Data Augmentation via Mixed Class Interpolation using Cycle-Consistent Generative Adversarial Networks Applied to Cross-Domain Imagery

Paper # 1401

PS T1.7 (DAY 2 - Jan 13)

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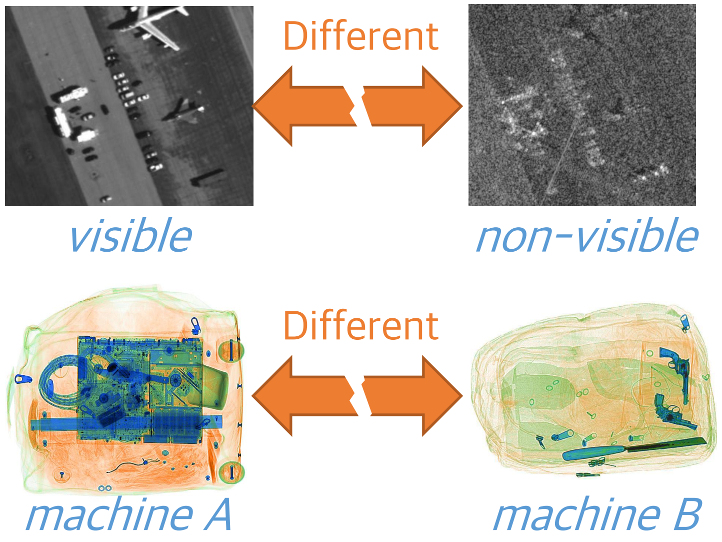
Issue

Limited Data Availability

for Non-visible Domain Object Classification / Detection

Infrared (IR), synthetic aperture radars (SAR), X-ray, etc.

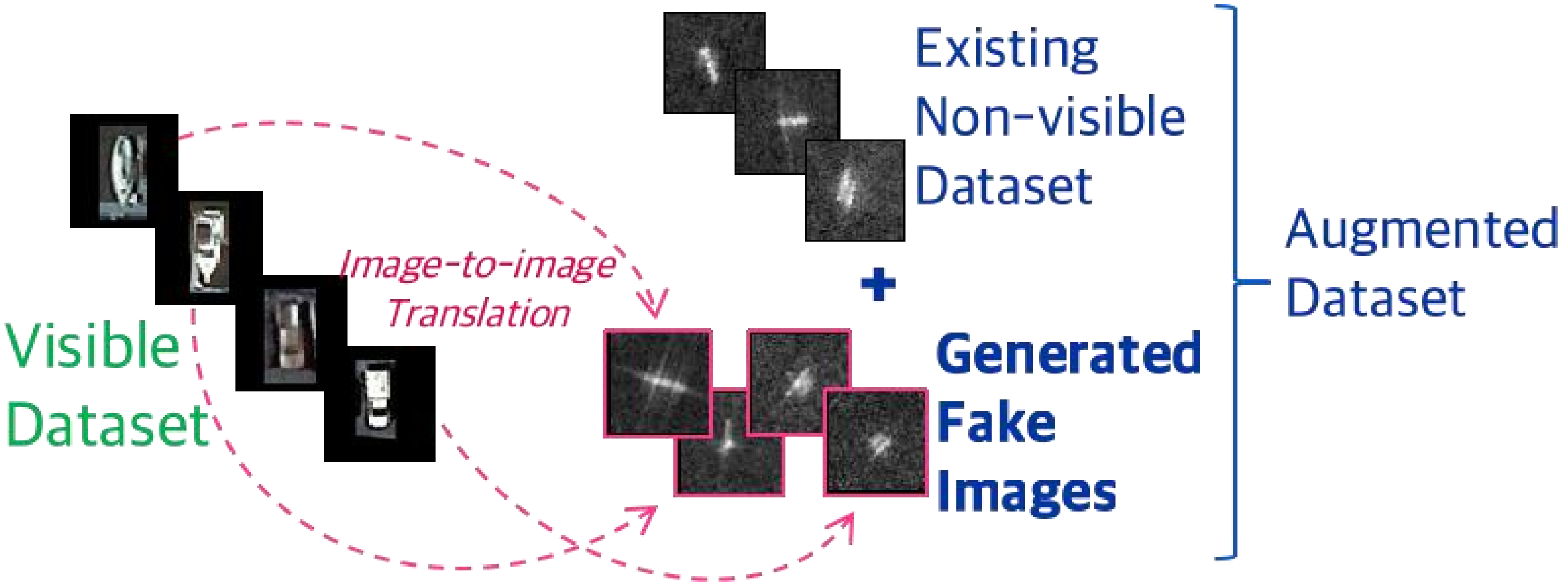
Expensive sensors
(or export controlled)



