Feature Constrained by Pixel: Hierarchical Adversarial Deep Domain Adaptation

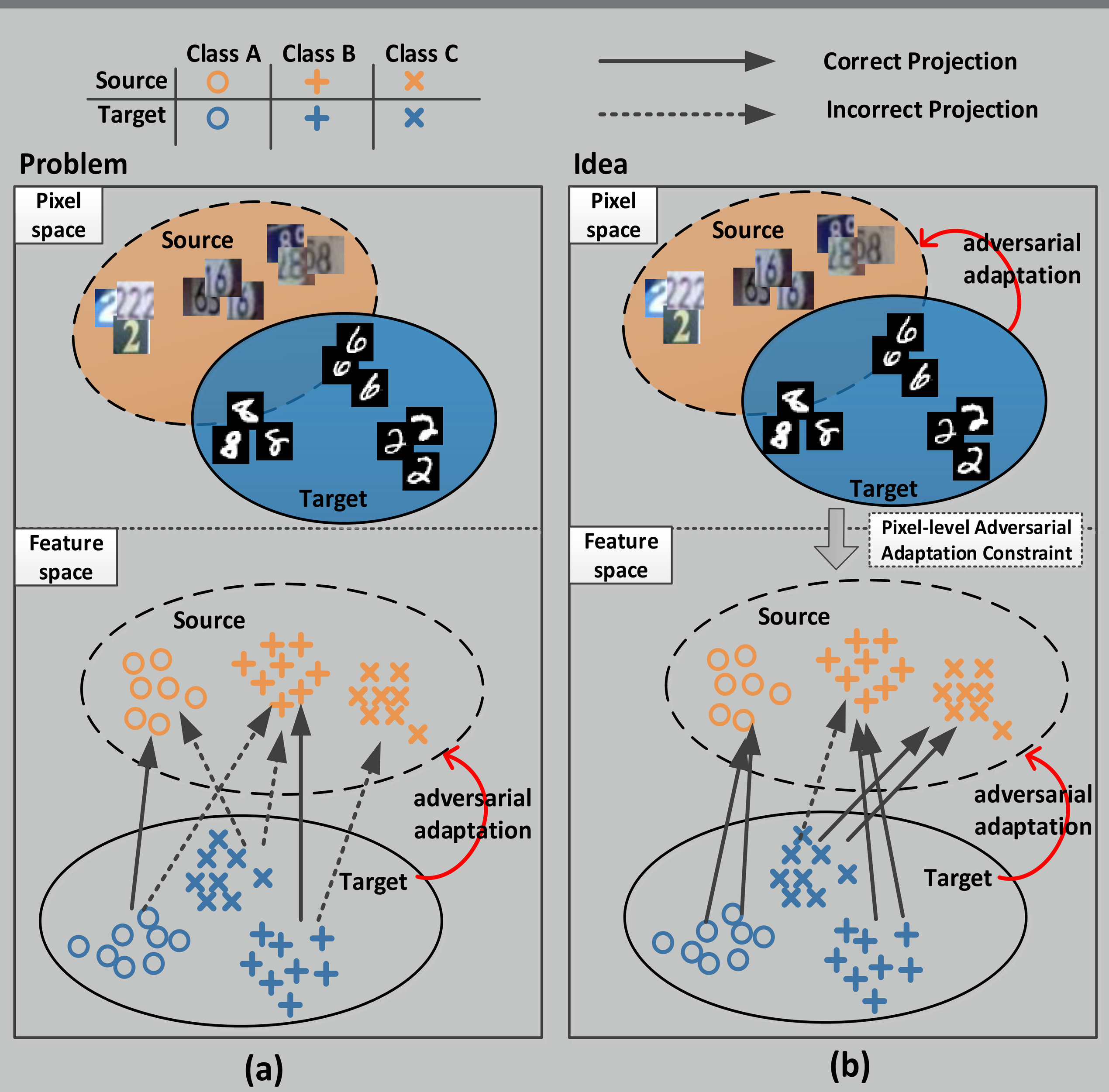
Rui Shao, Xiangyuan Lan, Pong C. Yuen
Department of Computer Science, Hong Kong Baptist University

DEPARTMENT OF COMPUTER SCIENCE 計算機科學系

Objective

1. Reduce the domain discrepancy by aligning feature representations of two domains without using any target domain labels.
2. Classifier trained with source labels can be adapted on the target data.

