Unsupervised Domain Adaptation for Low-dose CT Reconstruction via Bayesian Uncertainty Alignment

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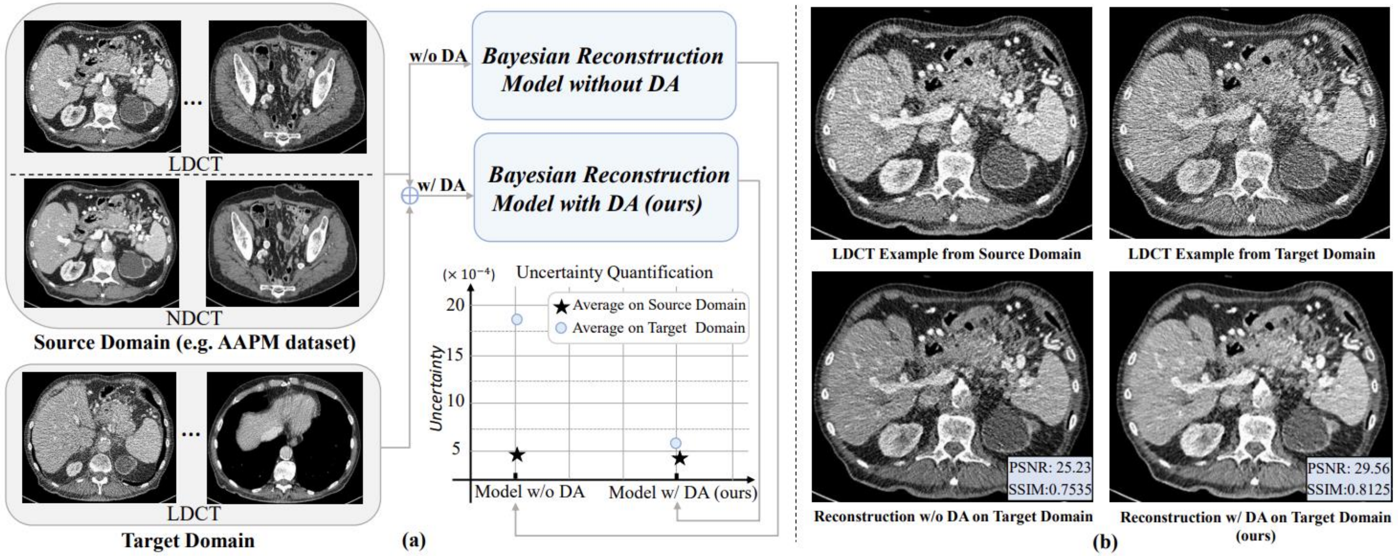
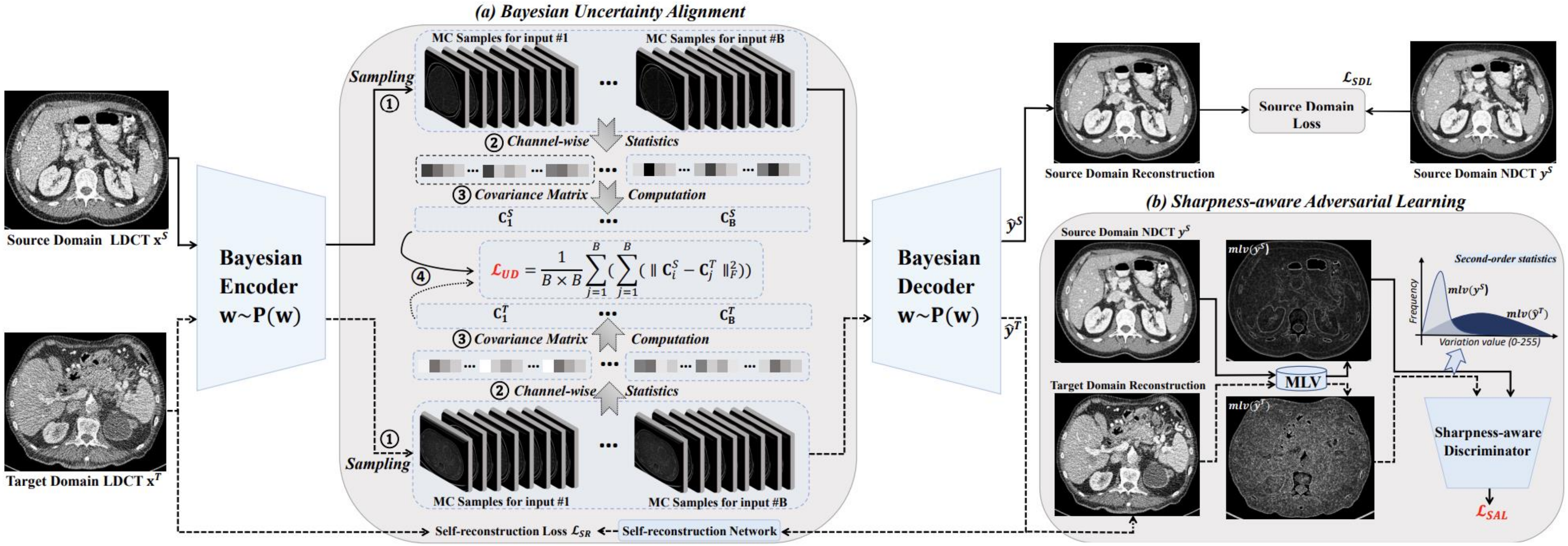
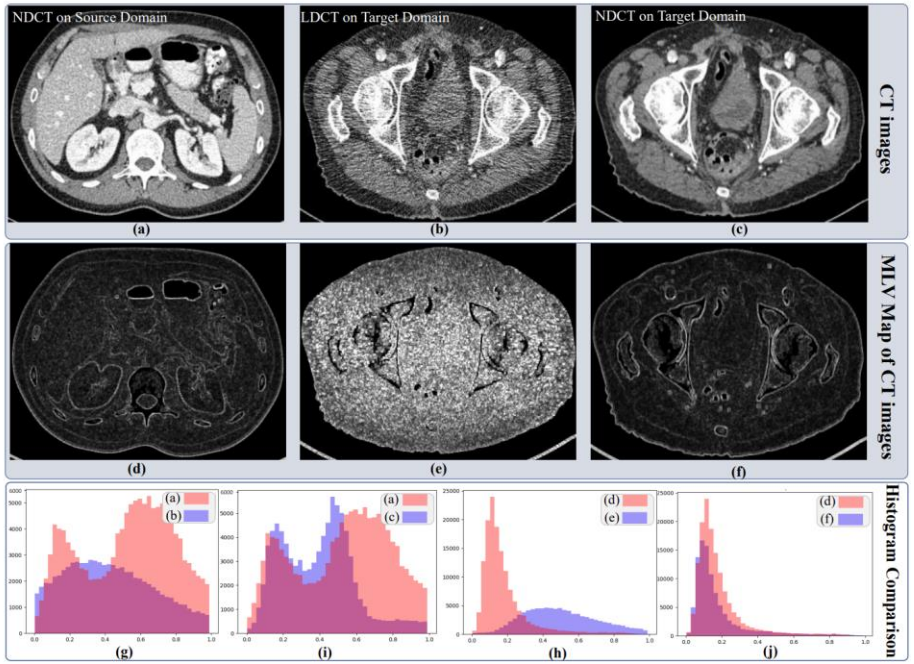
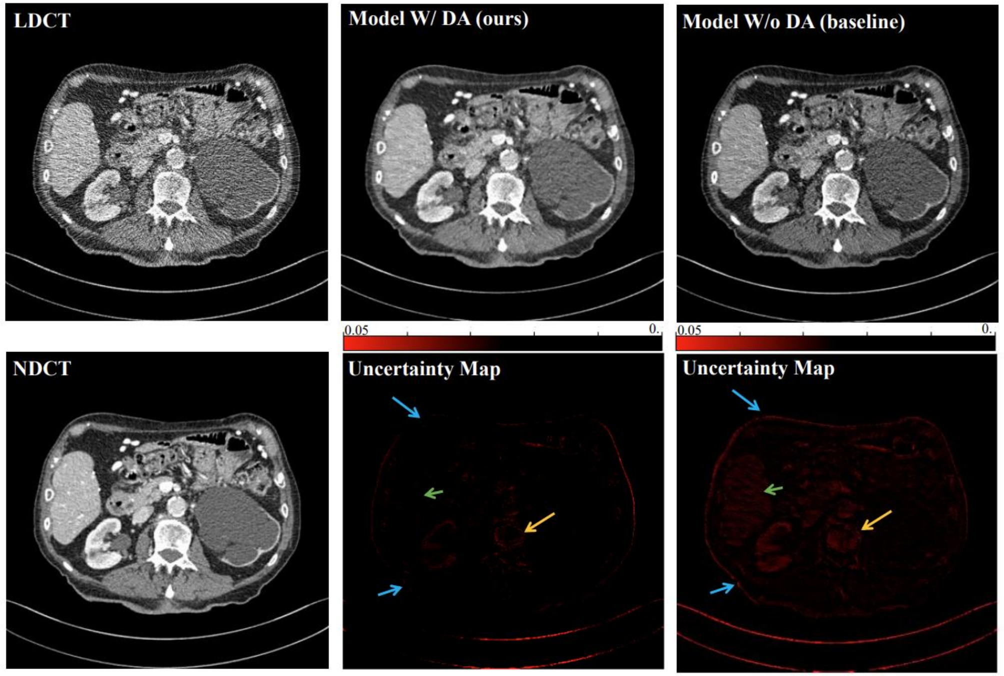


