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How Distance Transform Maps Boost Segmentation CNNs: An Empirical Study

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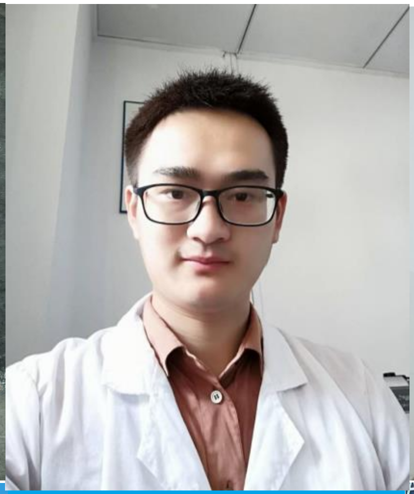


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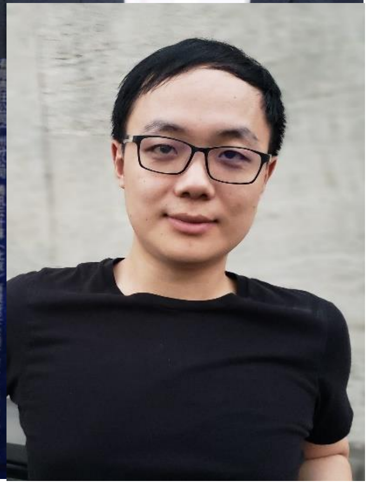


Gaoxiang Chen | Chao Peng | Lei Wang | Yunpeng Wang | Jianan Chen

CNN + Distance Transform Map

An emerging trend for medical image segmentation.

First author	Title	Official Code	Publication
Yuan Xue	Shape-Aware Organ Segmentation by Predicting Signed Distance Maps	None	AAAI 2020
Hoel Kervadec	Boundary loss for highly unbalanced segmentation	pytorch	MIDL 2019
Davood Karimi	Reducing the Hausdorff Distance in Medical Image Segmentation with Convolutional Neural Networks (arxiv)	None	TMI 2019

First author	Title	Official Code	Publication
Yan Wang	Deep Distance Transform for Tubular Structure Segmentation in CT Scans	None	CVPR2020
Shusil Dangi	A Distance Map Regularized CNN for Cardiac Cine MR Image Segmentation (arxiv)	None	Medical Physics
Fernando Navarro	Shape-Aware Complementary-Task Learning for Multi-organ Segmentation (arxiv)	None	MICCAI MLMI 2019

There are many great studies, but

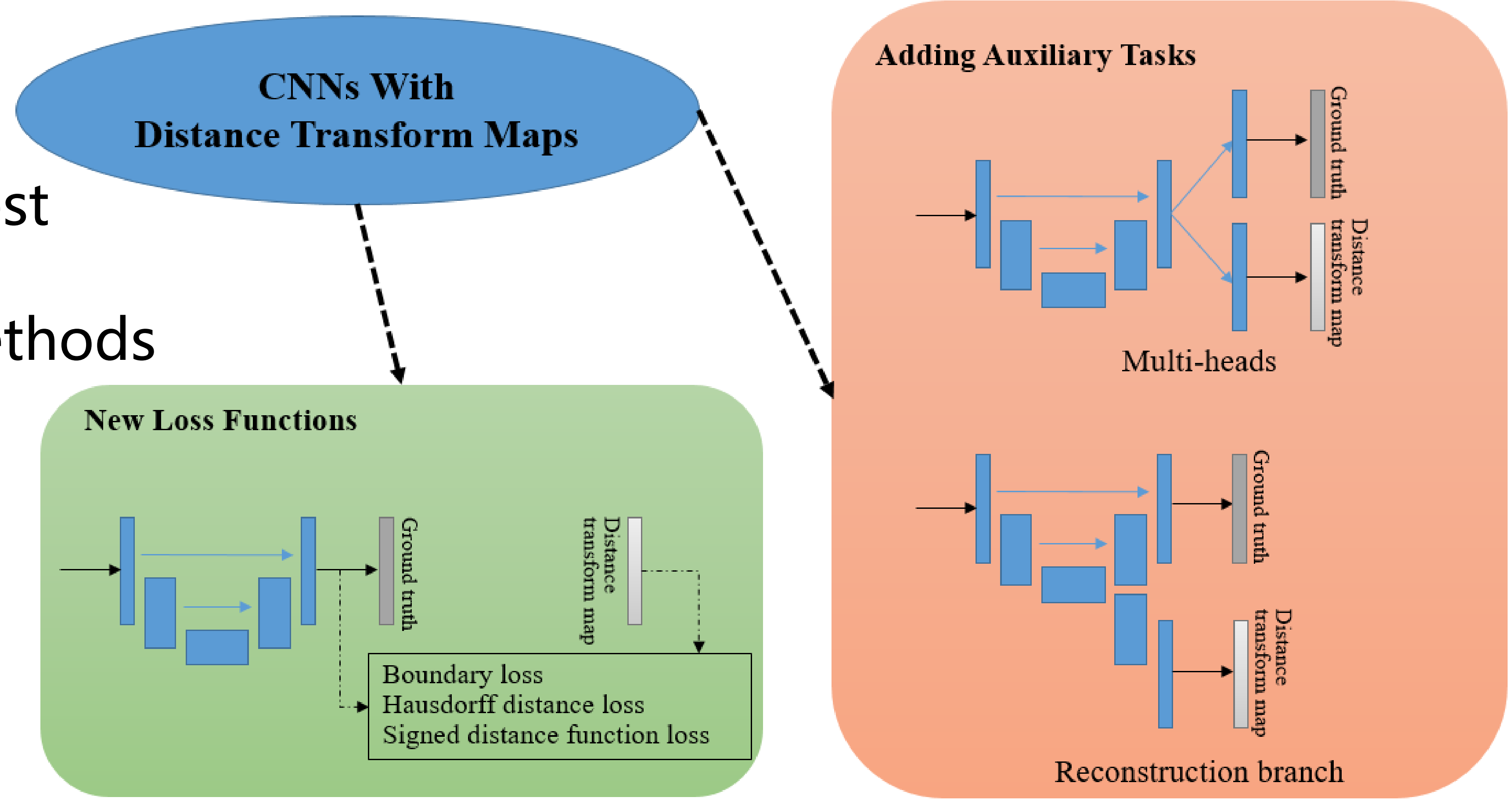
- these methods are tested on different datasets;
- the comparison among them has not been well studied.

