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

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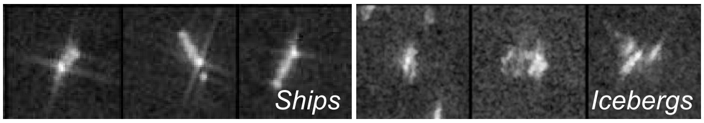


Examples of non-visible imagery (Synthetic Aperture Radar images [1])

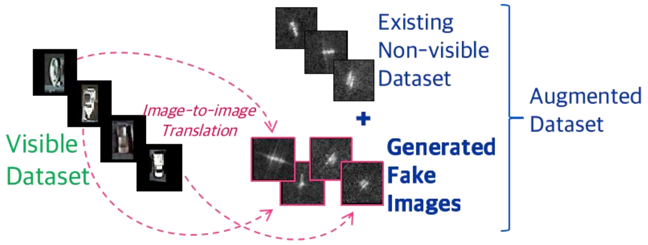
Issue

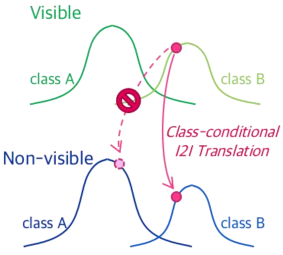
Limited availability of non-visible imagery poses a significant challenge in object detection, classification and recognition.

Approach

Conditional CycleGAN Mixup Augmentation (C2GMA)

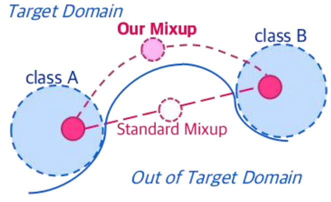
(1) Increase non-visible datasets via **image-to-image translation** from visible datasets.

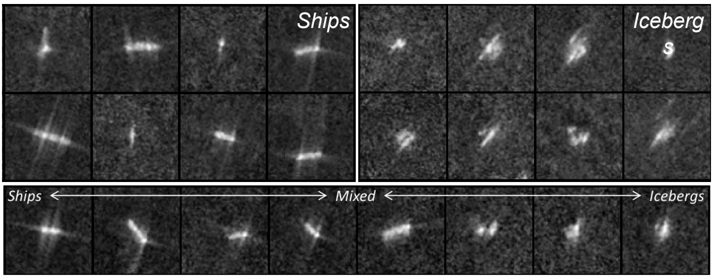




(2) Modify CycleGAN model to use conditional GAN and train the model with class labels to enable **class-specific image synthesis**.

(3) Infer class-interpolated images using the trained conditional CycleGAN to **improve mixup**.

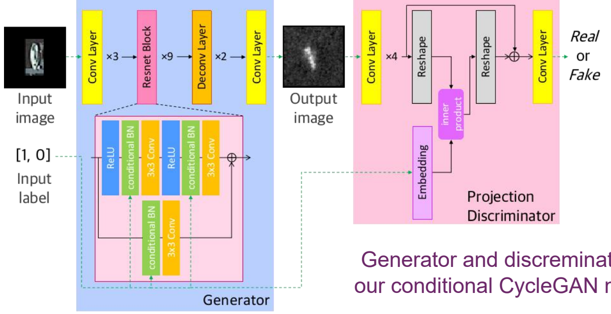




Examples of generated SAR ships, icebergs and class-interpolated images

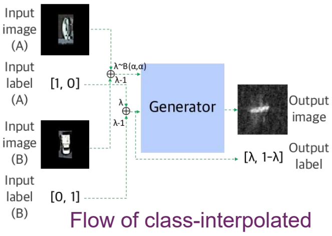
C2GMA Architecture & Training

(1) **Add** the **conditional batch normalization layer** and the **projection discriminator** into CycleGAN.
(2) **Train** the model using visible and non-visible images **with one-hot class labels**.



Generator and discriminator of our conditional CycleGAN model

(3) **Infer** the **class-interpolated images** using the trained model and blended visible images / labels as input.
(4) **Augment dataset** with the generated non-visible images.



Flow of class-interpolated image generation (inference)

Evaluation

Task: SAR ships / icebergs classification via AlexNet [4]
Benchmark Dataset: Variation of Statoil/C-CORE dataset [1]
Baseline: [BL] without data augmentation
[ROT] BL + rotated images
[MIXUP] BL + Mixup [3]
[MIXCG] BL + MixCycleGAN [5]

	Average			
	A	P	R	F1
BL	0.551 ± 0.142	0.562 ± 0.160	0.575 ± 0.130	0.568 ± 0.145
ROT	0.549 ± 0.137	0.554 ± 0.146	0.571 ± 0.124	0.562 ± 0.135
MIXUP [9]	0.715 ± 0.044	0.739 ± 0.051	0.719 ± 0.049	0.729 ± 0.050
MIXCG [27]	0.730 ± 0.048	0.752 ± 0.039	0.739 ± 0.045	0.745 ± 0.042
C2GMA (Ours)	$\mathbf{0.754 \pm 0.056}$	$\mathbf{0.777 \pm 0.042}$	$\mathbf{0.762 \pm 0.053}$	$\mathbf{0.769 \pm 0.047}$

Classification results: accuracy (A), precision (P), recall (R), and F1 scores (F1)

Conclusion

- A novel data augmentation for non-visible imagery:
  - ➢ Visible to non-visible image translation via class-conditioned CycleGAN-based method.
  - ➢ Trained model generates class-interpolated images improving mixup.
- Outperforms other traditional data augmentation approaches on a SAR ship / iceberg classification task.

[1] Statoil/C-CORE Iceberg Classifier Challenge, https://www.kaggle.com/c/statoil-iceberg-classifier-challenge
[2] J. Zhu, et al “Unpaired image-to-image translation using cycle-consistent adversarial networks,” ICCV, 2017.
[3] H. Zhang, et al “mixup: Beyond empirical risk minimization,” ICLR, 2018.
[4] A. Krizhevsky, et al, “Imagenet classification with deep convolutional neural networks,” NeurIPS, 2012.
[5] D. Liang, et al, “Understanding mixup training methods,” IEEE Access, vol. 6, pp. 58 774–58 783, 2018.

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