Fig. 1. Left: Uncertainty quantification on source and target domains using BNN-based reconstruction model with DA strategy (`Model w/ DA` trained by paired data from the source domain and LDCT images from the target domain) and BNN-based reconstruction model without DA strategy (`Model w/o DA` trained by source domain data only). A higher level of uncertainty is observed on the target domain for the model without DA strategy. Besides, the level of uncertainty on the target domain is close to the source domain by adopting our proposed DA method. Right: Examples of an LDCT image from the source domain, an LDCT image from the target domain, and corresponding reconstructed results on target domain data. The display window is [-160,240] HU.


(a) Bayesian Uncertainty Alignment
MC Samples for input #1
MC Samples for input #B
Sampling
① Sampling
② Channel-wise Statistics
③ Covariance Matrix Computation
$\mathbf{C}_1^S$ $\mathbf{C}_B^S$
④
$\mathcal{L}_{UD} = \frac{1}{B \times B}\sum_{j=1}^{B}(\sum_{j=1}^{B}(\| \mathbf{C}_i^S - \mathbf{C}_j^T \|_F^2))$
$\mathbf{C}_1^T$ $\mathbf{C}_B^T$
Source Domain LDCT $\mathbf{x}^S$
Target Domain LDCT $\mathbf{x}^T$
Bayesian Encoder w~P(w)
Bayesian Decoder w~P(w)
$\hat{y}^S$
$\hat{y}^T$
Source Domain Reconstruction
Source Domain Loss
$\mathcal{L}_{SDL}$
Source Domain NDCT y^S
(b) Sharpness-aware Adversarial Learning
Source Domain NDCT y^S
Target Domain Reconstruction
$mlv(y^S)$
$mlv(\hat{y}^T)$
MLV
Second-order statistics
Frequency
Variation value (0-255)
Sharpness-aware Discriminator
$\mathcal{L}_{SAL}$
Self-reconstruction Loss $\mathcal{L}_{SR}$
Self-reconstruction Network


NDCT on Source Domain
LDCT on Target Domain
NDCT on Target Domain
CT images
(a)
(b)
(c)
MLV Map of CT images
(d)
(e)
(f)
Histogram Comparison
(g)
(i)
(h)
(j)


LDCT
Model W/ DA (ours)
Model W/o DA (baseline)
NDCT
Uncertainty Map
Uncertainty Map