https://github.com/JunMa11/SegWithDistMap

CNN + Distance Transform Map: Two Categories

Our contributions:

- summarizing the latest developments;
- benchmarking five methods on two datasets.



Answer the question:

How can distance transform maps boost segmentation CNNs?

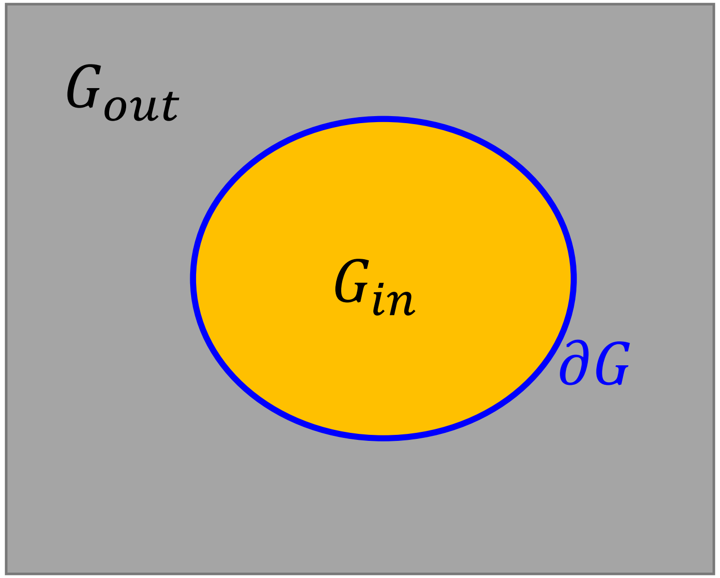
Basic Notation

- **Distance transform map (DTM)**

$$G_{DTM} = \begin{cases} \inf_{y \in \partial G} \|x-y\|^2, x \in G_{in} \\ 0, \quad\quad\quad\quad\quad\quad others \end{cases}$$

- **Signed distance function (SDF)**

$$G_{SDF} = \begin{cases} -\inf_{y \in \partial G} \|x-y\|_2, & x \in G_{in} \\ 0, & x \in \partial G \\ \inf_{y \in \partial G} \|x-y\|_2, & x \in G_{out} \end{cases}$$

