Unsupervised Domain Adaptation for Brain Vessel Segmentation through Transwarp Contrastive Learning

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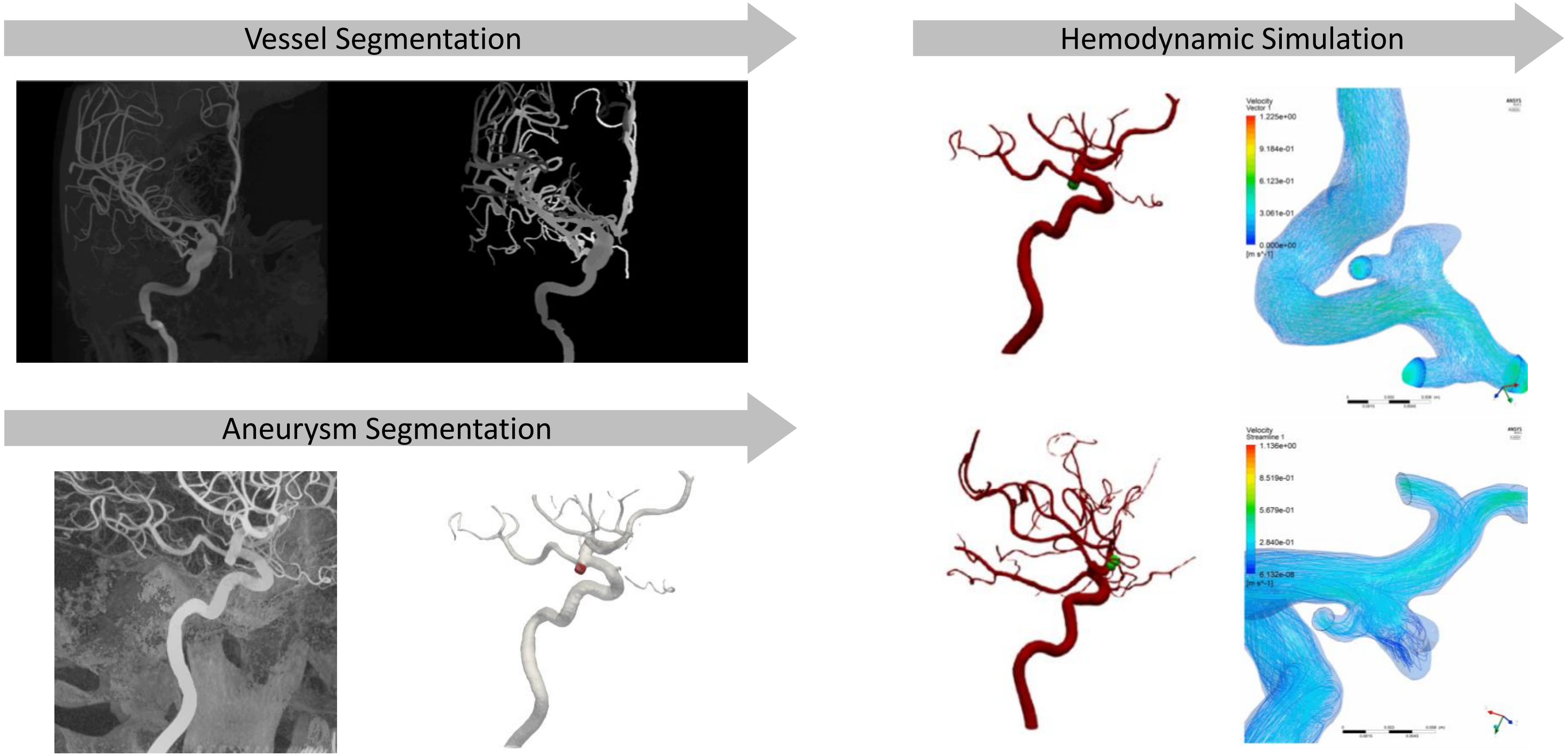
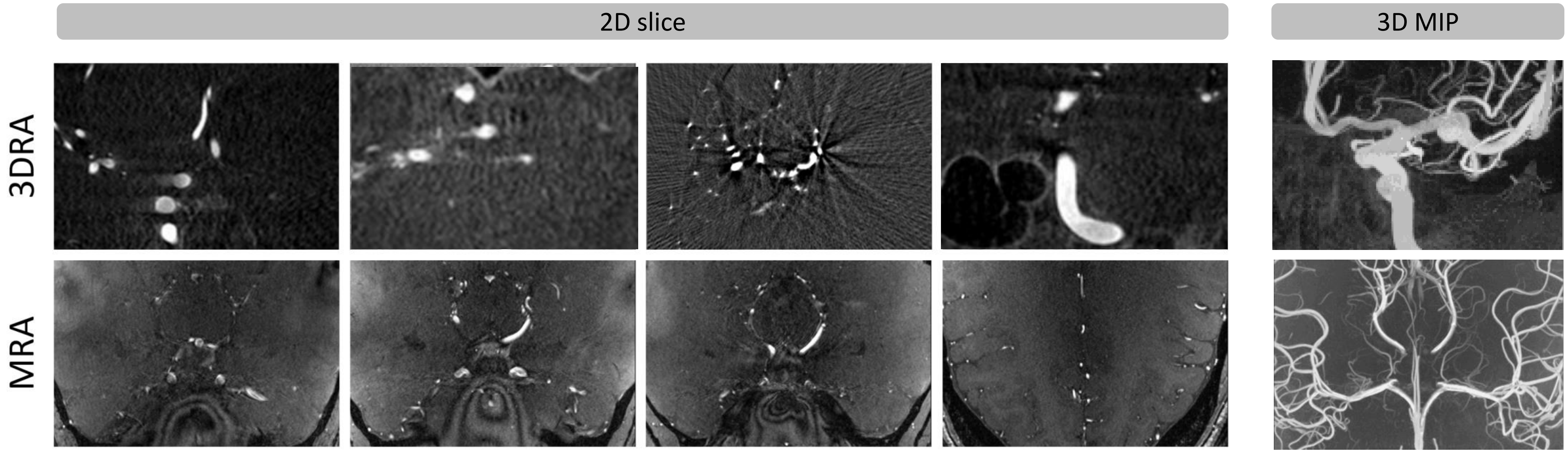
Motivations of vessel segmentation

