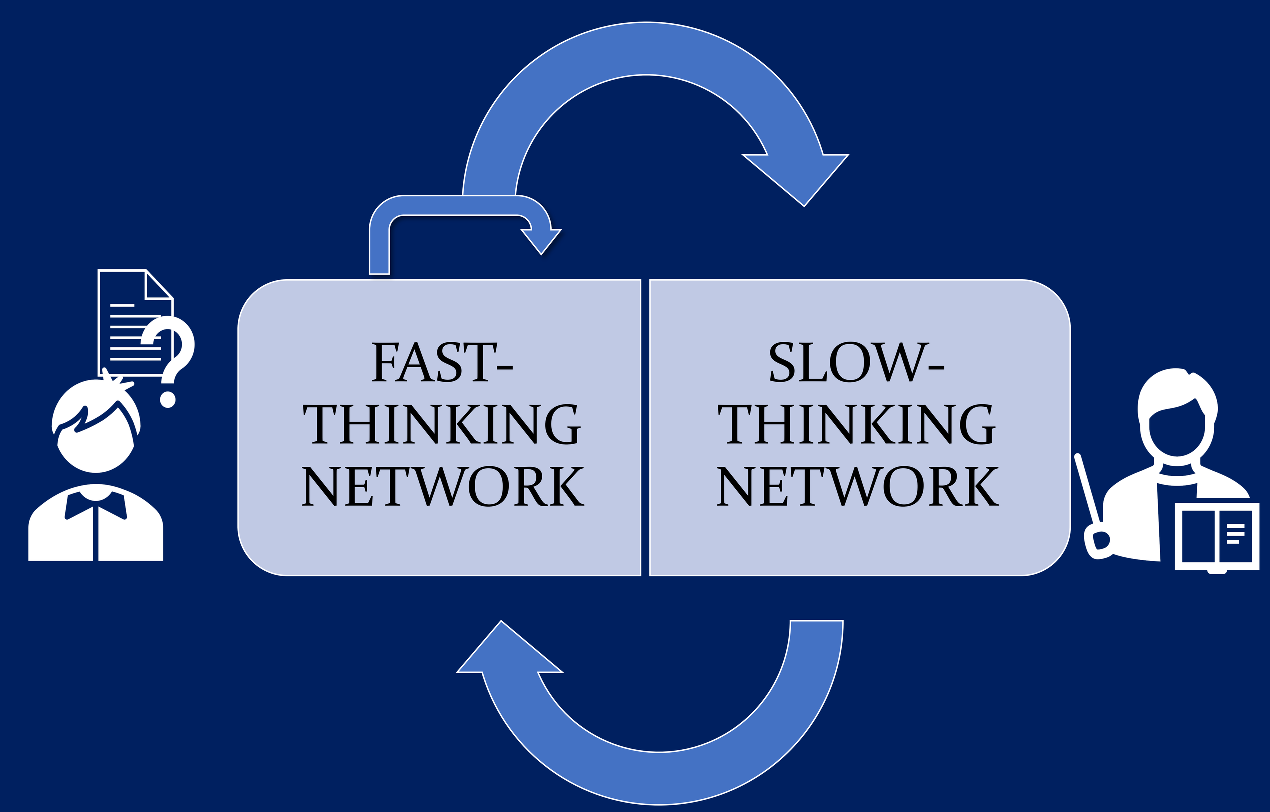
A cooperative training method to improve model **cross-domain** performance using **single-domain** data only

Generate hard examples via **latent space masking** to enhance training



Learn the shape knowledge to guide optimization and inference

Cooperative Training and Latent Space Data Augmentation for Robust Medical Image Segmentation