Domain Generalization with Small Data

International Journal of Computer Vision (IJCV) 2024

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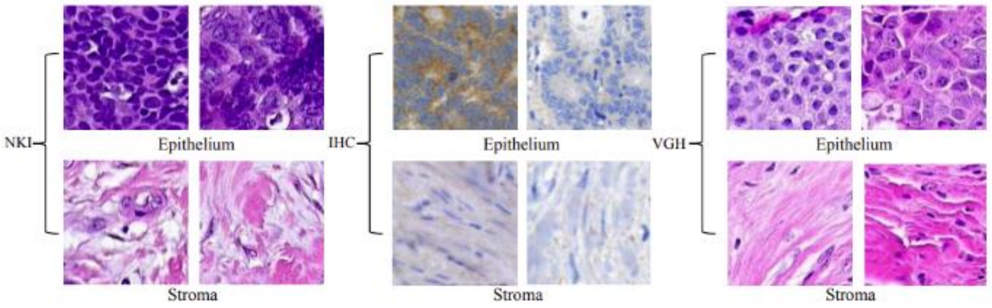
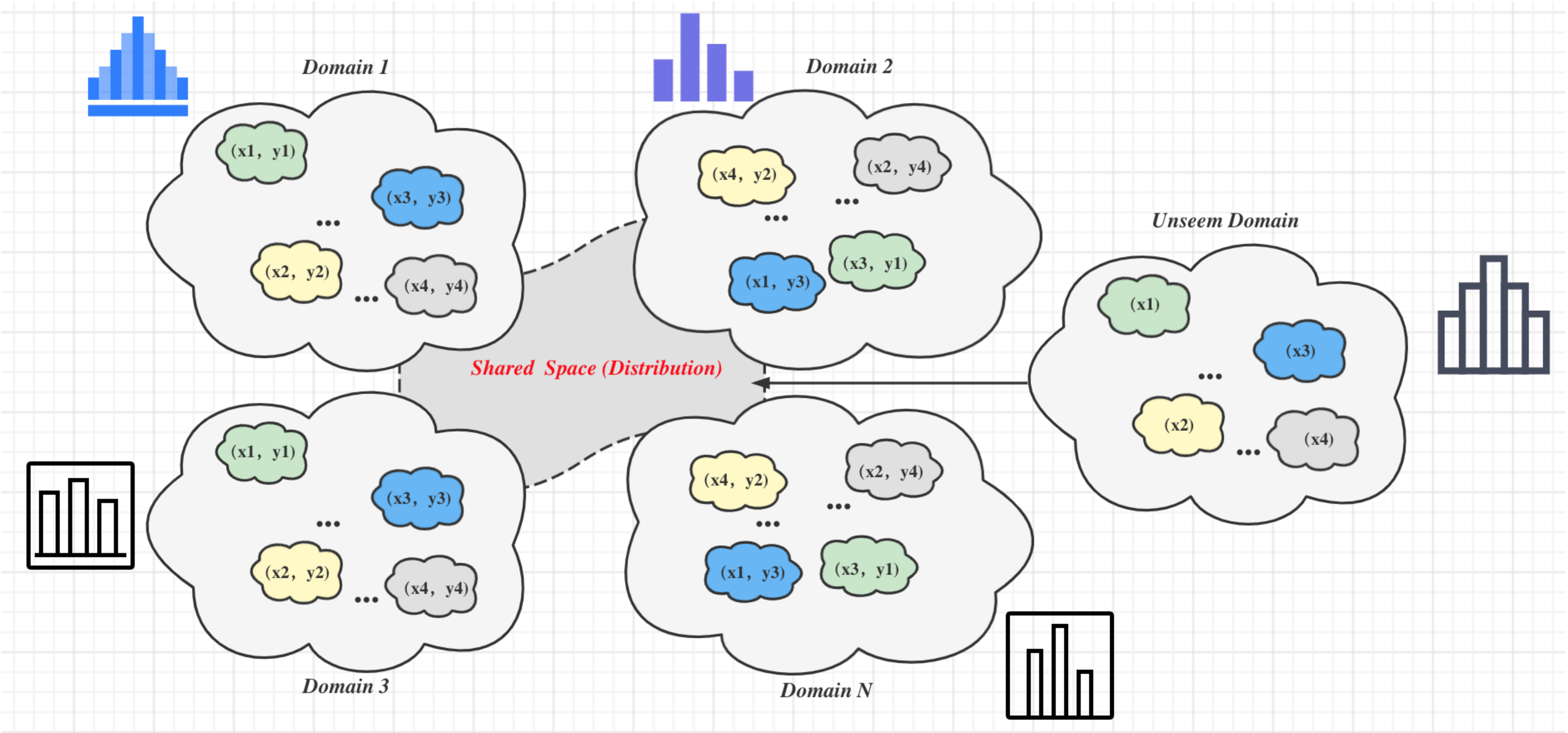
Paper Code Details