- Accurate diagnosis and surgery planning
- Design medical devices for different patients

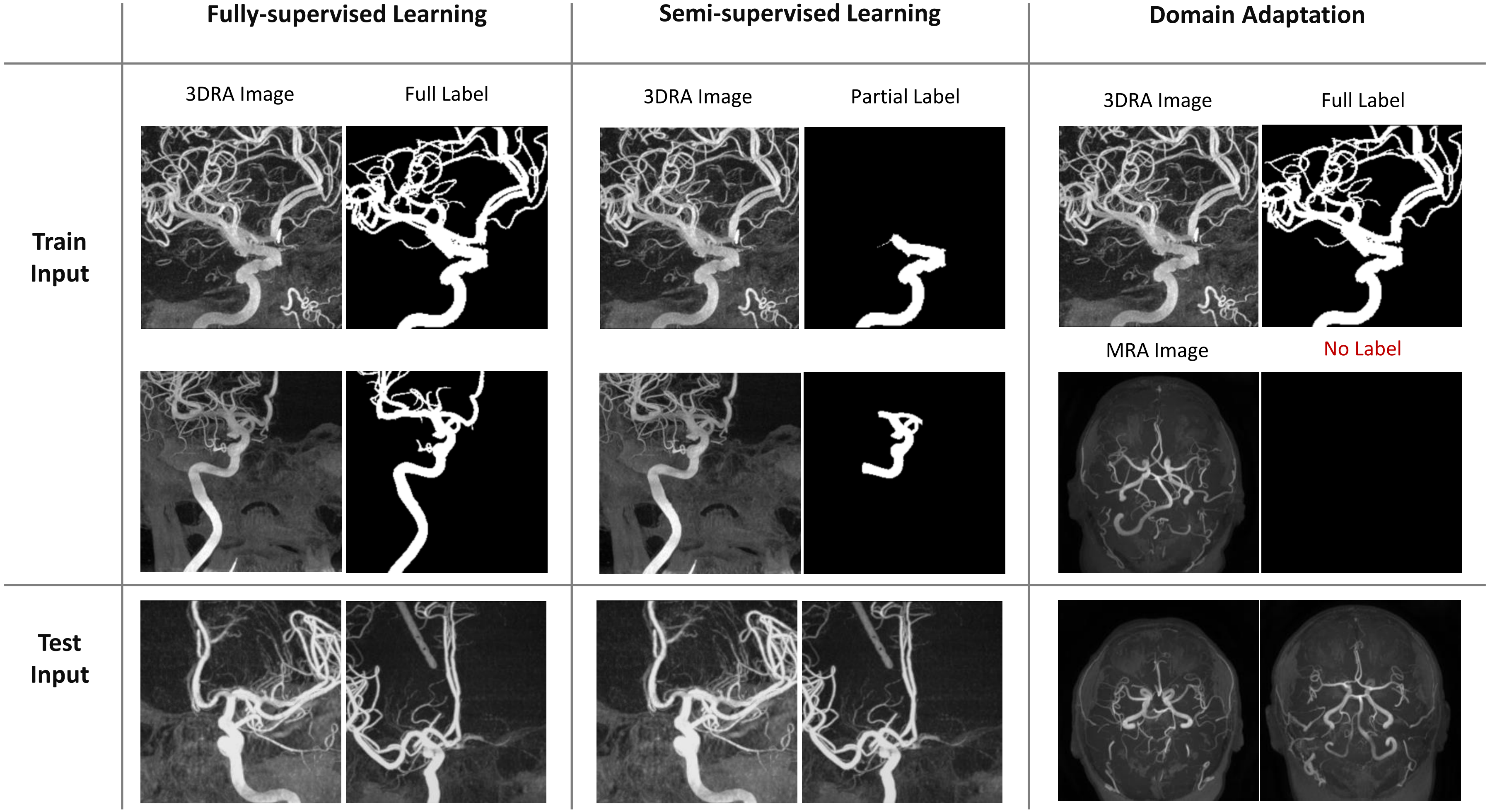


[1] Lin, Fengming, Yan Xia, Shuang Song, Nishant Ravikumar, and Alejandro F. Frangi. "High-throughput 3DRA segmentation of brain vasculature and aneurysms using deep learning." Computer Methods and Programs in Biomedicine 230 (2023): 107355.

- Modalities of cerebral vessel analysis
  - 3DRA, MRA, DSA, CTA …
- Challenges
  - Cross modality: domain shift between 3DRA and MRA