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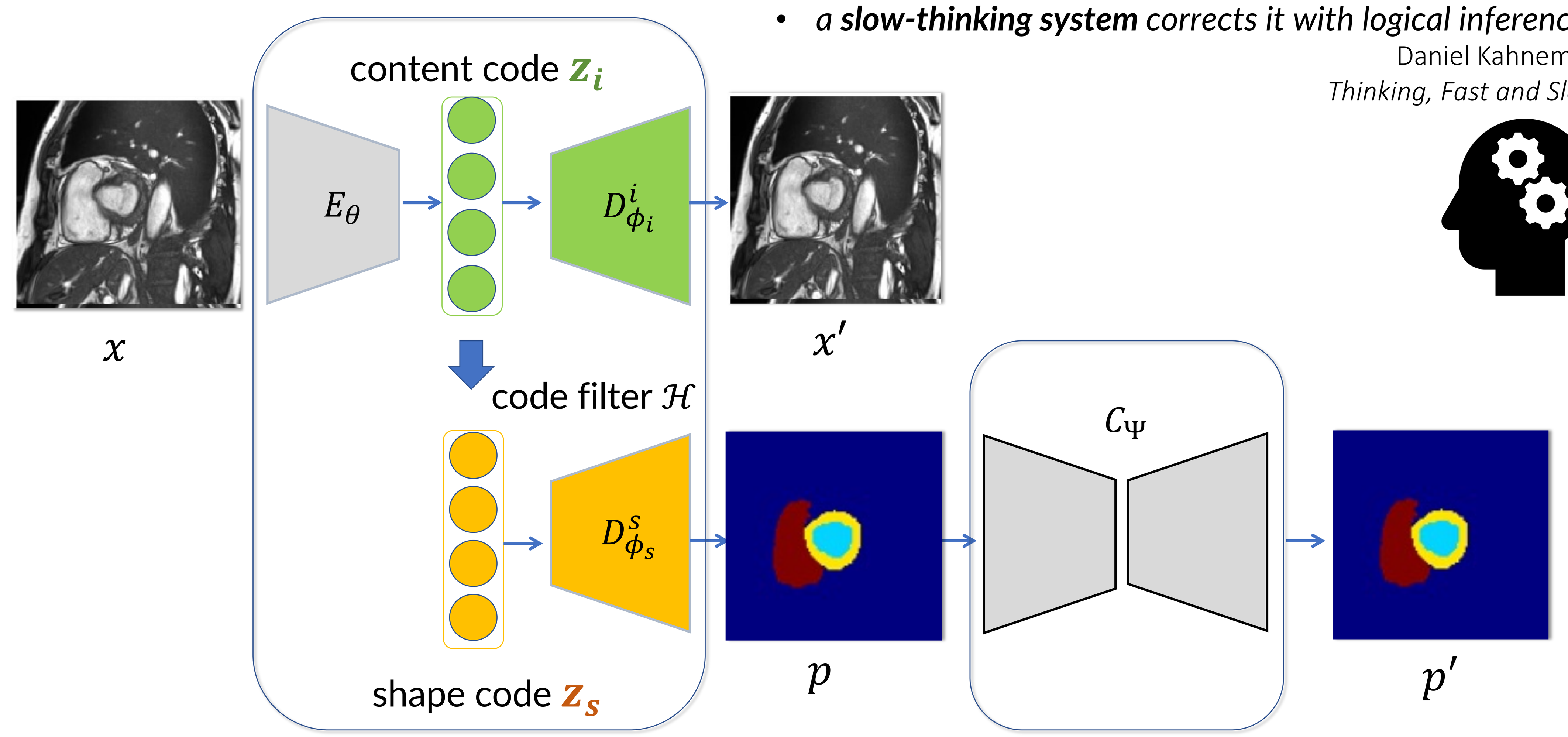
GitHub

Dual-Thinking Framework

Two networks cooperates both at training and testing for improved performance

When facing with unfamiliar scenarios, human have
- *a **fast-thinking system** makes intuitive judgment*
- *a **slow-thinking system** corrects it with logical inference.*

