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Satellite Imagery Noising With Generative Adversarial Networks

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ABSTRACT

Using satellite imagery and remote sensing data for supervised and self-supervised learning problems can be quite challenging when parts of the underlying datasets are missing due to natural phenomena (clouds, fog, haze, mist, etc.). Solving this problem will improve remote sensing data augmentation and make use of it in a world where satellite imagery represents a great resource to exploit in any big data pipeline setup. In this paper, the authors present a generative adversarial network (GANs) model that can generate natural atmospheric noise that serves as a data augmentation preprocessing tool to produce input to supervised machine learning algorithms.

KEYWORDS

Artificial Neural Networks, Data Augmentation, EUMETSAT, Generative Adversarial Networks, MDEO, MetOp, Remote Sensing, Satellite Imagery

INTRODUCTION

Remote sensing data is the cornerstone of modern environmental monitoring. Both rule-based and AI-powered systems heavily rely on high-resolution satellite imagery in domains such as agriculture, forestry, disaster management, geology and many more.

In recent years, many deep learning architectures have been used to tackle some of the most challenging remote sensing-related problems, new state-of-the-art results are established in far-apart domains such as building footprints (Bischke, B, 2019), land use classification (Zhang, C, 2018), iceberg detection (Zhang, X, 2018), deforestation (Shah, U, 2017), weather forecasting (Lin, S, 2018), Poverty estimation (Perez, A, 2019), and more. This surprising success is linked to the massive amounts of daily imagery collected from satellites, and, in many cases, to the high spectral resolution that comes with the data, including up to dozens of visual bands and allowing for rich data mining using deep neural networks.

A common issue when pre-processing satellite imagery for self-supervised tasks is the lack of adequate input (or data features), we only have real (ground-data) images and we're responsible for creating input data features to learn a certain task, a prime example is when we want to create an image-to-image interpolator where the input image has some missing pixels and the output image is complete, this problem is the main motivator behind the proposed approach.

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Generally speaking, when collecting sensor information, we are dealing with data that is incomplete, and we want to learn the distribution of that missing information so we can reproduce it while engineering training input data. In our case, we are interested in augmenting synthetically generated noise to satellite images so that downstream models are trained for real-world cases. For a problem like image interpolation, the pre-processed input data should simulate the incompleteness of the remote sensing data we receive.

The goal of this paper is to synthetically generate remote sensing noise that simulates natural noise found while directly collecting satellite imagery, the main contribution of this work consists of a model architecture based on generative adversarial networks (or GANs). We trained a model that can learn the underlying noise structure from pre-processed 50×50 pixel patches containing missing/damaged pixels represented by 0, and healthy pixels represented by 1. After training, the generator produces noise samples that are indistinguishable from the real distribution of satellite noise images.

The proposed generative adversarial network is comprised of the following elements described below.

Real Data

A collected and pre-processed data set consisting of 1M 50x50 pixel images with noise associated with natural phenomena such as atmospheric and weather conditions, sensor quality, and satellite position. Each image pixel is either a valid measurement represented by 1 or an invalid, missing, or damaged pixel, represented by 0 the original imagery is directly collected from MDEO's (El Amrani, C, 2013) data pipeline, we discarded the actual measurements to focus on learning the 2D noise distribution instead of the distribution of the underlying values. Following are the data pre-processing steps to get the final patches:

1. Download image tiles without time nor location filters from MDEO's storage servers;
2. Extract $N \times N$ patches from all image tiles.
3. Filter to keep patches with noise pixel (represented as 0s) percentage ranging from 40% to 60%.
4. Assign a random value ranging from 0 to 0.3 to each missing pixel, and a random value ranging from 0.7 to 1. to each healthy pixel.

Random Input

Uniformly random vectors fed to the generator, sometimes called input entropy, represent the Input to the Generator Network. In Our case, these random vectors are comprised of 100 uniform random values $\in \left[0,1\right]$.

The Generator

Responsible for producing vector representations of 50×50 pixel patches with noise ranging from 40% to 60% zeroed pixels. The generator is trained using the feedback loop coming from the discriminator's decisions, in other words, the error is back-propagated using predictions coming from the discriminator.

The Discriminator

Represents a feed-forward neural network responsible for deciding whether a noised satellite patch is real or not. Simply put, it's a binary classifier trained on both real patches coming from the pre-processed data distribution and fake image patches produced by the Generator.