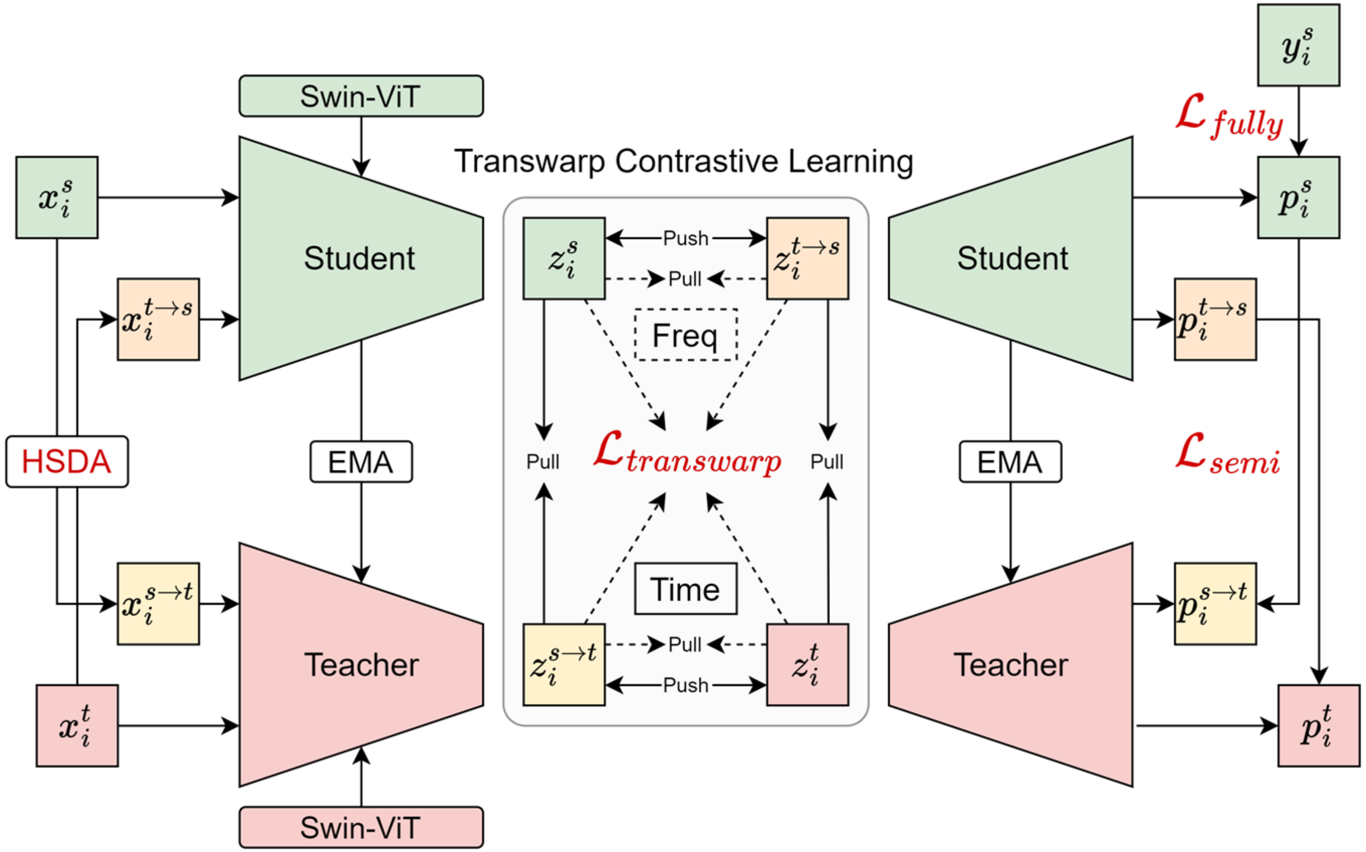


- To deal with domain shift: unsupervised domain adaptation
  - Fully-supervised Learning => Train with x_{3DRA} , y_{3DRA} ; Test with x_{3DRA}
  - Semi-supervised Learning => Train with x_{3DRA} , $y_{3DRA}^{partial}$; Test with x_{3DRA}
  - Un-supervised Domain Adaptation => Train with x_{3DRA} , y_{3DRA} , x_{MRA} ; Test with x_{MRA}



Methods

- Pre-processing: Homocentric Squares Domain Adaptation (image style transfer)
- Network structure: teacher-student
- Loss function: fully-supervised loss + semi-supervised loss + transwarp contrastive loss