Daniel Kahneman
Thinking, Fast and Slow

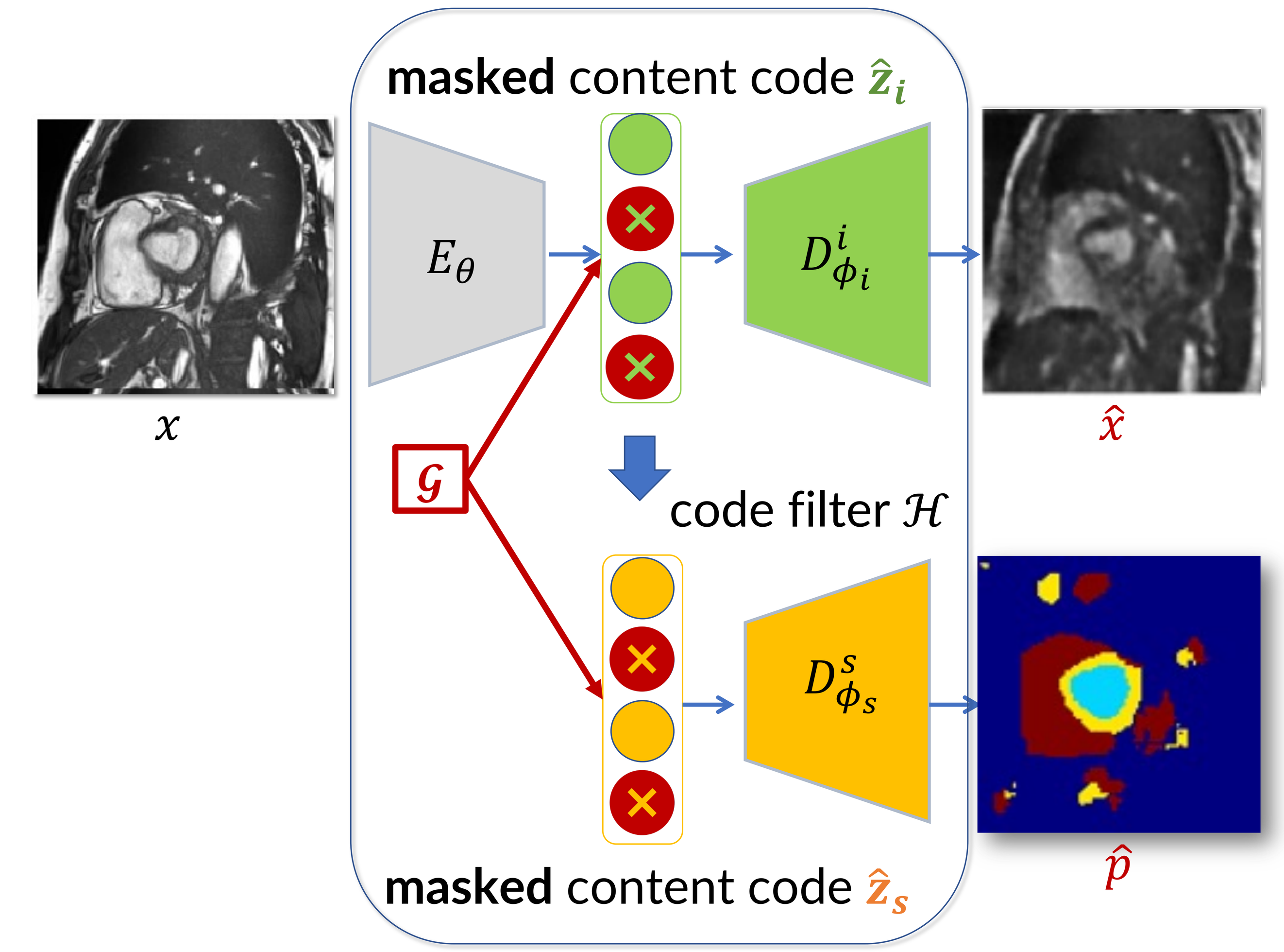


Fast-thinking network (FTN)
Image representation learning and segmentation

Slow-thinking network (STN)
Shape correction

Latent Space Masking-based Data Augmentation

Self-generates hard examples to train both FTN and STN