Idea

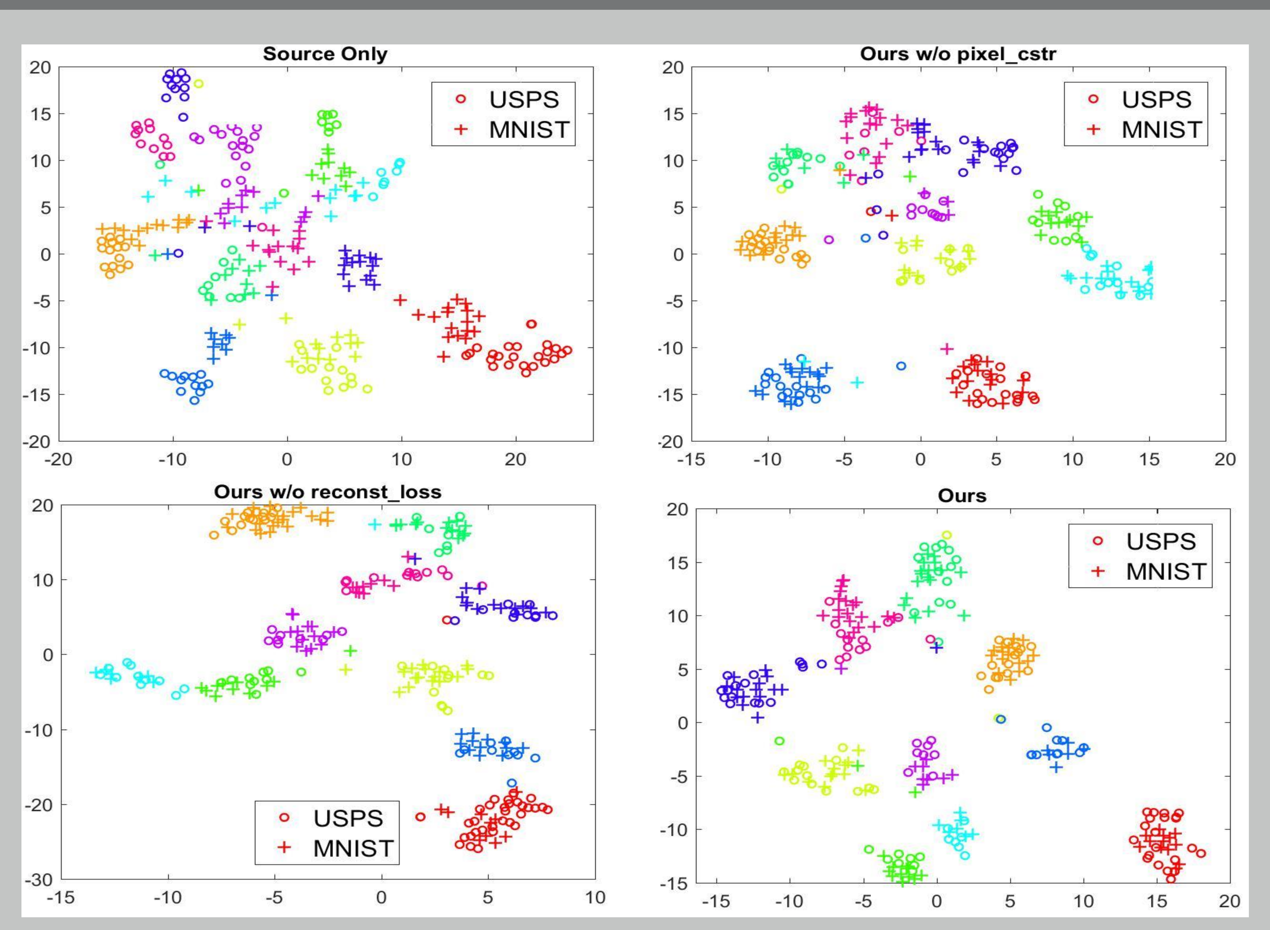


- Adversarial adaptation in the feature space degraded by the large low-level domain variances in pixel space.
- Pixel-level adversarial adaptation exploited to alleviate low-level domain variances.

Contribution

- Exploiting the pixel-level adversarial adaptation as the constraint on feature-level adaptation, by which image quality degradation issue can be avoided while the low-level domain variance can be alleviated.
- A new hierarchical model based on Generative Adversarial Network for UDA, which exploits pixel-level adversarial adaptation as guidance to facilitate the feature-level adaptation.