Low inter-task availability

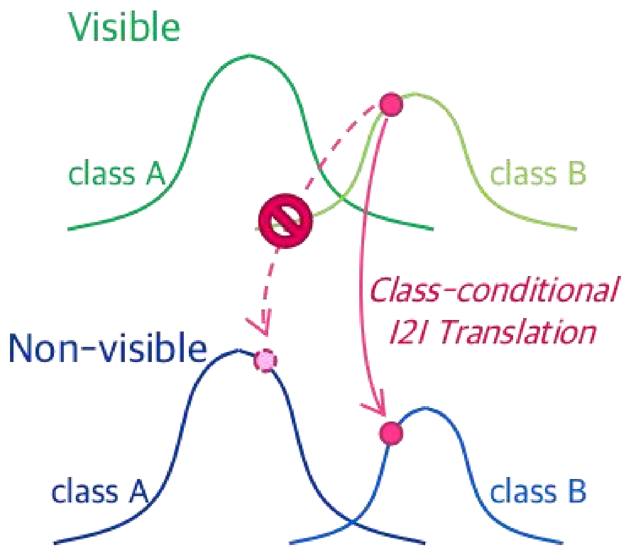
Approach
- Data Augmentation - (1/2)

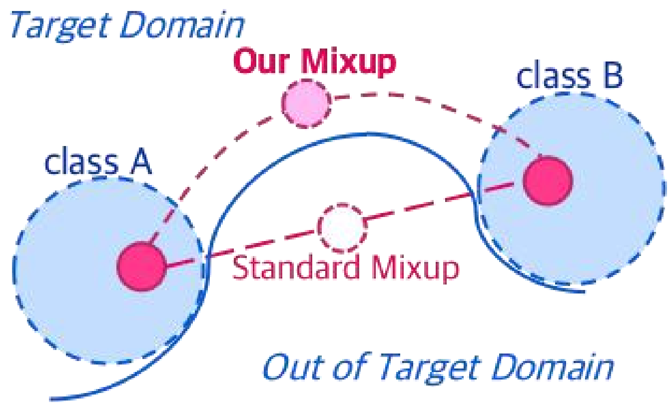
Increase non-visible dataset via **image-to-image translation** from visible dataset



Approach
- Data Augmentation - (2/2)

- Use CycleGAN[1]-based model conditioned by image labels (object classes) for **class-specific image** synthesis
- Infer **class-interpolated images** to improve Mixup[2]