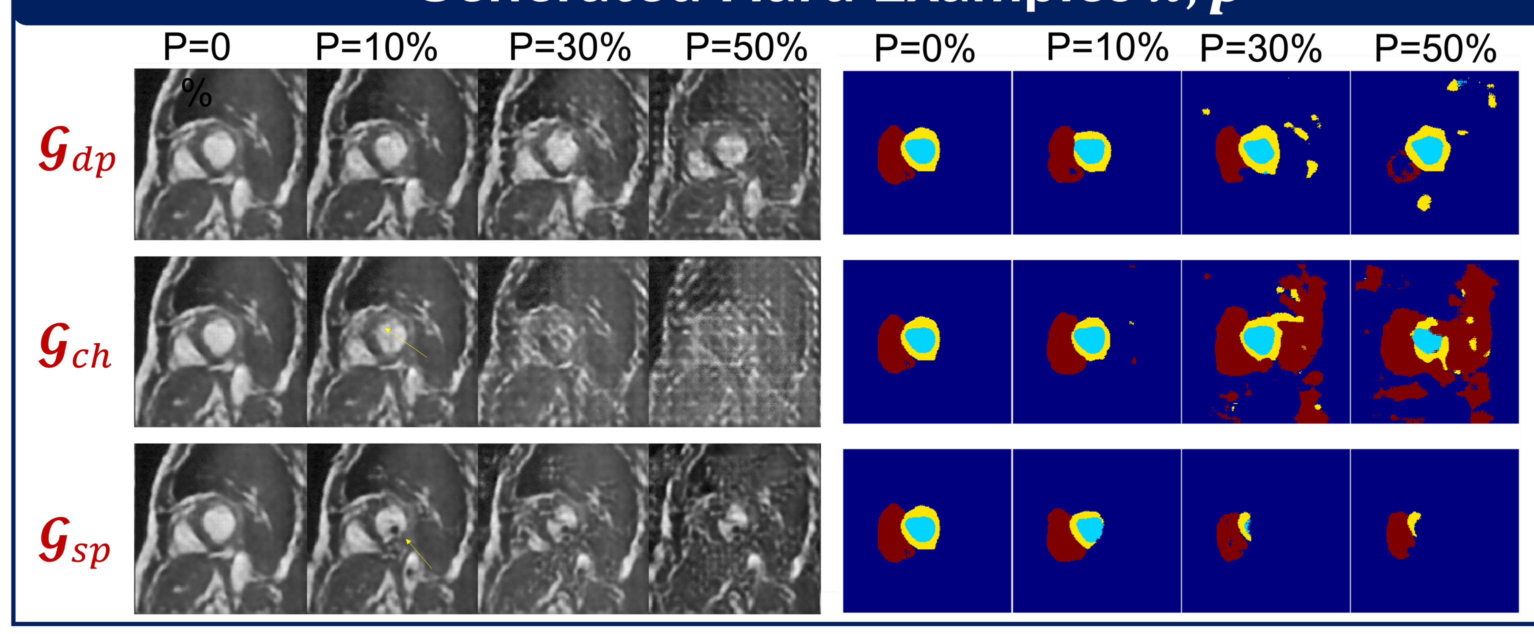


Three types of mask generators $\{\mathcal{G}\}$ to select:
- $\mathcal{G}_{dp}$: random channel-wise dropout
- $\mathcal{G}_{ch}$: targeted channel-wise soft masking*
- $\mathcal{G}_{sp}$: targeted spatial-wise soft masking*

*use gradient information to identify *salient* features to mask.