Feature Visualization



Method

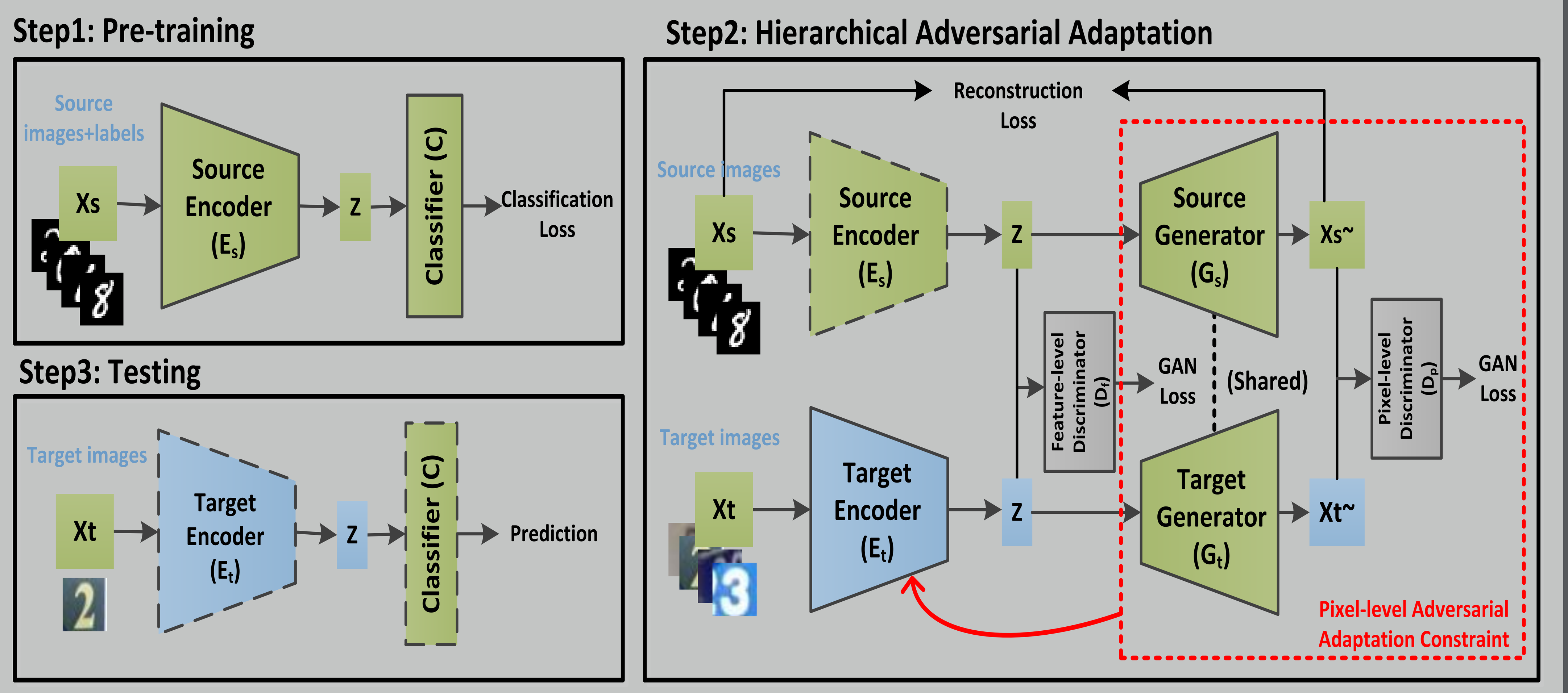


Figure 1: An overview of our proposed method.

- Overview:

$$\min_{\Phi\cup\Omega} \mathcal{L}_{\text{HAND}}(\mathbf{X}_s, \mathbf{X}_t, E_s; E_t, G_s, G_t, D_f, D_p) = \min_{\Phi} \mathcal{L}_{\text{adv feature}}(\mathbf{X}_s, \mathbf{X}_t, E_s; E_t, D_f) \quad \text{s.t.