Out-of-distribution (OOD) problem always exists in real-world, e.g., healthcare, auto-driven scenario.
How to learn across-domain knowledge/information?

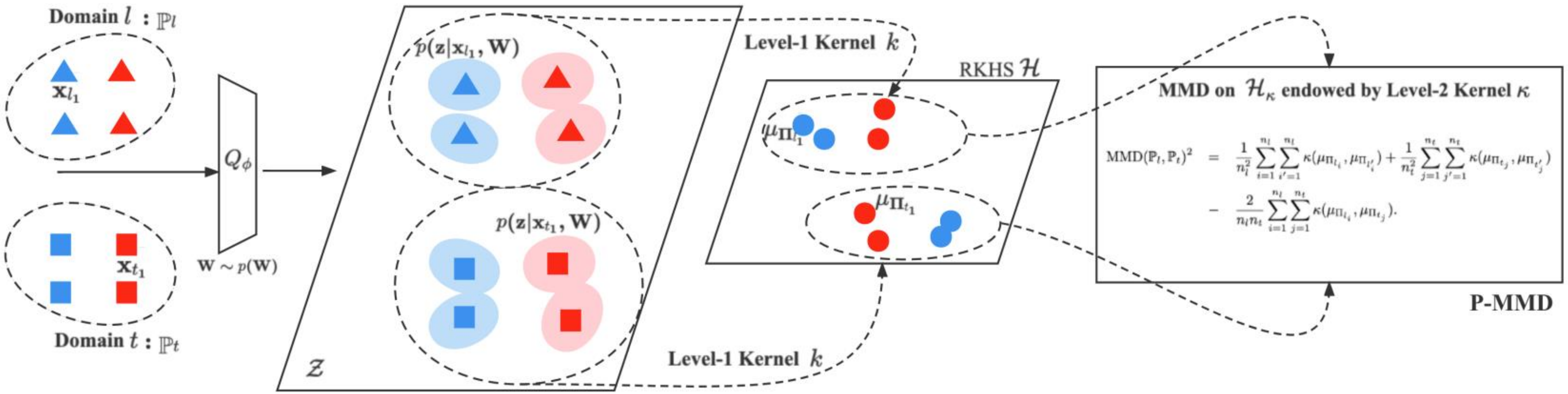


Fig. 2 A visualized computational process for probabilistic MMD (P-MMD) on two source domains. The same color for samples in different domains denotes the same label.

Measure discrepancy between distributions

$$\mathrm{MMD}\left(\mathbb{P}_l, \mathbb{P}_t\right)^2 = \| \frac{1}{n_l} \sum_{i=1}^{n_l} \phi\left(\mathbf{z}_{l_i}\right) - \frac{1}{n_t} \sum_{j=1}^{n_t} \phi\left(\mathbf{z}_{t_j}\right) \|_{\mathcal{H}}^2 \tag{2}$$