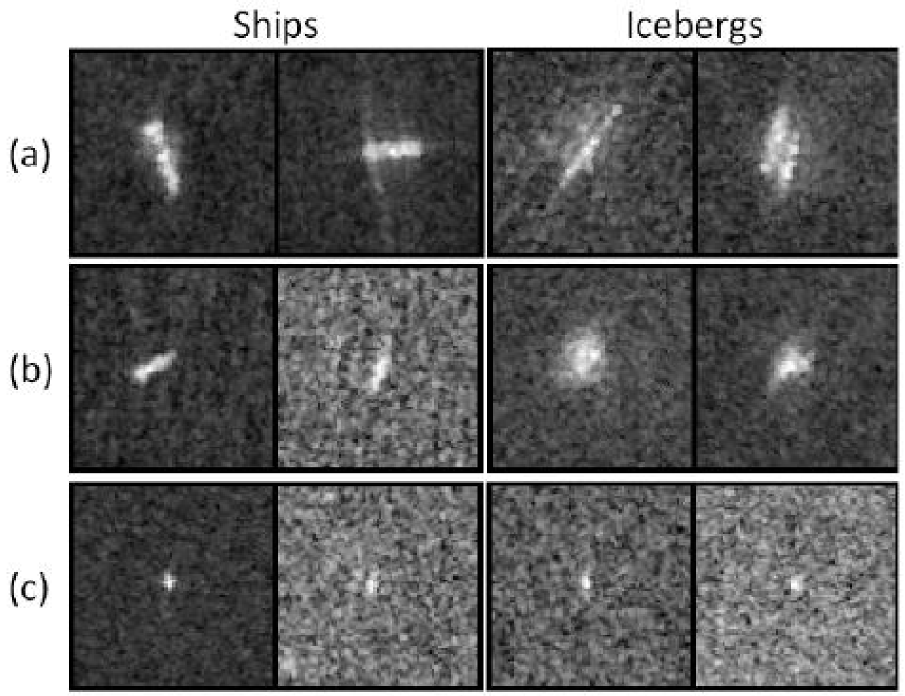


[1] J. Zhu, et al "Unpaired image-to-image translation using cycle-consistent adversarial networks," ICCV, 2017.
[2] H. Zhang, et al "mixup: Beyond empirical risk minimization," ICLR, 2018.

Experiment (Dataset Setup)

Statoil/C-CORE Iceberg Classifier Challenge[3]

