A2V: A Semi-Supervised Domain Adaptation Framework for Brain Vessel Segmentation via Two-Phase Training Angiography-to-Venography Translation

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Context & Objectives

Anatomical differences between arteries and veins results in a ***large domain gap.***

Domain Adaptation (DA) tackles the problem of distribution shifts across image modalities. However:

- ***Small objects*** are not preserved during translation.
  - Vessels are merged with the background.
- ***Label-altering features*** are erroneously translated.
  - Vessels are changed in size or position.
- Arteries and veins are ***not linked*** during translation.
  - Vessels are left untransformed, thus not segmented.

We introduce a ***semi-supervised DA framework*** for segmenting brain veins using primarily annotated angiographies. We combine image translation and semantic segmentation by relying on a combined and disentangled latent representation.

Method

Setup: Images x_i from source domain $\mathcal{S}$ and target domain $\mathcal{T}$ are fed into our model, composed of:

▪ a generator G ▪ a discriminator D ▪ an encoder E

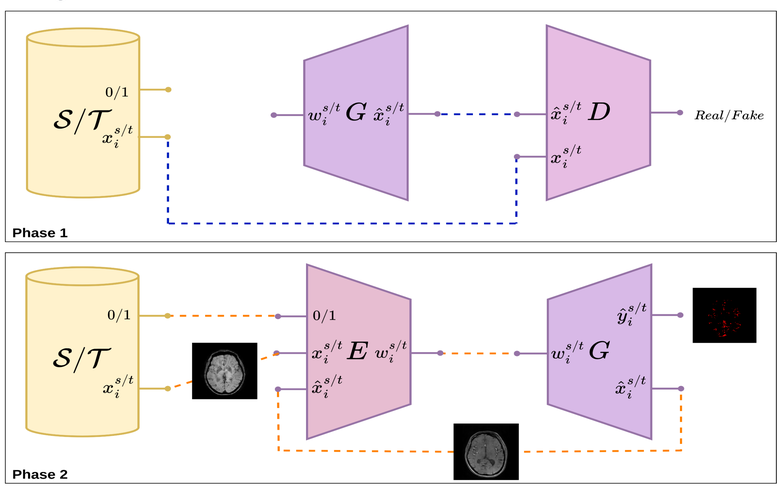

Fig 1. *Two-phase training algorithm.*

The modules are trained in two separate phases.

Phase 1: G maps latent vectors $w_i \in \mathcal{W}$ into an x_i, in $\mathcal{S}$ or $\mathcal{T}$. D discriminates real and fake samples.

Disentanglement guarantees label-preserving translation between the two domains. Hence, E can handle individual features independently from others, discovering high-level mappings that differentiate between various vessel characteristics. This allows to alter vessel intensities, while preserving compromising ***volume-related*** and ***vessel-related*** properties, such as image spacing or vessel arrangement.

Phase 2: E reconstructs or transforms an image in $\mathcal{S}$ and $\mathcal{T}$. G has a label-synthesis branch for segmentation.

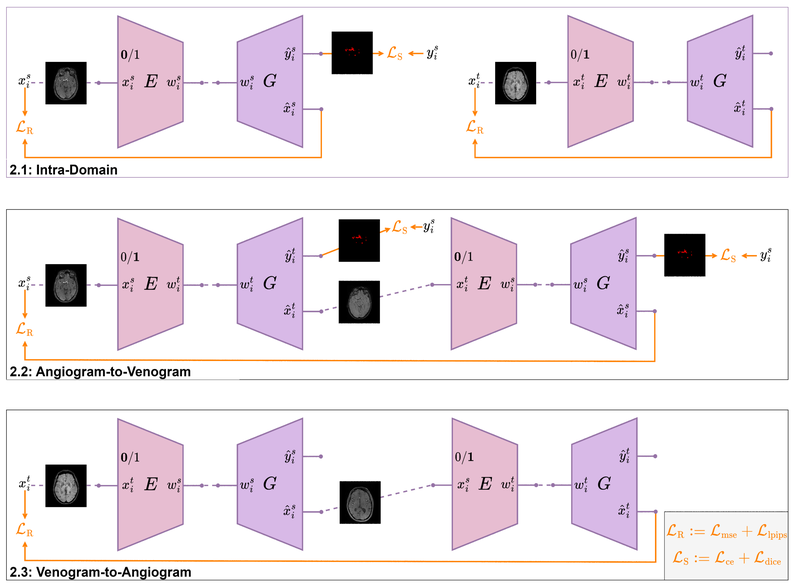

Fig 2. *Phase 2 of the training algorithm alternating intra-domain (2.1) and inter-domain (2.2 and 2.3) configurations*

Experiments & Results

We used ***time-of-flight MR*** angiographies as $\mathcal{S}$, and ***susceptibility weighted imaging*** venographies as $\mathcal{T}$.

Method*	Brain Dice	Vessels Dice	Vessels clDice
SIFA	91.5 ± 0.4	0.8 ± 0.2	0.8 ± 0.2
SynthSeg	79.6 ± 3.8	37.3 ± 4.4	48.2 ± 4.7
CS-CADA	91.5 ± 0.8	51.4 ± 1.7	58.0 ± 2.8
DCDA	-	4.5 ± 0.4	3.9 ± 0.2)
Sato	-	44.2 ± 7.2	50.0 ± 6.7
Ours	**97.5 ± 0.2**	**70.4 ± 2.4**	**74.8 ± 2.4**

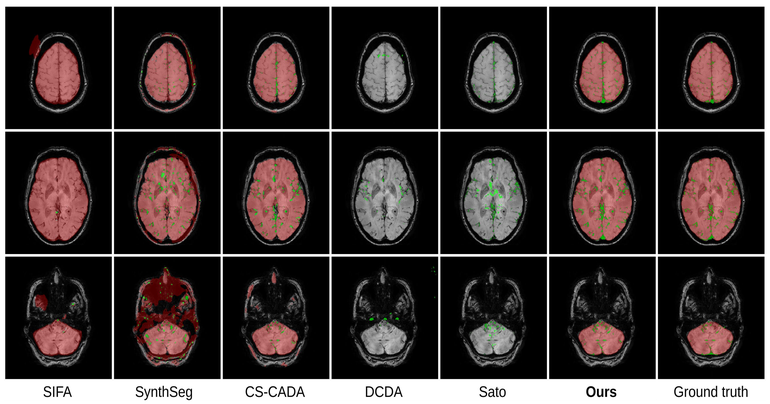

Fig. 3*. Visual comparison.*

Conclusions

- ***Accurate*** segmentation of 3D brain vessels using primarily annotations from arterial images.
- ***Optimized*** cycle-based network, counting two essential components, G and E.
- ***Two-phase*** learning algorithm, guaranteeing that only D is involved with adversarial training, and discarded after Phase 1.
- Code ***freely available***:

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