Detecting Contrails using Deep Learning Techniques

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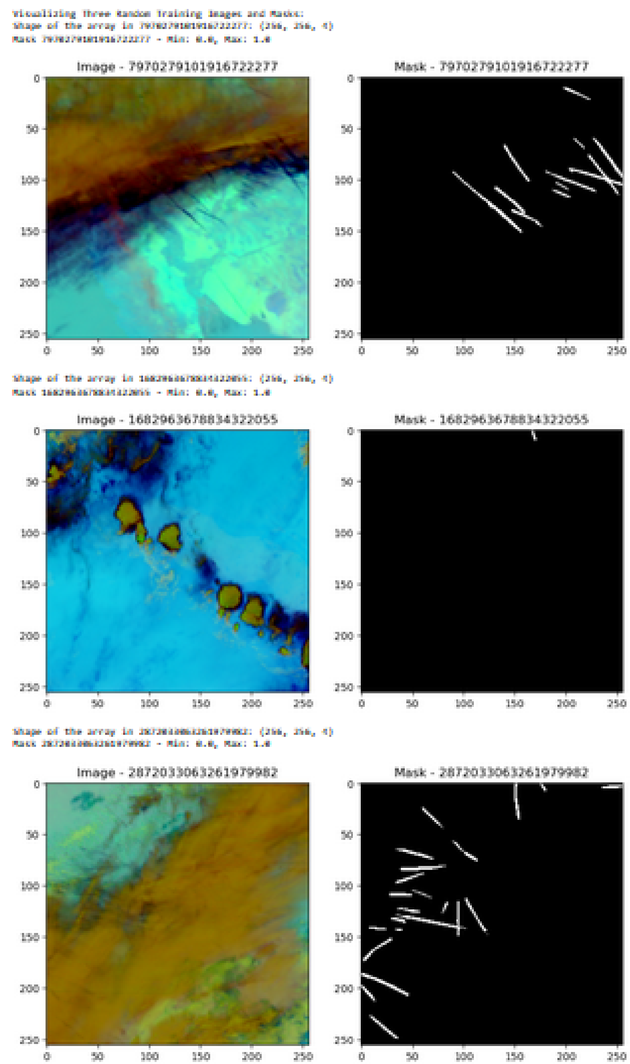
Abstract

Contrails, the line-shaped ice clouds formed by aircraft, represent a substantial contributor to aviation-induced climate change. Addressing this environmental concern necessitates effective contrail avoidance strategies, which offer a potentially economical means to mitigate the overall climate impact of aviation. To develop and evaluate such contrail avoidance systems, the implementation of an automated contrail detection system is crucial. In this paper, we introduce two deep learning techniques designed for contrail detection, utilizing data from the GOES-16 Advanced Baseline Imager (ABI). These techniques leverage temporal context to enhance detection accuracy, providing a more robust framework for identifying contrails in satellite imagery. The proposed methods contribute to the ongoing efforts in developing sustainable aviation practices by offering advanced tools for precise contrail detection, thereby facilitating the implementation of effective contrail avoidance strategies and reducing the aviation industry's environmental footprint.

1. INTRODUCTION

Contrails, commonly known as condensation trails, are an atmospheric phenomenon arising from the interaction of aircraft with cold and humid atmospheric conditions, giving rise to line-shaped cirrus clouds. These trails inadvertently contribute to climate change by trapping infrared radiation that would otherwise escape into space, thereby imparting a warming effect on Earth's atmosphere. Recent research has underscored the significance of contrail-induced warming, revealing its comparability to the impact of carbon dioxide (CO_2) emissions from global aviation [1][2].

The nuanced nature of contrail-induced warming is highlighted by studies indicating that a substantial proportion of this effect can be attributed to a limited number of flights. Furthermore, it has been suggested that modifying flight routes can significantly mitigate the



warming impact of contrails [3][4]. However, addressing this environmental challenge is hindered by uncertainties surrounding the overall impact of contrails [2] and the ability to predict their formation and persistence accurately. To overcome these challenges, it is imperative to enhance our understanding of the spatial and temporal distribution of contrail formation, a task achievable through the development of an automated contrail detection system offering extensive spatio-temporal coverage.