} \quad \Omega = \arg\min \mathcal{L}_{\text{adv pixel}}(\mathbf{X}_s, \mathbf{X}_t, E_s; E_t, G_s, G_t, D_p) \tag{1}$$

- Hierarchical Adversarial Adaptation:

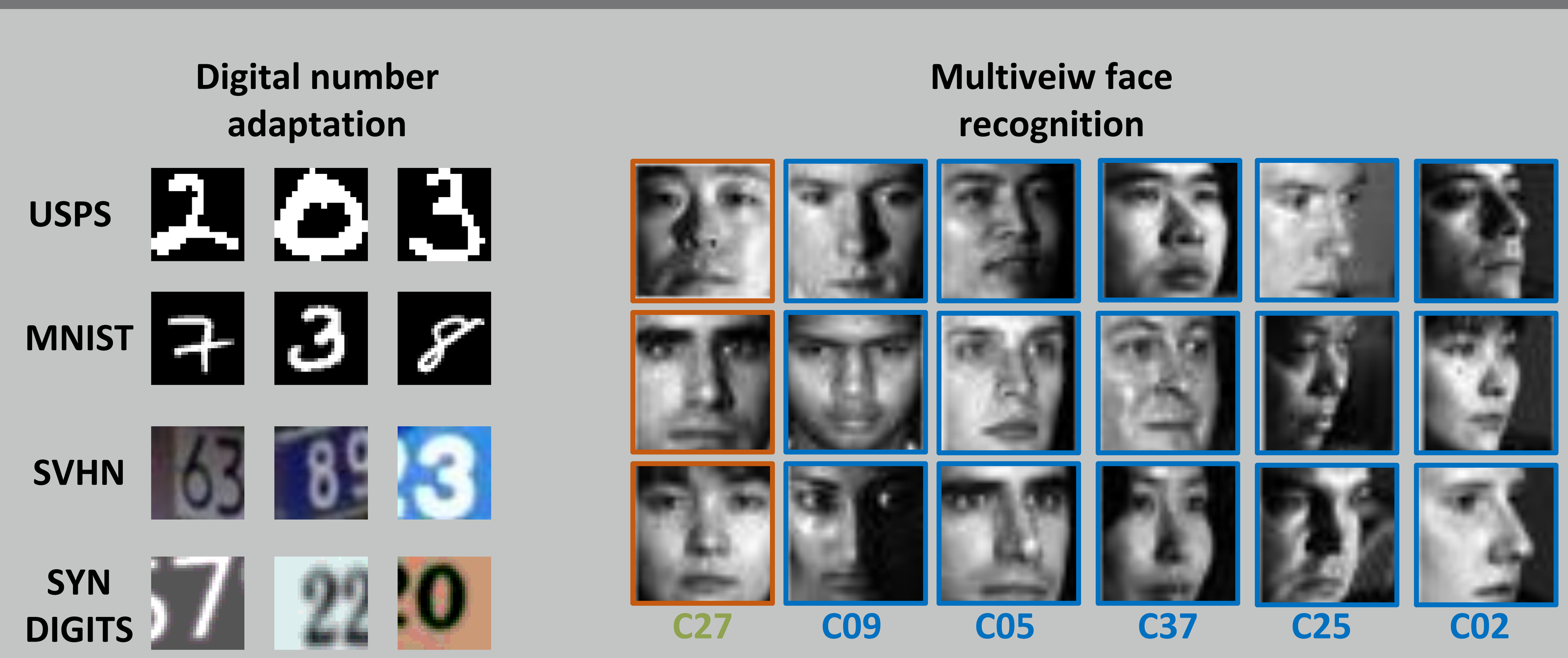
$$\mathcal{L}_{\text{adv feature}} = \mathcal{L}_{\text{GAN}}(\mathbf{X}_s, \mathbf{X}_t, E_s; E_t, D_f) \tag{2}$$