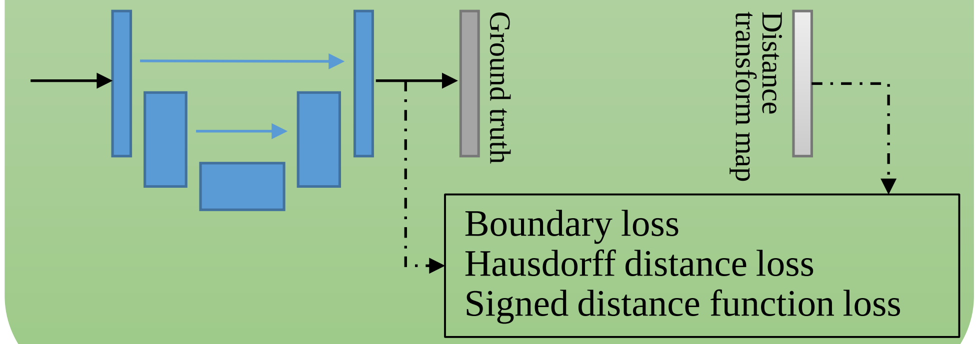


Ground truth G of image I

Category 1: New Loss Functions

CNNs With Distance Transform Maps

New Loss Functions



- **Boundary loss**

$$L_{BD} = \frac{1}{|\Omega|}\sum_{\Omega} G_{SDF} \circ S_{\theta}$$

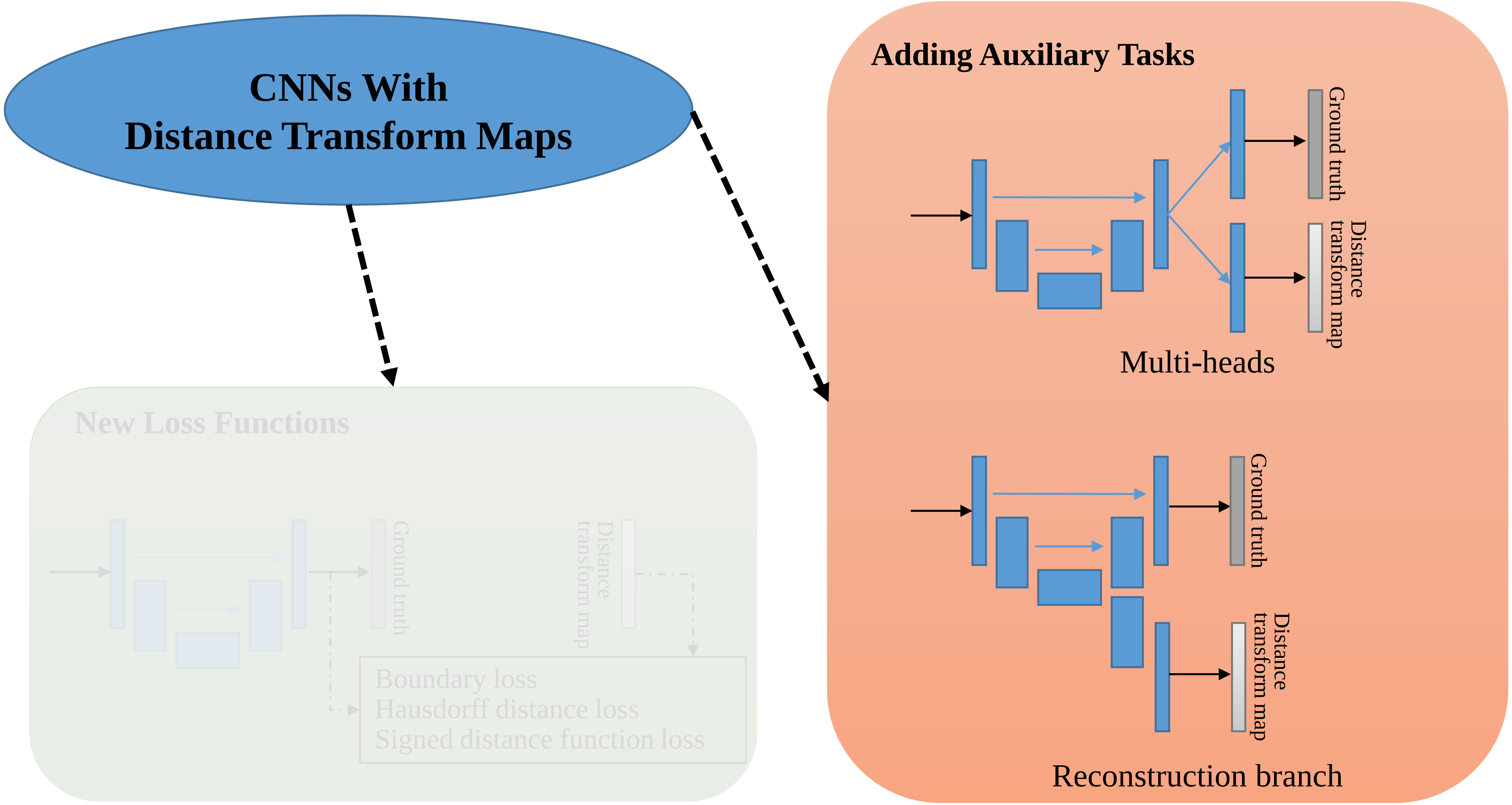
- **Hausdorff distance loss**

$$L_{HD} = \frac{1}{|\Omega|}\sum_{\Omega} (S_{\theta} - G)^2 \circ (G_{DTM}^2 + S_{DTM}^2)]$$

- **Signed distance function loss**

$$L_{SDF} = -\sum_{\Omega} \frac{G_{SDF} \circ S_{SDF}}{G_{SDF}^2 + S_{SDF}^2 + G_{SDF} \circ S_{SDF}}$$

