Using GANs To Augment Data For Cloud Image Segmentation Task

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Introduction

- Determining cloud coverage and distribution helps in analysis and forecasting of key weather related parameters like solar irradiance, rainfall and humidity
- WSIs provide cloud images with high temporal and spatial resolution than satellites at low cost
- Supervised methods superior than unsupervised methods for cloud image segmentation
- But, supervised methods need vast amount of labelled data for training
- GANs proven useful for data augmentation
- Must generate ground-truth maps along with raw sky/cloud images to make them useful in this case
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Dataset and Pre-processing

- **SwinSeg**\(^1\) dataset contains 115 images with \(500 \times 500\) pixel resolution
- All images are accompanied with ground truth binary maps
- Contain night-time cloud/sky images only
- Extracted \(R - B\) channel only to diminish the blur between cloud edges and night sky\(^2\)
- To train image segmentation model, data splitting was done as follows:
  - Training Set: 69 Images (60%)
  - Validation Set: 18 Images (15.65%)
  - Test Set: 28 Images (24.35%)

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Sample images from the used SWINSEG dataset. *First column:* original RGB images. *Second column:* extracted $R - B$ channel. *Last column:* corresponding ground-truth binary segmentation maps.
Process Pipeline

1. **Generate Sky/Cloud Image using GAN**
2. **Estimate Segmentation Map using Unsupervised Clustering**
3. **Train supervised image segmentation model (PLS Regression Model)**
   - **Validation Loss (VL1)**
   - **VL1 ≥ VL2?**
     - Yes: **Select the augmented image/segmentation map pair**
     - No: **Discard the augmented image/segmentation map pair**
4. **Train supervised image segmentation model (PLS Regression Model)**
   - **Augmented Dataset**
### Results

| Cases                        | $R^2$ (Training) | $R^2$ (Test) |
|------------------------------|------------------|--------------|
| Without Augmentation         | 0.568            | 0.372        |
| After Augmentation           | 0.539            | 0.377        |

Coefficient of determination ($R^2$) as calculated when the PLS model was trained without augmenting the training set and after augmenting the training set.
• Augmenting images using GANs helps in reducing the problem of overfitting
• PLS, being a relatively simple segmentation model, can be trained quickly and hence can be used to discard poorly generated image-segmentation map pairs
• Augmentation by basic image transformation techniques can still be applied to GAN augmented images
• In future, we would like to
  • use the augmentation method to improve the accuracy of state-of-the-art cloud/sky image segmentation models
  • modify the GAN architecture such that they may generate the corresponding segmentation maps too
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Conclusion & Future Work

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Thank you for your attention! 

https://github.com/jain15mayank/GAN-augmentation-cloud-image-segmentation.