$$\min_{D_f} \mathcal{L}_{\text{adv}_D}(\mathbf{X}_s, \mathbf{X}_t, E_s; E_t) = -\mathbb{E}_{x_s\sim X_s}[\log(D_f(E_s(x_s)))] - \mathbb{E}_{x_t\sim X_t}[\log(1 - D_f(E_t(x_t)))] \tag{3}$$

$$\mathcal{L}_{\text{adv pixel}} = \mathcal{L}_{\text{LSGAN}}(\mathbf{X}_s, \mathbf{X}_t, E_s; E_t, G_s, G_t, D_p) + \lambda\mathcal{L}_{\text{Rec}}(\mathbf{X}_s, E_s; G_s) \tag{4}$$

$$\min_{E_t, G_s, G_t} \mathcal{L}_{\text{adv}_{E,G}}(\mathbf{X}_s, \mathbf{X}_t, E_s; D_p) = \mathbb{E}_{x_s\sim X_s}[(D_p(G_s(E_s(x_s))) - 1)^2] + \mathbb{E}_{x_t\sim X_t}[(D_p(G_t(E_t(x_t))) - 1)^2] + \lambda \parallel \mathbf{X}_s - G_s(E_s(x_s)) \parallel_2^2 \quad \text{s.t.} \quad G_s = G_t \tag{5}$$

Results



Accuracy (mean%) values for digital number adaptation task.

Method	MNIST to USPS	USPS to MNIST	SVHN to MNIST	SYN DIGITS to SVHN
Source Only	77.22	58.22	61.13	87.06
DDC	79.10	66.50	68.10	-
DAN	-	-	71.10	88.00
DANN	77.10	73.00	73.90	91.10
CORAL	-	-	63.10	85.20
DRCN	91.80	73.67	81.97	-
DSN w/MMD	-	-	72.20	88.50
DSN w/DANN	-	-	82.70	91.20
CoGAN	91.20	89.10	did not converge	-
ADDA	89.40	90.10	76.00	-
Ours	91.89	95.98	84.89	92.51

Accuracy (mean%) values for multiview face recognition task.

Method	C27 to C09	C27 to C05	C27 to C37	C27 to C25	C27 to C02	Ave.
1-NN-s	92.5	55.7	28.5	14.8	11.0	40.5
SVM-s	87.8	65.0	35.8	15.7	16.7	44.2
GFK-PLS	92.5	74.0	32.1	14.1	12.3	45.0
SA	97.9	85.9	47.9	16.6	13.9	52.4
CORAL	91.4	74.8	35.3	13.4	13.2	45.6
ILS	96.6	88.3	72.9	28.4	34.8	64.2
PUnDA	94.3	92.2	78.8	28.9	34.7	65.7
Ours	98.9	94.2	91.7	44.6	53.2	76.5

ruishao@comp.hkbu.edu.hk