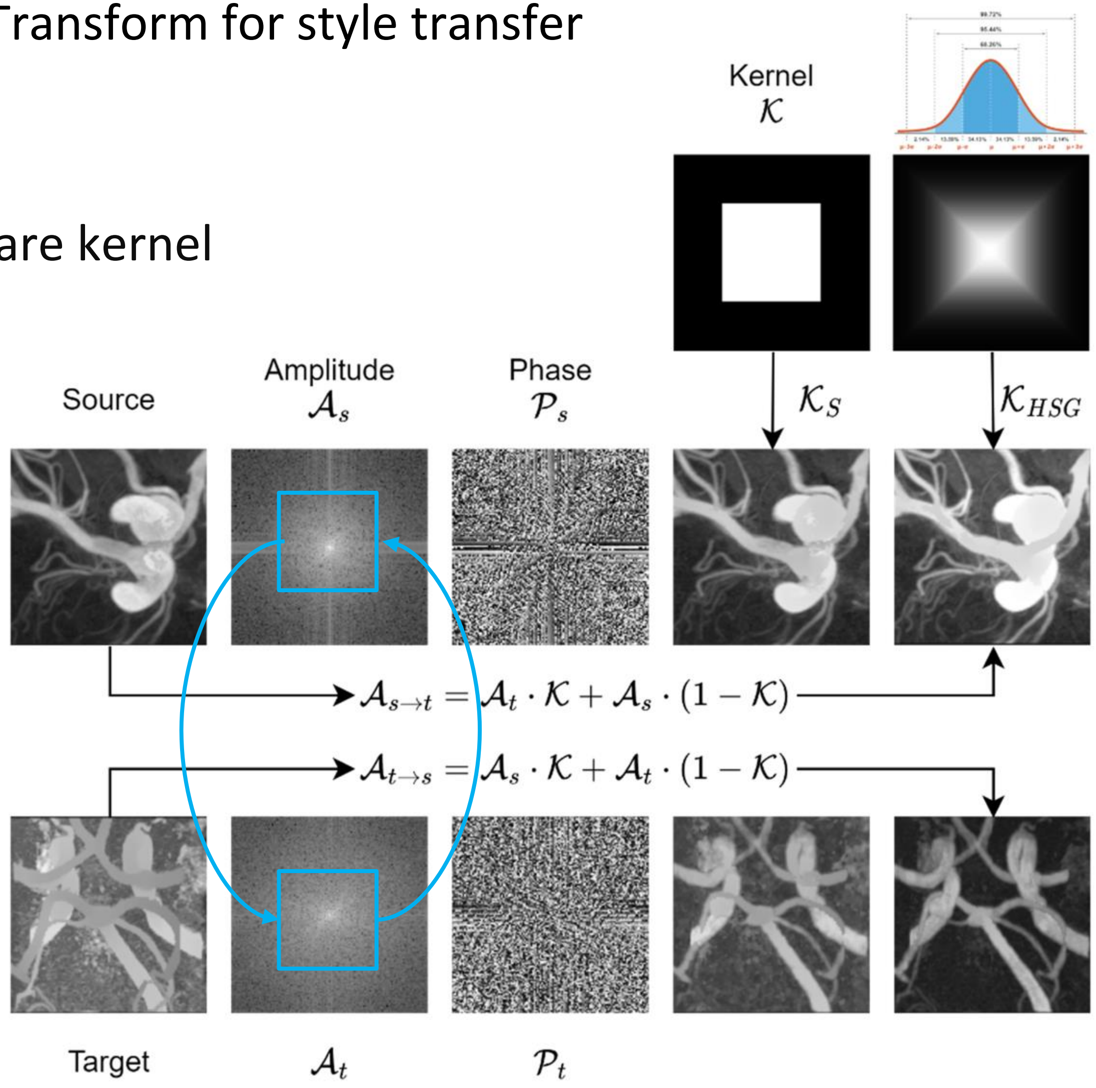
- Homocentric Squares Gaussian Kernel: Fourier Transform for style transfer
  - Low frequency: style information.
  - High frequency: content information.
  - Change square kernel into homocentric square kernel decaying in Gaussian distribution.

Fourier transform

$$\widehat{f}(\xi) = \int_{-\infty}^{\infty} f(x)\, e^{-i2\pi\xi x}\, dx. \quad \textbf{(Eq.1)}$$

Inverse transform

$$f(x) = \int_{-\infty}^{\infty} \widehat{f}(\xi)\, e^{i2\pi\xi x}\, d\xi, \quad \forall\, x \in \mathbb{R}. \quad \textbf{(Eq.2)}$$