Detecting contrails in satellite imagery presents a formidable challenge due to their visual resemblance to natural cirrus clouds. Particularly, the focus of this study lies in identifying contrails in their initial linear form, as they present a distinct visual signature that differentiates them from natural cirrus clouds. Despite significant strides in computer vision enabled by large-scale datasets like ImageNet [5] and the application of neural networks, challenges persist in the domain-specific context of infrared satellite imagery analysis. Unlike conventional object recognition tasks where textures and colors serve as informative features, contrails often exhibit similarities to, or are indistinguishable from, natural cirrus clouds.

Moreover, recognizing contrails demands consideration of their unique characteristics, including the linear shape and rapid temporal evolution. While traditional visual cues such as color and texture may be insufficient, experts must leverage a holistic understanding of contrail morphology and dynamics for accurate identification. In light of these challenges, this research aims to contribute to the development of a robust contrail detection system by employing advanced deep learning techniques applied to data from the GOES-16 Advanced Baseline Imager (ABI) [6], with a specific emphasis on incorporating temporal context for improved accuracy.

1.1. Related Work

Contrail-induced climate change has been the focus of extensive research over the years [1],[2]. Early simulations emphasized the disproportionate impact of a select set of flights on contrail warming, suggesting the potential for strategic adjustments in flight routes to mitigate global warming [3], [4].

Empirical analyses of contrails in satellite imagery have evolved with advancements in technology and methodologies. Mannstein et al. pioneered contrail detection by proposing an algorithm reliant on filters and brightness temperature thresholds [7]. Subsequent studies in the last two decades continued to refine this approach [8], [9]. Zhang et al. contributed to the field by training convolutional neural networks on Himawari-8 satellite images, specifically evaluating contrail coverage [10]. Meijer et al. extended this approach to GOES-16 images, exploring the impact of reduced flight traffic during the COVID-19 pandemic on contrails. However, a notable limitation in these studies is the lack of publicly available datasets and contrail detections. Additionally, Meijer et al. focused solely on labeling the continental US (CONUS) region.

McCloskey et al. took a different approach by releasing a contrail dataset based on Landsat-8 data [11]. While Landsat-8 offers high spatial resolution, its constraints, such as a sun-synchronous orbit and limited availability for scenes mostly during the daytime, restrict its suitability for large-scale contrail research. In contrast, our work leverages the higher spatio-temporal coverage of GOES-16 ABI images, obtained from a geostationary orbit, providing a foundation for comprehensive contrail warming impact assessments and validation of contrail avoidance experiments in the western hemisphere.

In the realm of deep learning, extensive applications in contrail detection have emerged, and framed as an image segmentation task, it benefits from the success of deep neural networks. Our approach builds upon this trend, employing advanced image segmentation techniques such as the U-net and a variant with hough transform for enhanced contrail detection accuracy.

2. DATASET

The dataset utilized in this research originates from the GOES-16 Advanced Baseline Imager (ABI) imagery dataset, as made publicly available in the paper "OpenContrails: Benchmarking Contrail Detection on GOES-16 ABI" by Joe Yue-Hei Ng et al [6]. This dataset serves as a foundational resource for developing and evaluating contrail detection models, contributing to the broader efforts aimed at addressing the environmental impact of contrails on climate change.

The dataset comprises 20,544 examples in the training set and 1,866 examples in the validation set. Random partitioning was applied, with scenes identified as likely to have contrails by Google Street View included only in the training set. Of the training examples, 9,283 contain at least one annotated contrail. Approximately 1.2% of the pixels in the training set are labeled as contrails. The dataset exhibits a diverse array of times and locations, as visually depicted in Figures 5 and 6, with non-uniform distribution due to strategic sampling for increased contrail representation. Provided in TFRecord format, each example includes a 256 × 256 image with multiple GOES-16 ABI brightness temperatures and brightness temperature differences.