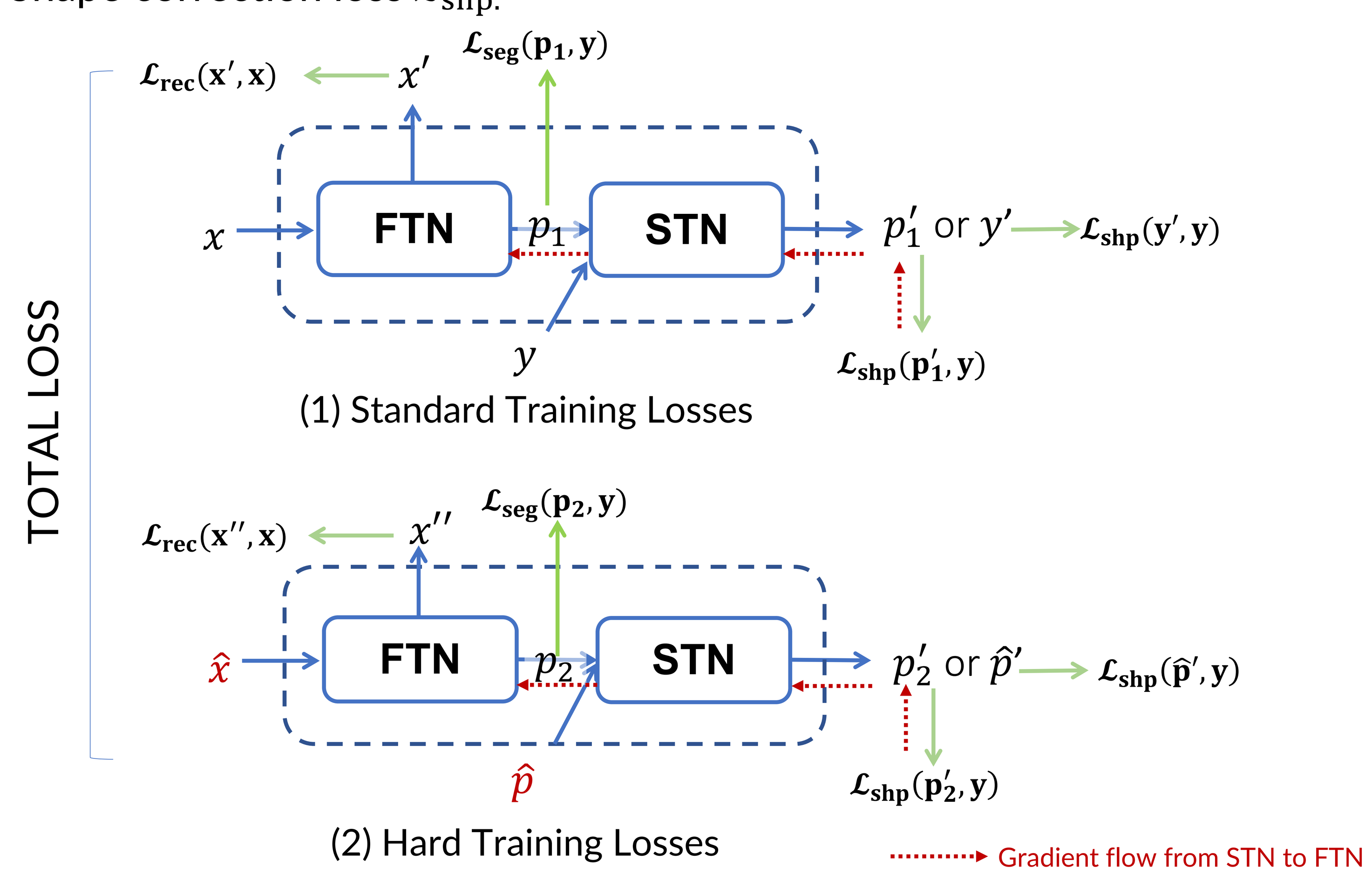
MORE

Generated Hard Examples $\hat{x}, \hat{p}$



Cooperative Training

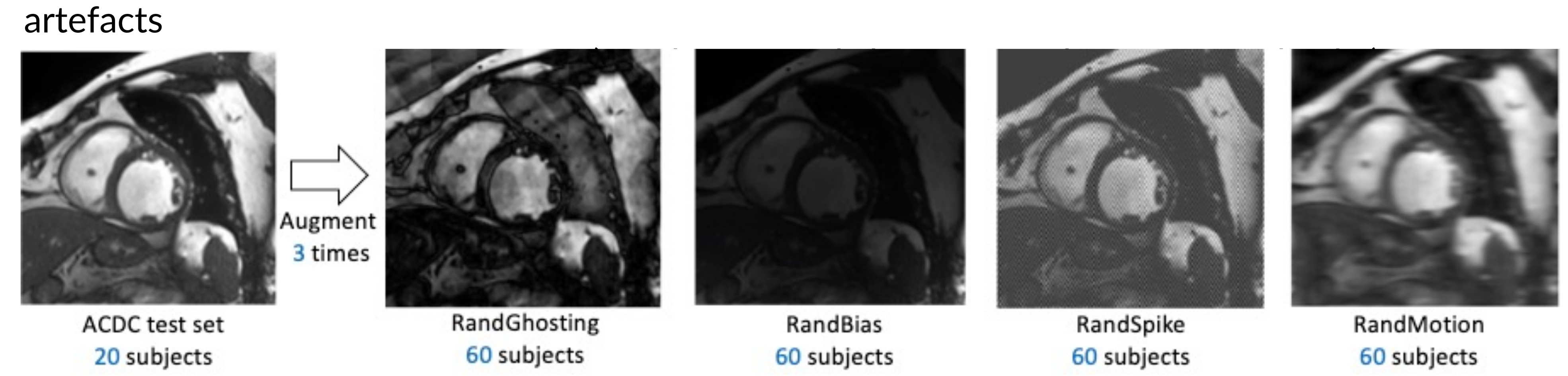
Multi-task loss computed on original and hard examples for joint optimization: a) Image reconstruction loss $\mathcal{L}_{\text{rec}}$; b) Segmentation loss $\mathcal{L}_{\text{seg}}$; c) Shape correction loss $\mathcal{L}_{\text{shp}}$.



Experiments and Results

More results are available online

- Task: Cardiac MR segmentation
- Training data: 10 ACDC[1] subjects (**single** site)
- Test data:
  - 1 Intra-domain test set: 20 ACDC subjects
  - 2 Unseen domain test sets :
    - M&Ms[2] for *cross-domain* test: 150 subjects collected from **multiple** sites
    - ACDC-C sets for *robustness* test: 240 corrupted ACDC test subjects with 4 types of common artefacts



[1] Olivier Bernard, TMI'18 [2] Víctor M. Campello, TMI'21

Segmentation results across different test sets

