Project Report on

Cloud Removal in Satellite Images using Conditional GAN

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I. Motivation

In the analysis of temporary satellite imagery, cloud coverage in the earth's atmosphere is a major problem. In satellite imagery, clouds, dense or small, hide elements of the earth and hide important details. The aim of this project is to create an automatic pipeline based on in-depth reading to eliminate cloud cover in the visual satellite image. Cloud-based satellite imagery was mapped in its cloudless proportions using a conditional structure of GANs.

II. Related Work

pix-2-pix (picture-to-picture) GAN model is used to read a cloud image map with its cloudless proportions. Trained using a controlled process with conditional vector conditions. Photo pairs are cloudy and cloudless, separated by two days, used for model training. The pix-2-pix model uses a pixel-to-pixel image retrieval method to create a cloudless pixel with any cloudy pixel.

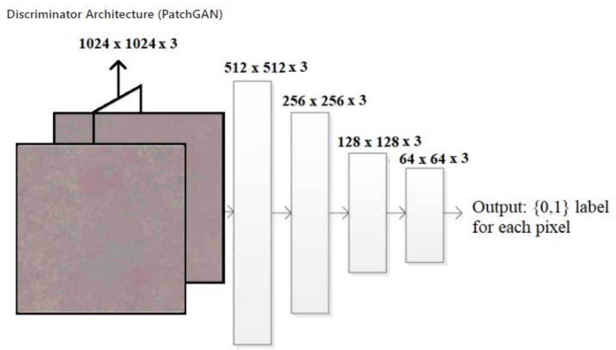

Figure 1 Discriminator Architecture (PatchGAN)

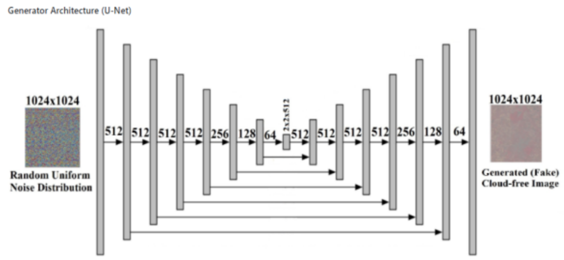

Figure 2. Generator Architecture (U-Net)

III. Approach

1. Removal of cloud cover in Sentinel 2 satellite images using optical data and augmented training approach using conditional GANs.

2. Coding the pix2pix GAN model architecture. This step consists of coding the architecture of the proposed GAN model. This will be done in three parts - implementing the discriminator, implementing the generator, and linking the two

3. Training the model and predicting the cloud free image.

4. Evaluation and result analysis based on the model trained on an augmented dataset generated from a single pair of cloudy and cloud-free images (Sentinel 2A/B), with a temporal gap of 3 days.

IV. Data Source and Tools

Sentinel-2 is part of the European Space Agency's open-source Earth-observation mission called Copernicus. It provides multispectral data with high temporal resolution (13 bands) and spatial resolution of 10m. Green, Red, and NIR bands are used in the False Color Composite Images. The study location was selected based on the availability of phenological characteristics (crops/agriculture). Removing cloud cover in Sentinel-2 satellite images using only optical data and a novel augmented training approach using conditional GANs.

The training dataset is currently augmented by a single pair of cloudy and cloud-free images classified as True and False images and used as Training and Test Data.

The initial augmentation will be performed only by rotation of 0, 90, 180, and -90 degrees which give us 4 pairs, say 1,2,3, and 4. These four pairs will then be stacked iteratively 10 times as shown here: [1,2,3,4,1,2,3,4,1,2]. More data augmentation is to be later introduced by applying skew operations to cloudy and cloud-free images, followed by rotation operations. Now there are 4 pairs of original (unskewed) images, say, [1, 2, 3, 4] and 4 pairs of the skewed images, say [1', 2', 3', 4'] which are stacked as [1,2,3,4,1',2',3',4',1,1'].

