MSc in Computational Software Techniques in Engineering

Generating Images of Aircraft Pressure Refuelling Scenes in Various Weather Conditions

1. Abstract

The aviation industry is undergoing a transformative shift towards implementing "Smart Airport". In this research, it is proposed an unsupervised and unified multi-domain image-to-image translation model specifically for ground refueling image weather domain translation. By exploring existing methods that have demonstrated efficiency, it is further addressed this challenging problem with our unique training and testing model. We investigate several critical design choices to enhance the effectiveness of contrastive learning in the image synthesis setting. Notably, this approach incorporates a diverse set of loss functions and feature extraction techniques. With limited resources, We demonstrate that our framework not only generate image but improve performance as well.

2. Experiment Design

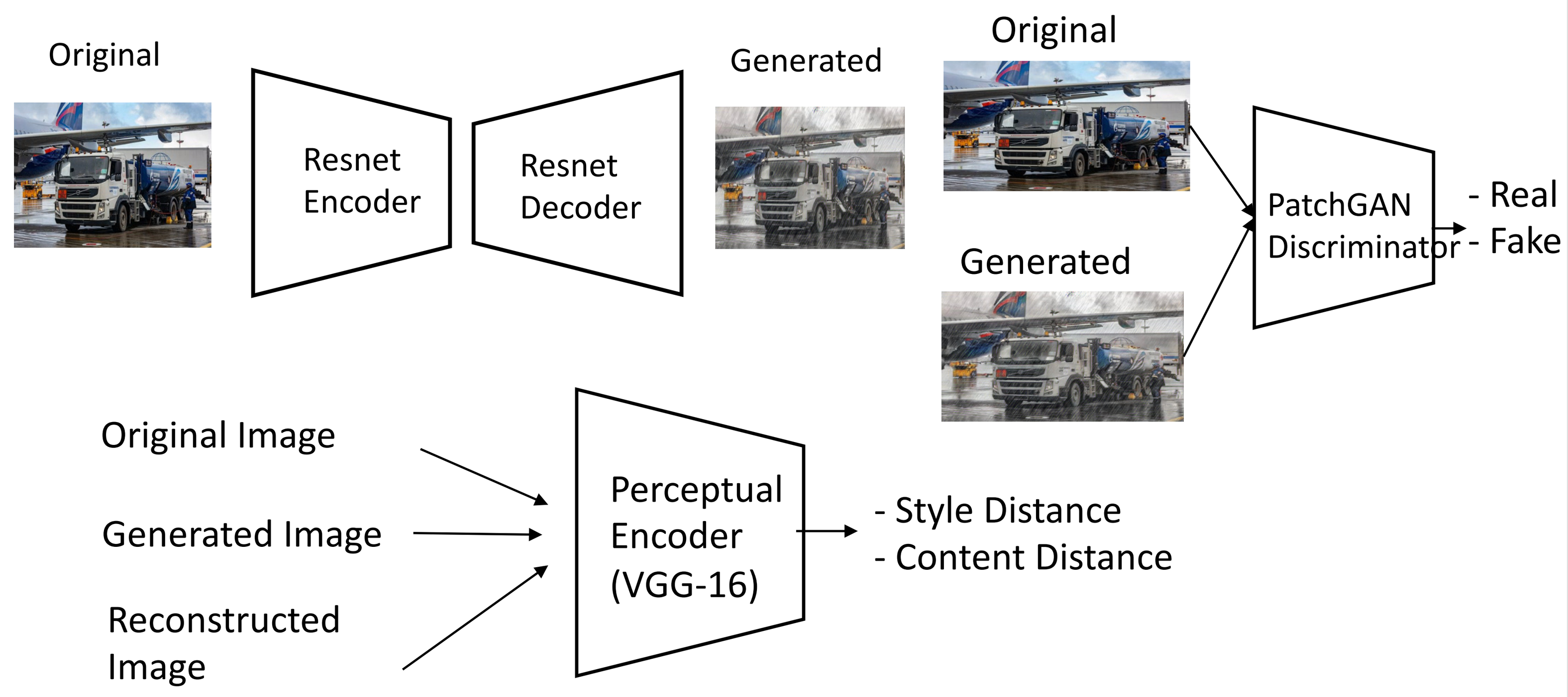

FIG. 1. The overall architecture of the proposed method based on ComboGAN [1] (a) The proposed shared generator architecture, (b) a PatchGAN Discriminator, (c) Perceptual Encoder [2] (bottom)

The final objective function combines the GAN loss, cycle-consistent loss, perceptual loss, and identity loss :

$$\mathcal{L}_{\text{total}}(G, F, D_A, D_B) = \mathcal{L}_{\text{Adversial}} + \lambda \cdot \mathcal{L}_{\text{cycle-consistency}} + \mathcal{L}_{\text{perceptual}} + \mathcal{L}_{\text{identity}}$$

Where:

- $\mathcal{L}_{\text{perceptual}}$ is a combination of content loss and style loss.
- $\mathcal{L}_{\text{identity}}$ encourages the generators to preserve the identity when images are already in the correct domain
- λ is the weight for the cycle-consistent loss.

3. Ablation Comparison

Domain	BDD dataset	AGR dataset
sunny -> cloudy	86.26	102.87
cloudy -> snowy	102.2	102.86
snowy -> foggy	110.25	120.92
rainy -> sunny	134.87	141.7

Table 1: FID scores on the BDD and AGR datasets. The model was trained on 300-400 images from the BDD100K dataset[3] and 30-50 images from the AGR dataset for each domain. Lower is better.

FIG. 1. The right image shows the original images, while the others are results depicting snowy and sunny conditions generated from cloudy images. (a) BDD 100k Road dataset (top) (b) AGR dataset featuring similar refueling scenes (bottom

FIG. 2. The comparison with ComboGAN and final approach on AGR validation dataset. The left image indicates input images, others are results. From left, its generated snowy, cloudy and sunny from original foggy image (a) Baseline ComboGAN model (b) ComboGAN + perceptual loss + cycle - consistent with weight

Model	FID	IS
ComboGAN	125	4.92
ComboGAN + perceptual loss	121	5.01
ComboGAN + consistency weight decay + perceptual loss	118	5.23

Table.2. The FID score and IS on different approached model. For FID, Lower is better and for IS, Higher is better. Last row is final approach.

4. Conclusion & Future works

Conclusion

- In this research, to generate ground refuelling in various weather conditions, a weaker form of cycle consistency is enforced by applying an L1 loss to the CNN features extracted by the corresponding discriminator, while perceptual loss is enhanced by incorporating style and content distances to address limitations due to a lack of training images. Consequently, the FID score, which reflects model performance, shows an average improvement of 5.6% over the baseline model, and the IS score improves by an average of 6.3%.

Future works

- It could involve calculating the perceptual loss using a self-trained image classification model rather than an existing pre-trained model like vgg-16, which might yield better results.

5. References

[1] ComboGAN, Asha Anoosheh, Eirikur Augutsson In Arxiv, 1712 (2017).
[2] Perceptual Loss, Justin Johnson, Alexandre Alahi, Li Fei-Fei In Arxiv, 1603 (2016).
[3] BDD 100k dataset https://doc.bdd100k.com/format.html

Ms. Hyejoon Lee

Dr. Boyu Kuang | Dr. Stuart Barnes