Measure discrepancy between mixture distributions (distribution over distributions)

$$\begin{aligned} \text{P-MMD}(\mathbb{P}_l, \mathbb{P}_t)^2 &= \| \frac{1}{n_l} \sum_{i=1}^{n_l} \psi(\mu_{\Pi_{l_i}}) - \frac{1}{n_t} \sum_{j=1}^{n_t} \psi(\mu_{\Pi_{t_j}}) \|_{\mathcal{H}_\kappa}^2 \\ &= \frac{1}{n_l^2} \sum_{i=1}^{n_l} \sum_{i'=1}^{n_l} K(\Pi_{l_i}, \Pi_{l'_i}) + \frac{1}{n_t^2} \sum_{j=1}^{n_t} \sum_{j'=1}^{n_t} K(\Pi_{t_j}, \Pi_{t'_j}) \\ &- \frac{2}{n_l n_t} \sum_{i=1}^{n_l} \sum_{j=1}^{n_t} K(\Pi_{l_i}, \Pi_{t_j}). \end{aligned} \tag{4}$$

Learning Robust Shape Regularization for Generalizable Medical Image Segmentation

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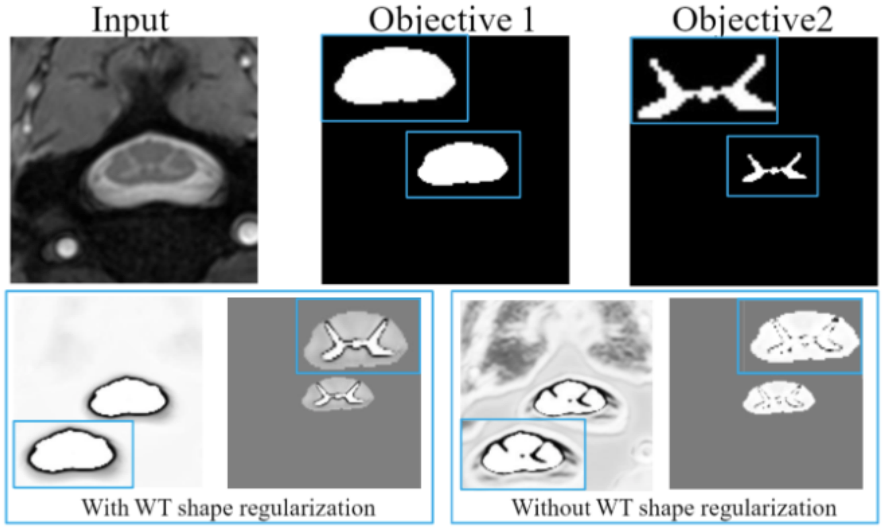
Paper Code