Training Data Source:

https://www.usgs.gov/centers/eros/science/usgs-eros-archive-sentinel-2?qt-science_center_objects=0#qt-science_center_objects

Libraries and Network Architectures:

- Keras (TF Backend)
- Numpy
- Matplotlib
- PatchGAN
- U-Net

V. Method

(a) Data Augmentation

This step consists of creating, actually augmenting train data, and testing data from one satellite imagery in sequence, of the same location. A train or TRUE image is a cloudless image and a Test or False image is a cloud image. Adding multiple images to both TRUE and FALSE images by performing tasks such as redirecting and photographing in any other photo axis to add a database of 10 images included.

We apply the data augmentation to both original and skew image for both train and test data as shown below

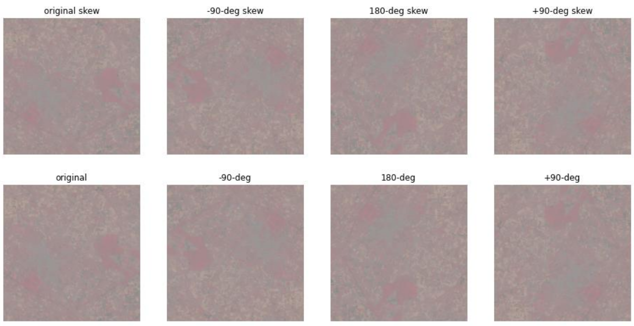

Figure 3. Train data image sample

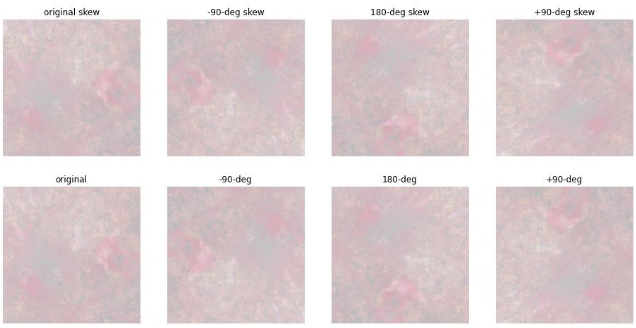

Figure 4. Test data image sample

(b) Training the Model of Original data

In this step, we train the predefined number model for epochs and save the model to disk for later uploading to produce images and experimental purposes.

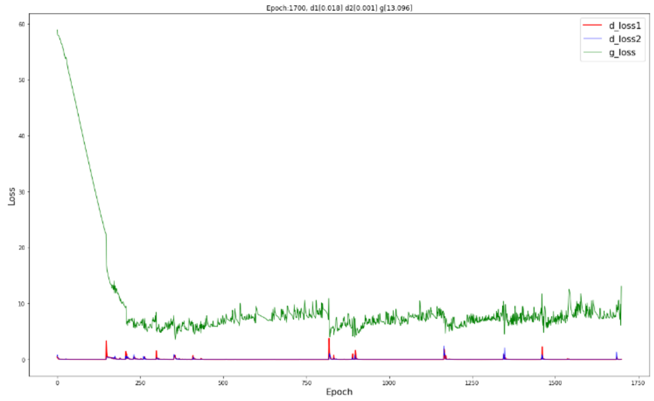

Figure 5. Training Model (Original Data input)

(c) Training the model for Skew Data

In this step, we train the model with a predefined number of epochs and save the model to disk for later uploading to produce images and experimental purposes.

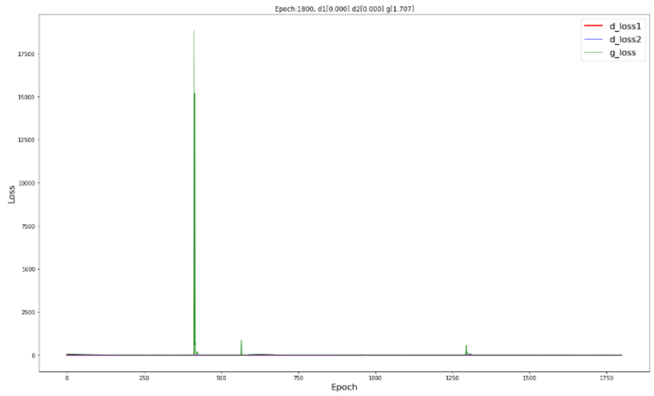

Figure 6. Training Model (Skewed Data input)

(d) Predicting the Cloud free image

In the previous step, we trained the model for a specific number of epochs and batch size. The model has been saved on the disc for each of the 100 epochs. From this point on, we can choose not to execute the previous steps as we now have the option of loading the model straight from the disk and making the prediction.