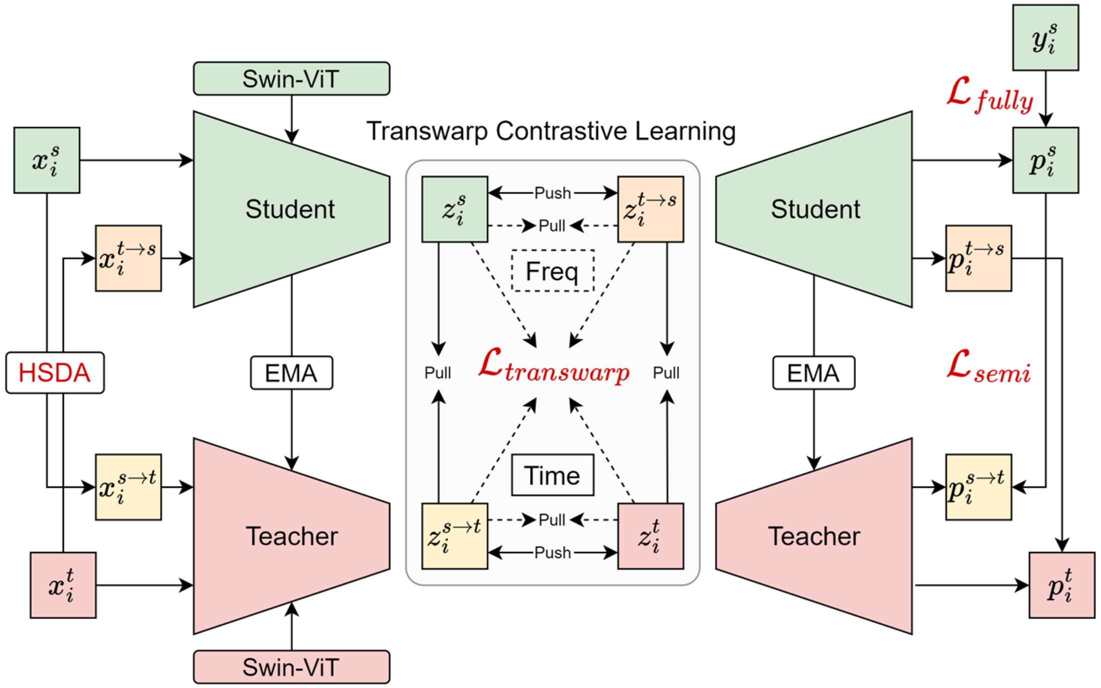


[2] Yang, Yanchao, and Stefano Soatto. "Fda: Fourier domain adaptation for semantic segmentation." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2020.

- Loss functions
- Transwarp Contrastive Learning

  Content
  - => Positive pair (time domain features from same patients)
  - => Negative pair (time domain features from different patients)

  Style
  - => Positive pair
  - (Frequency domain features from different modalities)
  - (Learning a unified style features across modalities)



$$\mathcal{L}_{fully} = \frac{1}{N_s} \sum_{i=1}^{N_s} \left(1 - \frac{2\left|p_i^s \cap y_i^s\right|}{\left|p_i^s\right| + \left|y_i^s\right|} - y_i^s \log\left(p_i^s\right)\right) \tag{2}$$

$$\mathcal{L}_{semi} = \frac{1}{N_s} \sum_{i=1}^{N_s} \left(p_i^s - p_i^{s\to t}\right)^2 + \frac{1}{N_t} \sum_{i=1}^{N_t} \left(p_i^{t\to s} - p_i^t\right)^2 \tag{3}$$

$$h(u,v) = \frac{u^T v}{\|u\|_2 \|v\|_2} \tag{4}$$

$$pos_i^c = h\left(z_i^s, z_i^{s\to t}\right) + h\left(z_i^{t\to s}, z_i^t\right) \tag{5}$$

$$neg_i^c = h\left(z_i^s, z_i^{t\to s}\right) + h\left(z_i^{s\to t}, z_i^t\right) \tag{6}$$

$$pos_i^s = h\left(s_i^s, s_i^{t\to s}\right) + h\left(s_i^s, s_i^t\right) + h\left(s_i^{s\to t}, s_i^t\right) + h\left(s_i^{s\to t}, s_i^{t\to s}\right) \tag{7}$$

$$\mathcal{L}_{transwarp} = -\frac{1}{N} \sum_{i=1}^{N} \log \frac{\left(e^{pos_i^c} + e^{pos_i^s}\right)/\tau}{e^{pos_i^c} + e^{pos_i^s} + e^{neg_i^c}} \tag{8}$$

$$\mathcal{L} = \lambda_1 \cdot \mathcal{L}_{fully} + \lambda_2 \cdot \mathcal{L}_{semi} + \lambda_3 \cdot \mathcal{L}_{transwarp} \tag{9}$$

