Multi-Task Deep Learning for Satellite Images Affected by Atmospheric Distortion

Stuart M. Jefferies
Georgia State University
sjefferies@gsu.edu

Daniel Pimentel Alacron
University of Wisconsin-Madison
pimentelalar@wisc.edu

Kehinde Adedare
Georgia State University
kadedara1@student.gsu.edu

Taslim Dosunmu
Georgia State University
tjdosunmu@gmail.com

Ryan Walden
Georgia State University
waldenr1@gmail.com

Abstract

Our project is to use deep-learning techniques to detect a satellite's model and its relative orientation using images captured of the satellite effected by varying amounts of atmospheric distortion. If we are able to demonstrate an effective use of deep-learning for this problem, this will be directly applicable to the field of space situational awareness. Such a method would allow potentially detecting anomalies in captured data, and even detection of satellite-based espionage.

1 Problem and Goal

There is value in the ability to determine characteristics of Satellites orbiting Earth. Perhaps one wants to know whether the satellite belongs to a particular organization, or whether records accurately reflect that a satellite is in the correct position, or even if a satellite is being used for spying. Two characteristics that would provide significant information are the model of the satellite and its orientation.

1.1 What Problem are We Solving?

These characteristics, an object's classification and its orientation, can be extrapolated from image data– there are existing solutions for this– however, because of how high in the atmosphere satellites orbit, there is a significant amount of atmospheric distortion. Captured images of satellites may have been so distorted that the representational pixels may only look like a scattering of bright dots, rather than a complete satellite.

We wish to determine if it is possible to retrieve some signal from the distorted images that provides enough information to determine the original satellite's model and orientation. Deep learning provides excellent capability to extract information from image data.

1.2 Why is this Important?

It would be beneficial to measure the amount of information that can be extrapolated from images that seem to have lost a lot information. Beyond the practical benefits this project would provide to the field of space situation awareness, any promising techniques or findings could be translated to other applications of information retrieval from degraded representations, such as data compression.

1.3 What Results Do We Expect?

Previous findings have determined that machine learning techniques can be applied to reconstruct the original satellite image without atmospheric distortion (error rate of 0.337)[1]. We believe we can achieve similar or better results, though our goal won't necessarily be to reconstruct the satellite image, but rather just extract the relevant characteristics.

2 Deep Learning Task Formulation

Our dataset will be composed of 512x512 greyscale images of satellites with different orientations. There will be various transformations, including atmospheric distortion effects, applied to the subjects of the image. We have software that is able to generate arbitrary images of various satellite models with different kinds of transformations. We will use this to generate a large set of images to work with.

2.1 Schedule

February 17th – Generate initial satellite image dataset

February 29th – Try a few different deep learning methods

March 10th – Determine the most promising method

March 13th – Report progress for midpoint check

March 27th – Adjust model architecture, and tune hyperparameters

April 10th – Work on final presentation

April 20th – Deliver final report with results and findings from work

2.2 Approaches

We are planning to experiment with several different approaches based on convolutional layers. In our intial approach, we will use supervised transfer learning to classify the satellite manufacturer and the satellite orientation. If we are able to achieve over 95% accuracy on our test data set before March 10th, we will use transfer learning from the trained network to form an autoencoder and add the additional task of image denoising. Once we have results from different trials, we will determine the most promising method and focus on using it for the rest of the project. If we have determined a final network before March 27th, we will allocate time towards deploying the model on a web server such that it can be queried as an API.

3 Tools

Collaboration has proved to be a challenging issue in machine learning operations. To overcome this, we will be using a variety of tools to ensure explainable and repeatable experiments across all team members.

3.1 Weights and Biases

Weights and Biases will be used to consolidate all information regarding model performance in a single web server. Model can easily be compared by hyper-parameter configuration, convergence performance, and hardware utilization. Reports can be generated which include written descriptions of experiments backed by the metrics collected by the web server. In addition, logging can allow us to generate plots and images simplifying any reports.

3.2 Colaboratory

Google Colab will be used to standardize the environment where we perform our training and evaluation sessions. It's flavor of Jupyter Notebook is designed to integrate easily with Google Drive and GitHub for data storage and documentation.

3.3 Tensorflow

We selectred the Tensorflow framework due to its familiarity to our team memebers. In addition, it has proven to integrate well with software used for scaling projects (GCP, AWS, Weights and Biases, Kubernetes, etc.) which may be of interest for conference demonstration purposes.

References

[1] Pimentel-Alarćon D. & Tiwari A. & Hope, D. & Jefferies, S. (2018) *Leveraging Machine Learning for High-Resolution Restoration of Satellite Imagery. AMOS.*