Figure 7. Predicting Cloud Free Image

VI. Evaluation

(a) Original Data

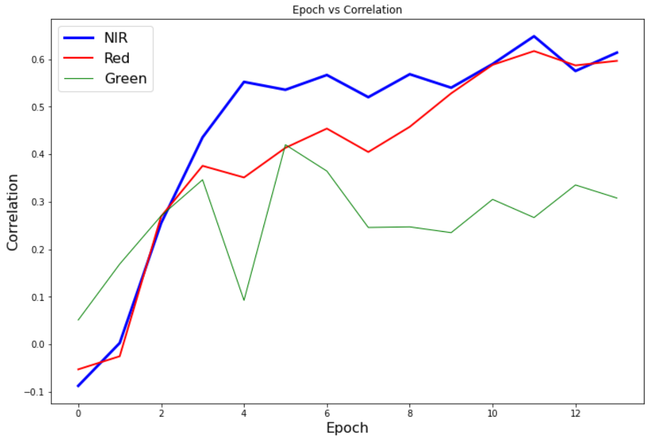

Figure 8. Epoch vs Correlation (Validation of Original data)

(b) Skewed Data

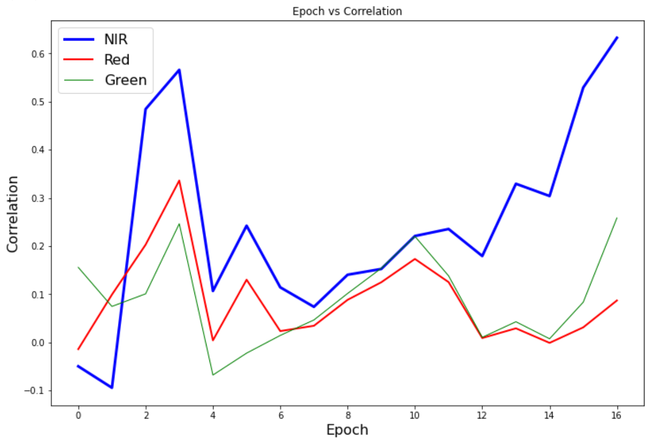

Figure 9. Epoch vs Correlation (Validation of Skewed data)

(c) Spikes in Skew dataset losses

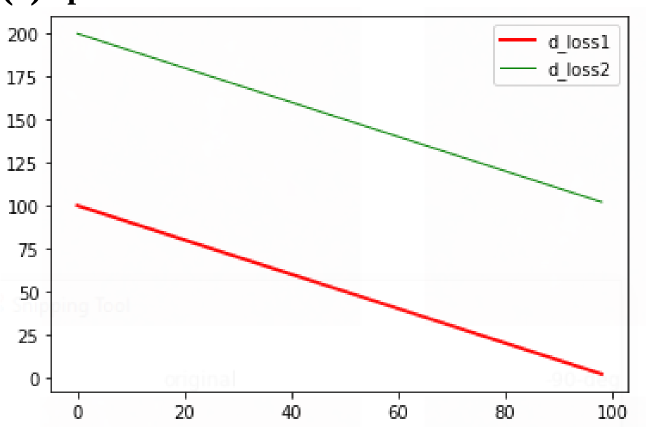

Figure 10. Spikes in Skew dataset losses

The spikes in the generator loss graph can be due to a few reasons such as the image dataset might have a few big contrasts due to augmenting the dataset and the Generator might have been stuck in a mode collapse (local minima) which when resolved resulted in very high spikes in the loss as the discriminator was quite good trained till then.

VII. Results and Analysis

The results and evaluation presented henceforth are based on the model trained on an augmented dataset generated from a single pair of cloudy and cloud-free images (Sentinel 2A/B), with a temporal gap of 3 days. The dataset consisted of 4 skews of the original image – {-90, 0, 90, 180} for both source and target sets. The model has been trained up to 1200 epochs with a batch size of 10 and patch size of 1024 x 1024. Figure 11 shows the loss graph of the generator and discriminator (for real and fake).