Results

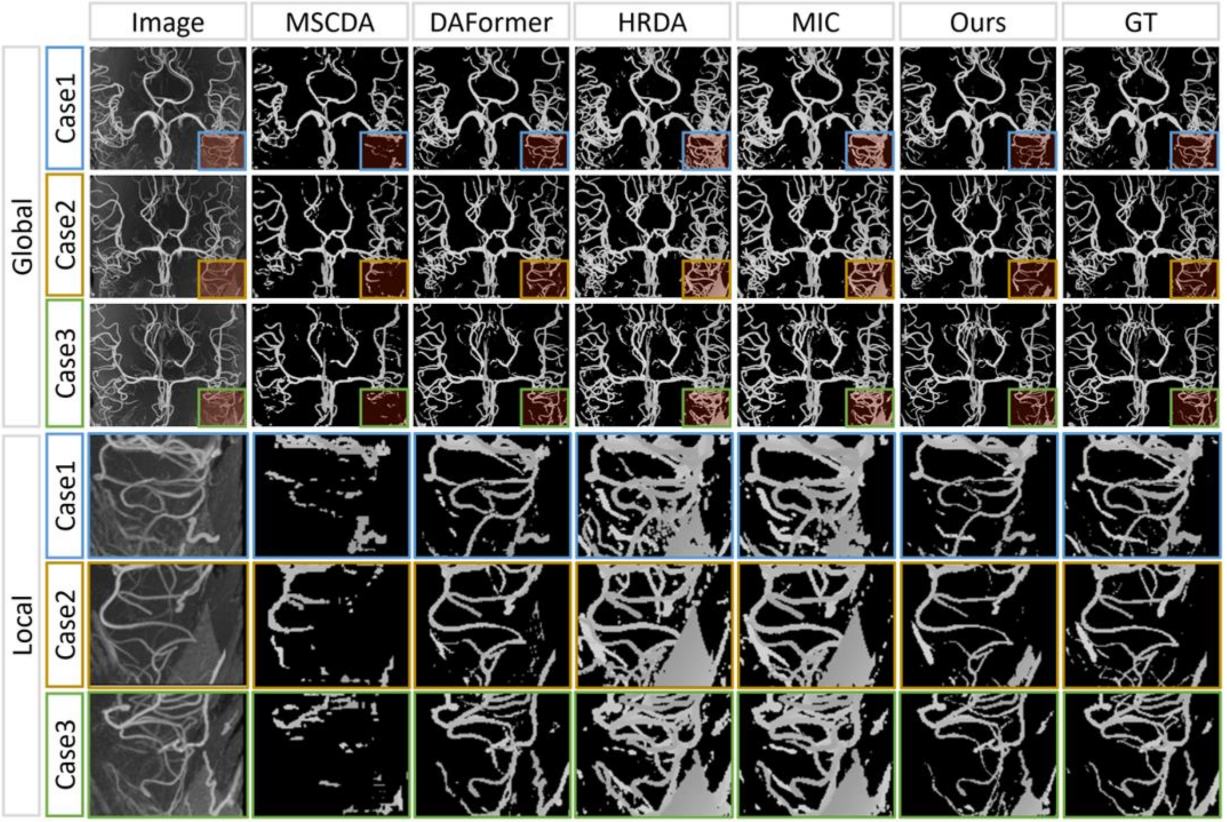


Table 1. Comparison of Segmentation Performance with UDA SOTAs and different training strategy.* indicates $p < 0.05$ in t-test.

Methods	DSC (%) ↑	Sen (%) ↑	Jac (%) ↑	VS (%) ↑
$\mathcal{S} \rightarrow \mathcal{T}$ [2]	31.48 ± 6.76	18.89 ± 5.00	18.88 ± 5.00	31.52 ± 6.75
MSCDA [12]	41.18 ± 4.70	27.57 ± 4.96	26.04 ± 3.84	49.12 ± 8.69
DAFormer [9]	57.75 ± 6.35	42.84 ± 8.07	40.89 ± 6.52	63.37 ± 9.70
MIC [11]	67.16 ± 2.02	59.07 ± 7.16	50.59 ± 2.27	84.18 ± 9.49
HRDA [10]	68.35 ± 2.74	60.03 ± 8.57	51.98 ± 3.14	83.31 ± 9.68
Ours	**72.65 ± 6.65** *	**64.75 ± 8.06** *	**57.46 ± 7.80** *	**85.47 ± 9.65** *
$\mathcal{T} \rightarrow \mathcal{T}$ [16]	79.76 ± 1.92	74.61 ± 7.77	66.37 ± 2.69	90.06 ± 5.74