➢ Satellite C-band SAR images of ships / icebergs



[3] https://www.kaggle.com/c/statoil-iceberg-classifier-challenge

separate training samples into 3 subsets

a) Easy to discriminate

b) Modelate to discriminate

c) Difficult to discriminate

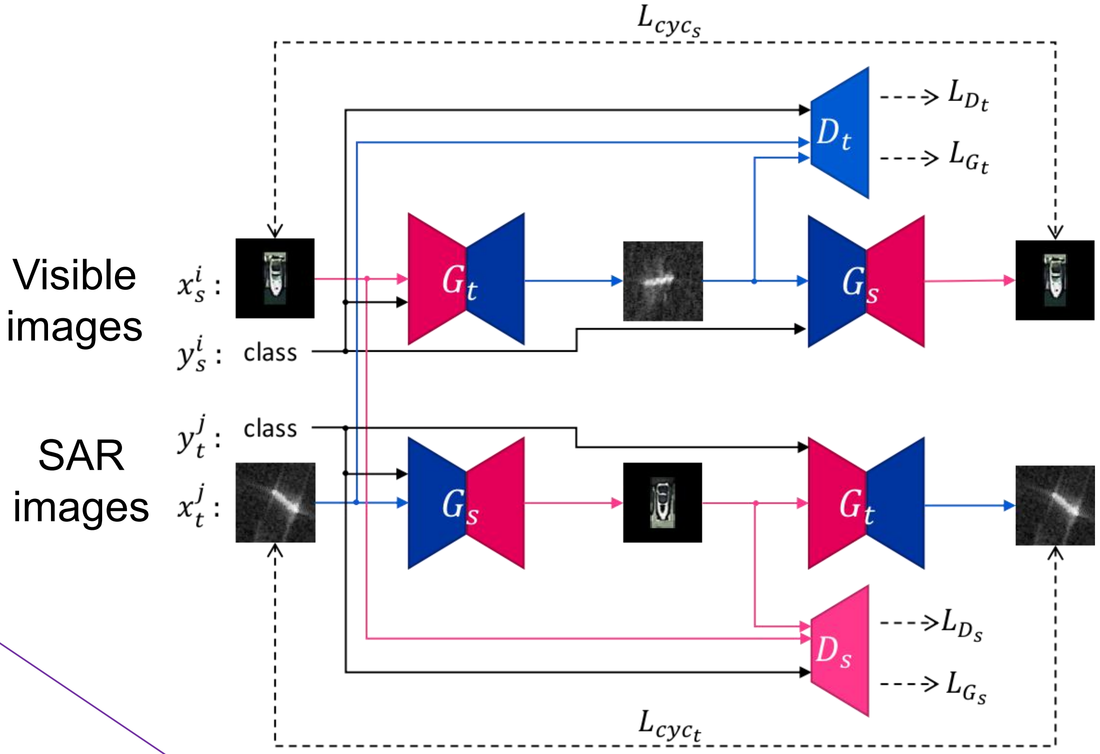
Number of samples

	Ship				Iceberg			
	(a)	(b)	(c)	total	(a)	(b)	(c)	total
Test	97	158	171	426	99	137	141	377
Train #1	96	15	17	128	99	13	14	126
Train #2	96	15	17	128	9	137	14	160
Train #3	96	15	17	128	9	13	140	162

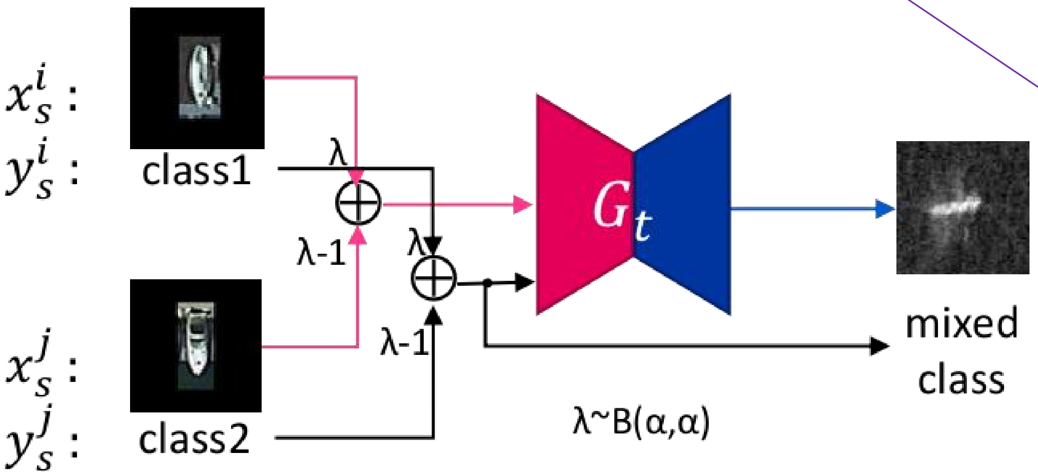
Experiment (Image Synthesis)

DOTA[4]

Model Training



Inference



[4] https://captain-whu.github.io/DOTA/index.html

Experiment (Result)

Train AlexNet[5] models with
5 different training data conditions
& compare the classification performances

	Acc.	Prec.	Rec.	F1
(1) only training dataset w/o data augmentation	0.551	0.562	0.575	0.568
(2) (1)+ 90/180/270 degree rotated training samplaes	0.549	0.554	0.571	0.562
(3) Mixup[2] of (1)	0.715	0.739	0.719	0.729
(4) (1) + synthesised images via MixCycleGAN[6]	0.730	0.752	0.739	0.745
(5) (1) + synthesised images via our approach	**0.754**	**0.777**	**0.762**	**0.769**

[5] A. Krizhevsky, et al, "Imagenet classification with deep convolutional neural networks," NeurIPS, 2012.
[6] D. Liang, et al, "Understanding mixup training methods," IEEE Access, vol. 6, pp. 58 774-58 783, 2018.

Conclusion

- A novel data augmentation for non-visible imagery.
- Visible to non-visible domain image translation via CycleGAN-based method.
- Our CycleGAN is conditioned for class-specific image synthesis.
- Class-interpolated image synthesis to improve Mixup.
- Outperforms other traditional data augmentation approaches on a SAR ships/icebergs classification task.

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