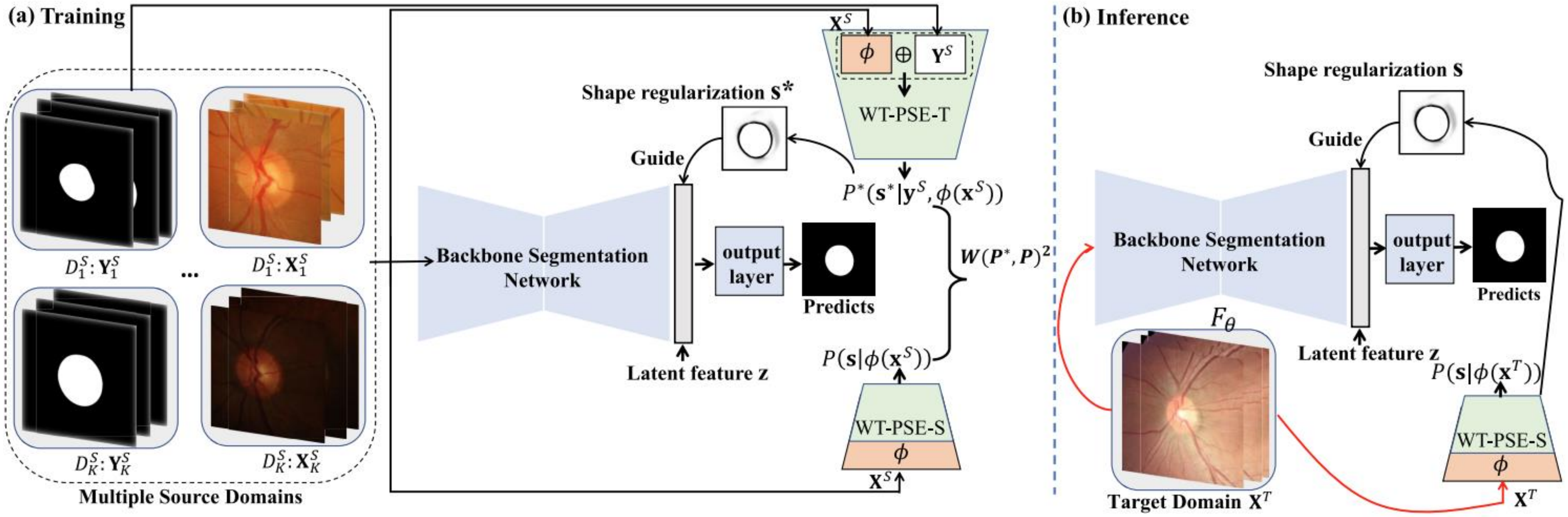


Fig. 2. Overall framework of the proposed method for generalizable medical image segmentation.

Whitening transform

$$\arg\min_{\mathbf{x}} \mathbb{E}[\|\boldsymbol{\Sigma}_\mu - \mathbf{I}\|_1] = \mathbb{E}[\|\boldsymbol{\Sigma}_{\mu(i,i)} - 1\|_1 + \|\boldsymbol{\Sigma}_{\mu(i,j)} - 0\|_1]$$
$$= \mathbb{E}[\|\frac{\mathbf{x}_i^\top \cdot \mathbf{x}_i}{HW} - 1\|_1 + \|\frac{\mathbf{x}_i^\top \cdot \mathbf{x}_j}{HW}\|_1] \quad (2)$$

$$\mathcal{L}_{ID-WT} = \lambda_1 \underbrace{\mathbb{E}[\ |\boldsymbol{\Sigma}_{\mu(i,i)} - 1\ |_1 + \ |\boldsymbol{\Sigma}_{\mu(i,j)} - 0\ |_1]}_{Instance} + \lambda_2 \underbrace{[\frac{1}{K^2} \underset{1\leq m,q\leq K}{\mathrm{MMD}} (\mathbf{V}_m, \mathbf{V}_q)]}_{Domain}, \quad (9)$$

Shape modeling and discrepancy measurement

$$P(\mathbf{s}|\mathbf{y}^S, \phi(\mathbf{x}^S)) = \mathcal{N}(\mathbf{s}|\boldsymbol{\mu}(\mathbf{y}^S, \phi(\mathbf{x}^S); \varphi_m), \boldsymbol{\Sigma}(\mathbf{y}^S, \phi(\mathbf{x}^S); \varphi_c)). \quad (5)$$

$$W(P^*, P)^2 = \sum_{i=1}^{d} (\mu_i^* - \mu_i)^2 + \sum_{i=1}^{d} \left(\sqrt{\boldsymbol{\Sigma}_{ii}^*} - \sqrt{\boldsymbol{\Sigma}_{ii}}\right)^2$$
$$= \sum_{i=1}^{d} (\mu_i^* - \mu_i)^2 + \sum_{i=1}^{d} (\sigma_i^* - \sigma_i)^2,$$