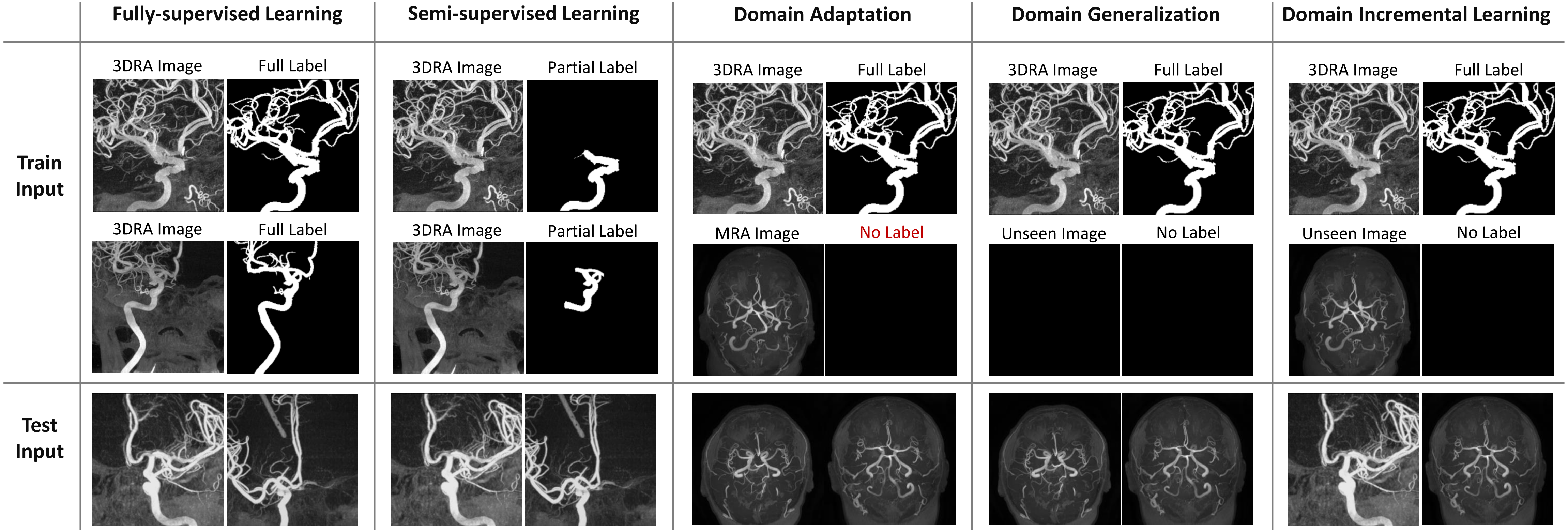
Table 2. Ablation Study: Gradual Addition of Components from Top to Bottom.

Components	DSC (%) ↑	Sen (%) ↑	Jac (%) ↑	VS (%) ↑
$\mathcal{L}_{fully}$	61.84 ± 7.08	46.29 ± 8.48	45.16 ± 7.77	64.88 ± 8.47
$\mathcal{L}_{semi}$	64.60 ± 7.36	49.08 ± 8.75	48.00 ± 8.17	67.48 ± 8.42
$\mathcal{L}_{transwarp}$	67.55 ± 6.81	52.75 ± 8.65	50.95 ± 7.67	72.16 ± 8.47
Ours HSDA	72.65 ± 6.65	64.75 ± 8.06	57.46 ± 7.80	85.47 ± 9.65

[3] Benkner S, Arbona A, Berti G, Chiarini A, Dunlop R, Engelbrecht G, Frangi AF, Friedrich CM, Hanser S, Hasselmeyer P, Hose RD. @ neurIST: infrastructure for advanced disease management through integration of heterogeneous data, computing, and complex processing services. IEEE transactions on information technology in biomedicine. 2010 Apr 29;14(6):1365-77.
[4] S. Chatterjee, H. Mattern, F. Dubost, S. Schreiber,A. N¨urnberger, and O. Speck, “Smile-uhura challenge 2023,” https://doi.org/10.7303/syn47164761, 2023

Future works

- Fully-supervised Learning => Train with x_{3DRA} , y_{3DRA} ; Test with x_{3DRA}
- Semi-supervised Learning => Train with x_{3DRA} , $y_{3DRA}^{partial}$; Test with x_{3DRA}
- Domain Adaptation => Train with x_{3DRA} , y_{3DRA} , x_{MRA} ; Test with x_{MRA}
- Domain Generalization => Train with x_{3DRA} , y_{3DRA} ; Test with x_{MRA}
- Domain Incremental Learning



Thank You

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VASeg

Domain

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