Method	ACDC	M&Ms	RandBias	RandGhosting	RandMotion	RandSpike	AVG (FTN)	AVG (FTN+STN)
Standard training	0.7681	0.3909	0.4889	0.6964	0.7494	0.4901	0.5970	0.6018
Rand MWM [1]	0.7515	0.3984	0.4914	0.6685	0.7336	0.5713	0.6024	0.6131
Rand Conv [2]	0.7604	0.4544	0.5538	0.6891	0.7493	0.4902	0.6162	0.6404
Adv Noise [3]	0.7678	0.3873	0.4903	0.6829	0.7543	0.6244	0.6178	0.6276
Adv Bias [4]	0.7573	0.6013	0.6709	0.6773	0.7348	0.3840	0.6376	0.6604
Proposed w. $\hat{x}$	0.7497	0.5154	0.5921	0.6921	0.7417	0.6633	0.6591	0.6709
Proposed w. $\hat{x}, \hat{p}$	0.7696	0.5454	0.6174	0.7073	0.7643	0.6226	0.6711	0.6901

- STN consistently improves the segmentation performance on **EVERY** test set
- Our latent space data augmentation (DA) outperforms SOTA image-space DA methods [1-4], achieving **TOP** average performance across all test sets

[1] Zongwei Zhou, MICCAI'19, MedIA'21 [2] Zhenlin Xu, ICLR'21 [3] Takeru Miyato, TPAMI'18 [4] Chen Chen, MICCAI'20

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