Dataset preparation for training Simple U-Net Model

To enhance the dataset for the purposes of contrail detection, a transformation process was employed, as detailed in the "False Color Dataset Generation

Notebook". This notebook outlines the steps taken to create a specialized dataset for training the Unet model.

The transformation process involves several key steps:

1. **Data Frame Creation:** Established train and validation data frames to organize record IDs for each image.

2. **Image Saving:** Saved labeled frames, human pixel masks, ash color images, and mask labels as numpy arrays, stored in single files for streamlined model access.

3. **Normalization and False Color Image Generation:** Normalized data ranges and generated false color images by combining specific bands, enhancing contrail visibility.

4. **Data Storage:** Stored resulting numpy files, containing ash color images and mask labels, in a designated directory in float16 dtype for optimized data size.

5. **Utilization in Unet Model:** Employed transformed numpy files as primary input data for training the Unet model, leveraging its effectiveness in image segmentation for contrail detection.

The specific bands used in the "False Color Dataset Generation Notebook" were selected to justify the emphasis on ice-clouds, to accurately detect contrails. To facilitate detection throughout both day and night, this imagery is transformed to an "ash" false color scheme. This scheme combines three longwave GOES-16 brightness temperatures, representing the 12µm, the difference between 12µm and 11µm, and the difference between 11µm and 8µm, respectively. This color scheme aids in identifying contrails by emphasizing ice-clouds as darker colors.

Dataset preparation for training U-Net Variant Model

1. **BTD Calculation:**
   - Calculate Brightness Temperature Differences (BTD) by subtracting 10.35 µm from 12.3 µm for GOES-16.
   - Isolate optically thin cirrus clouds and eliminate interference.

2. **Contrail Identification:**
   - Identify days and regions with contrail occurrence using BTD images.
   - Download GOES-16 data with goes2go.

3. **Image Generation:**
   - Process downloaded files with netCDF4.
   - Generate the final image by subtracting 10.35 µm from 12.3 µm.

4. **Projection Conversion:**
   - Convert the image to a local projection using pyproj.

5. **Contrail Tracing and Mask Generation:**
   - Use GIMP for tracing contrails and generating a mask.
   - Strokes of about two pixels represent contrail paths.

These steps enhance features for accurate contrail detection in satellite imagery during subsequent model training.

2.1. Evaluation Metrics

For a more comprehensive evaluation, we employ the global Dice coefficient and dice loss.

Evaluation Metric for Simple UNet Model

Dice Coefficient: This coefficient serves to compare pixel-wise agreement between predicted contrail segmentation and the corresponding ground truth. The Dice coefficient is calculated using the formula:

$$\text{Dice Coefficient} = 2 \cdot |X \cap Y| \; / \; |X| + |Y|$$

Here, X represents the entire set of predicted contrail pixels for all observations in the test data, and Y is the ground truth set of all contrail pixels in the test data. The global.

Dice Coefficient along with Accuracy are used as metrics.

Evaluation Metric for UNet Variant Model

Intersection over Union (IoU): The IoU is calculated as the ratio of the area of intersection between the predicted and ground truth regions to the area of their union. The formula is:

$$\text{IoU} = \text{Area of Intersection} \; / \; \text{Area of Union}$$

IoU values range from 0 to 1, where 0 indicates no overlap, and 1 indicates a perfect match between the predicted and ground truth regions.

3. MODELS

To enhance our model's capability to incorporate temporal context for contrail detection, we adopted the U-Net architecture, a well-established framework for semantic segmentation tasks. The U-Net architecture comprises an encoder-decoder structure with skip connections, proving effective for precise pixel-level segmentation. Here's a breakdown of our U-Net model:

Model 1 : Simple U-Net Architecture

1. **Encoder:**
   - Utilizes convolutional layers with increasing filters and 3x3 kernel sizes.
   - Applies Rectified Linear Unit (ReLU) activation functions.
   - Employs MaxPooling layers for spatial downsampling.
2. **Bottleneck:**
   - Features a bottleneck layer with two convolutional layers to capture high-level features.
3. **Decoder:**
   - Implements Transposed Convolutional layers for upsampling.
   - Incorporates skip connections by concatenating corresponding feature maps from the encoder.
   - Utilizes Convolutional layers with decreasing filters for refining segmentation details.
   - Applies ReLU activation functions.
4. **Output Layer:**
   - Comprises a convolutional layer with sigmoid activation for binary segmentation (contrail or non-contrail).