Category 2: Adding Auxiliary Tasks



Experiments

➢ Dataset

- Organ segmentation: left atrial (LA) MRI; 16 cases for training; 20 cases for testing
- Tumor segmentation: liver tumor CT; 90 for training; 28 for testing

➢ Network and training protocol

- V-Net; 5 resolutions; 16 channels in the 1^{st} resolution;
- Learning rate searching: 0.01, 0.001, 0.0001
- Adam optimizer

➢ Metrics

- Dice
- Jaccard
- 95% Hausdorff Distance
- Average surface distance (ASD)

Experimental Results on left atrial MRI Dataset

Methods	Dice (%) ↑	Jaccard (%) ↑	95HD ↓	ASD ↓
V-Net baseline	84.4 (5.70)	73.6 (7.00)	20.1 (13.8)	5.29 (3.43)
Boundary loss	85.0 (5.64)	74.2 (7.87)	20.8 (15.0)	5.43 (3.43)
Hausdorff distance loss	**85.5 (4.96)**	**75.0 (7.30)**	15.9 (13.3)	4.46 (3.68)
Signed distance function loss	84.2 (8.48)	73.5 (11.0)	**13.5 (11.2)**	**3.24 (3.10)**
Multi-heads: FG DTM-L1	83.7 (6.33)	72.5 (8.97)	24.7 (12.8)	6.62 (3.32)
Multi-heads: FG DTM-L2	82.6 (6.87)	71.0 (9.65)	15.5 (11.5)	4.10 (3.12)
Multi-heads: FG DTM-L1+L2	83.3 (10.7)	72.6 (12.6)	17.5 (12.1)	4.87 (3.12)
Multi-heads: SDF-L1	85.5 (7.82)	75.3 (10.2)	**11.8 (8.86)**	**2.65 (2.11)**
Multi-heads: SDF-L2	**87.0 (3.49)**	**77.2 (5.49)**	16.1 (13.5)	3.97 (3.14)
Multi-heads: SDF-L1+L2	84.5 (4.38)	73.5 (6.49)	24.7 (15.0)	6.09 (3.71)
Rec-Branch: FG DTM-L1	83.5 (5.91)	72.2 (8.30)	23.6 (14.8)	5.45 (3.57)
Rec-Branch: FG DTM-L2	81.5 (8.40)	69.5 (10.9)	19.5 (16.9)	4.49 (4.76)
Rec-Branch: FG DTM-L1+L2	83.8 (4.57)	72.3 (6.78)	28.5 (14.1)	7.47 (3.40)
Rec-Branch: SDF-L1	82.5 (9.05)	73.6 (10.9)	12.0 (4.61)	2.73 (1.38)
Rec-Branch: SDF-L2	**86.9 (4.43)**	**77.1 (7.92)**	**10.2 (6.03)**	**2.71 (1.68)**
Rec-Branch: SDF-L1+L2	85.1 (67.5)	74.6 (9.24)	16.7 (13.1)	4.00 (3.19)

Experimental Results on Liver Tumor CT Dataset

Methods	Dice ↑	Jaccard ↑	95HD ↓	ASD ↓
V-Net baseline	51.0 (28.8)	39.8 (21.6)	43.6 (45.2)	14.9 (22.3)
Boundary loss	**52.5 (24.1)**	**41.0 (21.1)**	**26.3 (33.7)**	7.70 (21.9)
Hausdorff distance loss	52.0 (25.4)	40.9 (22.6)	28.8 (34.3)	**7.56 (19.4)**
Signed distance function loss	47.6 (29.8)	37.5 (26.9)	31.1 (48.7)	11.2 (23.8)
Multi-heads: SDF-L1	48.1 (27.6)	38.2 (24.4)	31.5 (40.6)	8.11 (15.4)
Multi-heads: SDF-L2	47.1 (28.0)	37.0 (25.3)	25.5 (34.1)	8.82 (22.3)
Rec-Branch: SDF-L1	48.4 (27.7)	37.9 (25.3)	32.2 (48.6)	11.8 (31.1)
Rec-Branch: SDF-L2	48.6 (27.3)	38.5 (25.0)	31.0 (48.0)	7.52 (21.8)

Take Home Message

- First-try **recommendation**: multi-heads and reconstruction branch CNNs for organ segmentation; boundary loss and Hausdorff distance loss for tumor segmentation;
- **Implementation details** have remarkable effects on the final performance.
- **Unsolved open question:** how can we obtain **robust** performance gains when incorporating DTM into CNNs?
- Code is available: https://github.com/JunMa11/SegWithDistMap
- Limitation: Only V-Net and two datasets are used for experiments, which is not justified at all. More extensive experiments: SOTA networks, large datasets…

Thanks for watching!