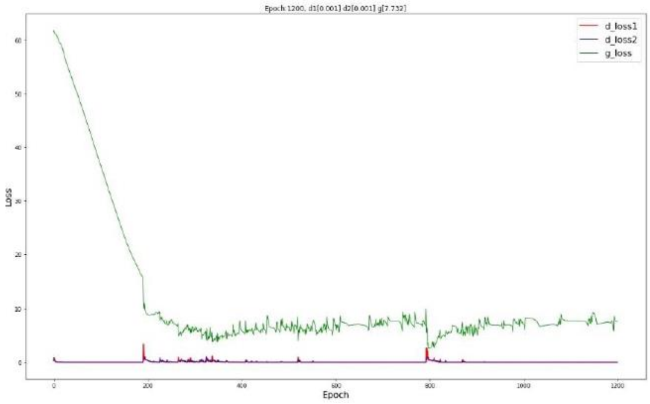

Figure 11. Cloudy vs Cloud-free comparison

	PSNR	
	Cloudy	Cloud-Free Gen
Scene 1 (Synthetic)	17.87923	29.34890052
Scene 2 (Synthetic)	15.90668	28.87507497
Scene 3 (Synthetic)	17.49845	29.86623155
Scene 4 (Synthetic)	13.03504	30.62344253
Scene 5 (Real)	14.41362	34.74536937

Table 1. Comparison

To evaluate model performance, 4 synthetic scenes and one real image from the image pair with 3 days temporal gap have been used. The synthetic scenes were generated by adding Perlin noise in different octaves to simulate a cloud cover on a cloud-free image. Hence, the temporal difference for the synthetic pairs is 0 days. To quantify the model performance for each source image, the Peak Signal to Noise Ratio (PSNR) metric has been used. Figures 12,13 and Table 1 show the PSNR values for each cloudy scene and the generated cloud-free scene, with respect to the original cloud-free scene.