Model 2 : U-Net variant with Hough Transform

The U-Net variant employed in our model for contrail segmentation combines the strengths of the U-Net architecture and ResNet (Residual Network) [12]. Here's a simplified overview of the architecture and the integration of U-Net and ResNet:

In addition to UNet's architecture,

1. **Residual Block in ResNet:**
- ResNet addresses training challenges in deep neural networks using residual blocks.
- Employs skip connections in addition to convolution layers.
- Learns the difference between input and desired output:

2. **Combining U-Net and ResNet (ResUNet):**
- U-Net with ResNet encoder serves as the segmentation model.
- ResNet acts as the backbone for feature extraction, while U-Net serves as the decoder for segmentation.
- Inherits U-Net's ability to capture fine feature details and ResNet's capability to learn deep representations.

SR Loss at Hough Space:

1. **Hough Space Transformation:**
   - Applies Hough transformation to convert linear representation to polar coordinate format.
   - Represents lines in the Cartesian coordinate system as points in Hough space.
2. **Contrail Segmentation Enhancement:**
   - Discretizes Hough space, associating points with possible lines in the image pixel space.
   - Selects lines close to masked pixels, constructing a two-dimensional point feature set in Hough space.
3. **SR Loss Function:**
   - Minimizes differences in Hough space between predicted contrail formations and the target.
   - Specifically considers the linear shape of contrails for improved segmentation.

This combined U-Net and ResNet architecture, along with the integration of Dice Loss and SR Loss at Hough space, forms the basis of our second segmentation model. The approach aims to leverage both fine-grained feature details and deep representations to enhance the accuracy of contrail detection.

3.1. Training

Training Simple U-Net Model

Model compilation with:
- Adam optimizer (with reduce LR)
- Binary cross-entropy loss function
- Evaluation metric - Dice coefficient, Accuracy

Transfer Learning Utilization:

Model is trained on ImageNet pre-trained weights.

Data Augmentation techniques performed:

Type 1 : Rotation, Scaling, Positions, Perspectives
Type 2: Brightness, contrast, and gamma adjustments

Model compilation with:

- Adam optimizer
- Loss functions: Dice Loss, SR Loss, Focal loss
- Evaluation metric: IoU

Transfer Learning Utilization:

The model employs transfer learning by leveraging a pre-trained ResNet backbone from ImageNet. This approach accelerates training by initially using general features and subsequently fine-tuning with a specific contrail dataset. This strategy optimizes both time and resource efficiency in model development.

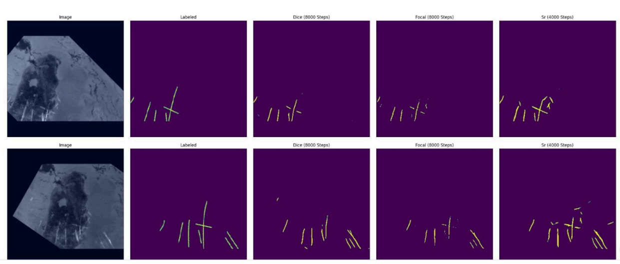
4. RESULTS AND DISCUSSION

Results for Simple UNet Model:

Accuracy: 98.46%
Train Dice Coefficient: 59.23
Validation Dice Coefficient: 60.94

Results for the UNet Variant Model:

IoU: 0.413



Model Prediction

5. GITHUB LINK

https://github.iu.edu/kmandak/dls_hasugum_kmandak_rsantha

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