.73	3.89 ± 0.14	2.52 ± 0.18
$\mathcal{L}_{perim}$	16.60 ± 10.06	36.21 ± 1.68	7.97 ± 6.33	3.10 ± 0.12
$\mathcal{L}_{Dice} + \mathcal{L}_{Boundary}$	62.86 ± 0.59	75.52 ± 0.48	3.18 ± 0.02	2.16 ± 0.02
$\mathcal{L}_{Dice} + \mathcal{L}_{HD}$	62.46 ± 3.34	74.12 ± 3.42	3.16 ± 0.04	2.44 ± 0.25
$\mathcal{L}_{Dice} + \mathcal{L}_{perim}$	**67.52 ± 0.21**	**79.80 ± 0.46**	**3.07 ± 0.03**	**2.01± 0.00**

- Improvement or maintenance (ACDC-LVC) of performance for close structures is achieved for Hippocampus and ACDC structures.
- Ability of the proposed loss to properly delineate neighboring structures.

Conclusion

- Proposed a novel contour-based loss that constrains the perimeter-length of organs.
- Achieved better than state-of-the-art performance on single and multi-organ medical image segmentation

Future Work

- Adapt the proposed loss to accommodate multi-connected component organs
- Investigate different weighting strategies for the multi-organ segmentation setting basing on the degree of border irregularity of the considered organs

Paper presented in Medical Imaging with Deep Learning conference (MIDL), Lübeck, Germany, 7 - 9 July 2021

Work supported by the National Council for Scientific Research of Lebanon, *Agence Française de la Francophonie*, and ANR-18-CE23-0014