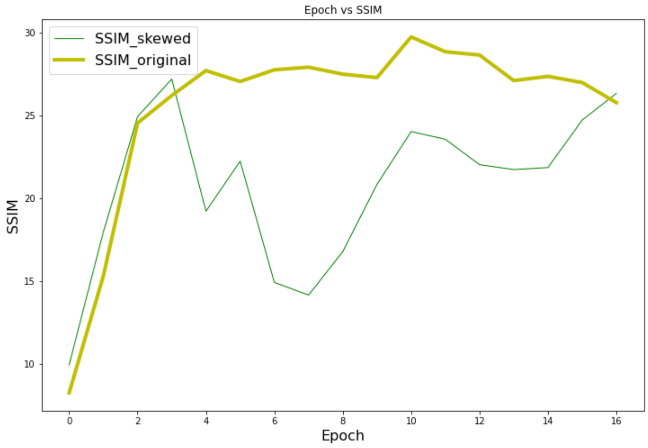

Figure 12. Structural Index Similarity (SSIM) Comparison

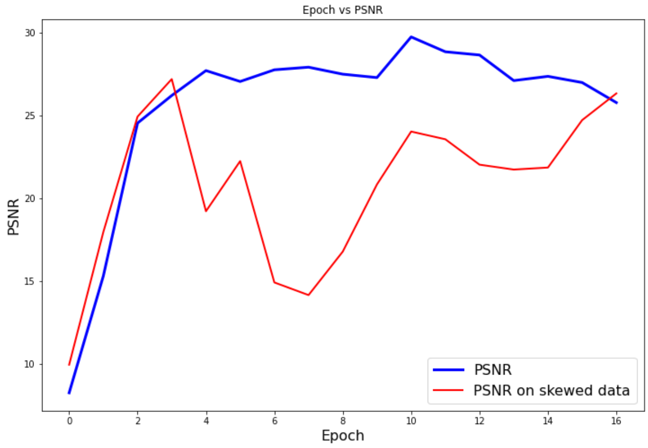

Figure 13. Peak Signal to Noise Ratio (PSNR) Comparison

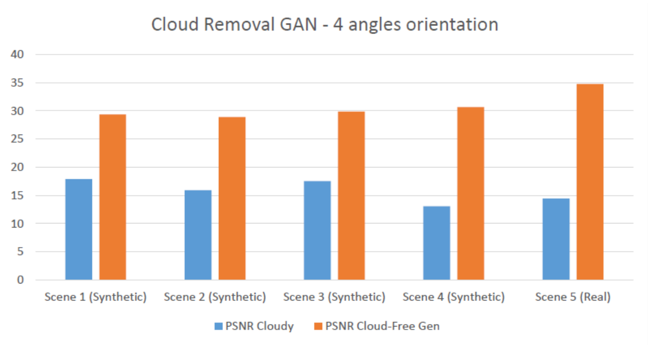

Figure 14. 4 angles of orientation.

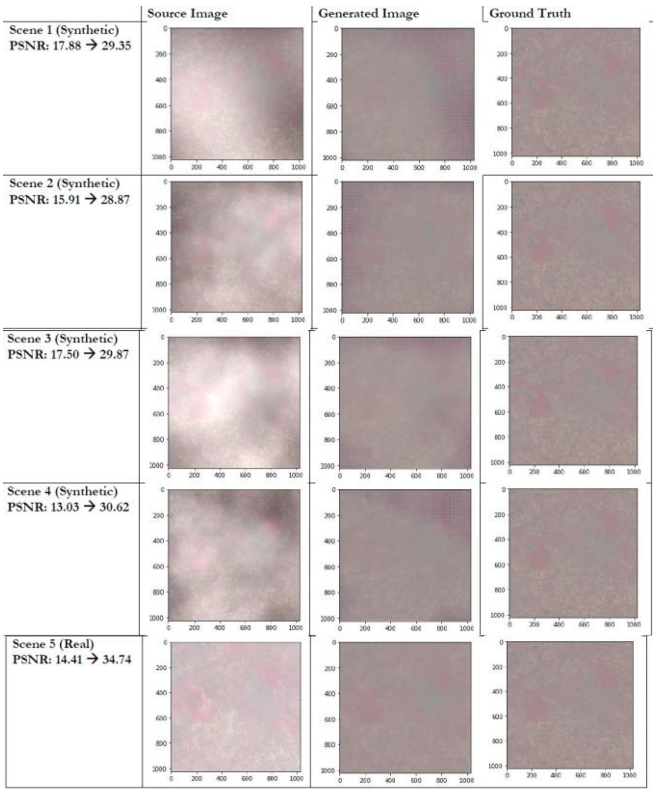

Figure 15. Final Comparison

VIII. Conclusion

The work of Copernicus Sentinel-2 consists of a set of two satellites orbiting the sunset in a single position to align the sun, separated by 180 ° from each other. It can help track global changes thanks to its large swath (290 km) and maximum recurrence period (10 days at the equator per satellite, and 5 days with two satellites under cloudless conditions leading to 2-3 days in between and scope). Sentinel-2 is part of Copernicus' open-source earth-observation mission. Provides maximum details of interim resolution (13 bands) in 10m local resolution. Combined Color Images (green, red, and NIR bands) are used. The study site is selected to be based on phenological factors (plants/agriculture).

The main aim is to remove cloud cover in Sentinel-2 satellite images using only optical data and a novel augmented training approach using conditional GANs. We used both original and skewed data to train and evaluate our model. For the evaluation comparison, we have used two popular image quality assessment metrics i.e., Peak to Noise Ratio (PSNR) and Structural Index Similarity (SSIM). Four simulated scenes and one real image from an image pair with a three-day temporal gap were used to assess model results. The synthetic scenes were created by adding Perlin noise in different octaves to a cloud-free image to simulate a cloud cover. As a result, the synthetic pairs' temporal gap is 0 days. The Peak Signal to Noise Ratio (PSNR) metric was used to measure model output for each source picture.

IX. Future Work

My future expectation is to use this same concept and try to achieve better results on the same dataset using different evaluation methods. As mentioned in the report earlier, I have used the dataset from Sentinel-2 which is one of the many open-source earths-observation missions. I would like to work on the various other versions of the Sentinel dataset.

X. References

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