Under review

TEST-TIME ADAPTATION FOR IMAGE COMPRESSION WITH DISTRIBUTION REGULARIZATION

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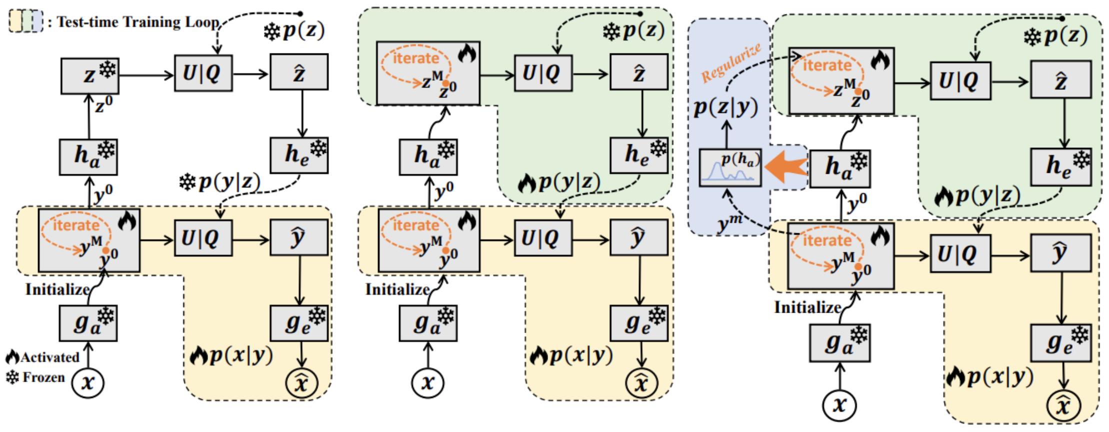


(a) BLR (b) HLR (c) Ours

Figure 2: Architectures of different latent refinement TTA-IC methods. $U|Q$ represents the quantization and entropy coding.

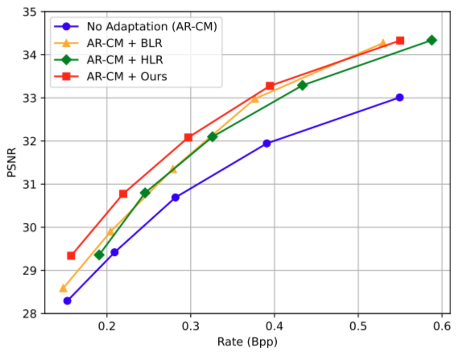
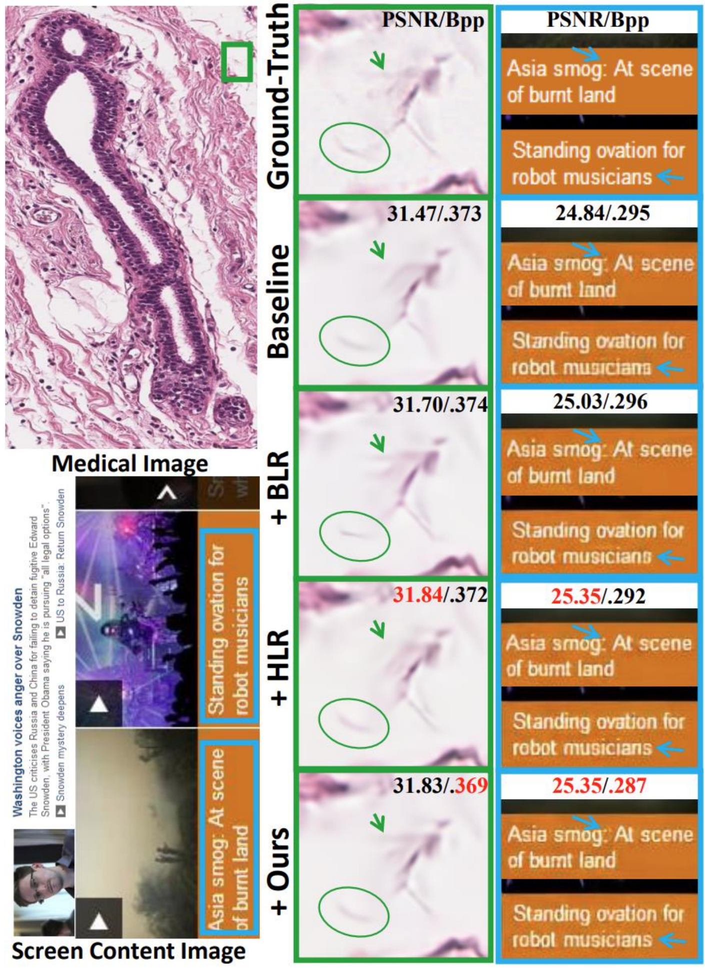


Figure 7: R-D performance on challenging medical images, where pathological breast cancer images are used for cross-domain compression (Niazi et al., 2019).



ITF Proposal