

Automatically Finding Ship-tracks to Enable Large-scale Analysis of Aerosol-Cloud Interactions

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Abstract

Ship-tracks appear as long winding linear features in satellite images and are produced by aerosols from ship exhausts changing low cloud properties. They are one of the best examples of aerosol-cloud interaction experiments. However, manually finding ship-tracks from satellite data on a large-scale is prohibitively costly while a large number of samples are required. Here we train a deep neural network to automate finding ship-tracks. The neural network model generalizes well as it not only finds ship-tracks labeled by human experts, but also detects those that are occasionally missed by humans. It finds more ship-tracks than all previous studies combined and produces a map of ship-track distributions off the California coast that matches well with known shipping traffic. Our technique will enable studying aerosol effects on low clouds using ship-tracks on a large-scale, which will potentially narrow the uncertainty of the aerosol-cloud interactions.

1. Introduction

Ship tracks in satellite images appear as semi-linear features and were first identified as ‘anomalous cloud lines’ (Conover, 1966). They result from aerosol particles formed from ship exhausts increasing droplet concentration and decreasing cloud droplet size in marine low clouds (Coakley et al., 1987; Radke et al., 1989; TWOMEY, 1974), which makes affected clouds appear brighter in spectral channels sensitive to cloud droplet size (Platnick, 2000). Ship tracks are a quintessential example of anthropogenic aerosol-cloud interactions and can be viewed as individual small-scale aerosol-cloud interaction experiments. They provide an ideal setting to study aerosol-cloud interactions (Baum et al., 1995; Bretherton, 2000), which is a major source of uncertainty in the current understanding of anthropogenic climate forcing (Seinfeld et al., 2016). Many field campaigns and satellite data analyses have been dedicated to studying cloud responses in ship-tracks (Durkee et al., 2000; Lu et al., 2007; Russell et al., 2013). The current understanding suggests that cloud responses to ship exhaust aerosols are complex and depend non-linearly on many factors both internal to the cloud system and environmental (Ackerman et al., 2003; J. Chen et al., 2016; Y.-C. Chen et al., 2012; Christensen & Stephens, 2011)(H. Wang et al., 2011). The complexity and nonlinearity call for large numbers of samples under various conditions. However, manually finding ship-tracks in satellite data is both challenging and time consuming. This is because satellite images of cloud fields can be quite complex and not all ship-tracks are readily seen in a large image. It is therefore extremely time consuming to zoom in each image and exhaustively scan for each ship-track. As a result, the largest database reported in a study to date includes about 4,200 ship-track samples (Segrin et al., 2007), which is far from enough to satisfy the need for samples in studying aerosol-cloud interactions despite the best effort.

Enter deep neural networks, a machine learning technique that has enjoyed major successes in analyzing complex visual images, in particular with the introduction of methods to train deep neural networks, i.e. networks of many layers (LeCun et al., 2015). Here we use ideas and techniques developed in the deep learning literature and apply them to automate the process of finding ship-tracks in satellite images. Our goal here is to separate each image pixel into either a ship-track pixel or a none ship-track pixel. In this paper, we introduce the model structure, training approach, and run-time techniques that make our approach ready for application to large amounts of data. We demonstrate the model’s skill by calculating its error statistics and its utility with results from its application to one year of data in the Northeast Pacific region.

2. Data

Both Terra and Aqua satellites have a 36-channel passive solar/thermal infrared sensor aboard, the MODerate resolution Imaging Spectroradiometer (MODIS). For this paper, we take advantage of the fact that liquid cloud droplets have substantial difference in absorption between a midwave infrared channel centered near $3.7\mu\text{m}$ and a thermal infrared window channel centered near $11\mu\text{m}$. We use the brightness temperature difference (BTD) between these two channels as a proxy for droplet size to identify ship tracks whose droplet sizes are smaller than those in surrounding clouds at nighttime (C. Wang, Platnick, Zhang, Meyer, Wind, et al., 2016; C. Wang, Platnick, Zhang, Meyer, & Yang, 2016). An example is shown in Figure 1 using data from Aqua MODIS. Ship-tracks are clearly visible as linear features of depressed values in BTD images.

The raw BTD images are used to create a database of manually labelled ship-tracks. We developed a graphic user interface (GUI) tool which ingests nighttime MODIS $3.7\text{-}11\mu\text{m}$ BTD imagery and allows manual identification and delineation of ship track boundaries on a full size (2030 x 1354 pixels) MODIS image. Because polluted cloud pixels have large negative BTDs in comparison with ambient pixels (e.g. figures 1 and 2), our team member find these narrow and quasi-linear

features and use the mouse to closely follow a ship-track’s boundary to draw a polygon that tightly fits a ship-track. The resulting position of the polygon is saved as a shape file and every pixel inside the polygon is flagged as a ship-track pixel. Ship track pixels inside of the boundaries are further filtered by using the MODIS 1km cloud thermodynamic phase (Cloud_Phase_Infrared_1km in MOD06 Level 2 product). We also use a code to divide individual ship-tracks into multiple small segments in order to study curvatures of ship tracks. Centers of the small segments are used to calculate direction vectors of a ship track. Ship track widths are then estimated by counting the number of 1-km pixels along the normal vectors (perpendicular to direction vectors) for all segments. This code is also used to analyze the length, averaged and minimum/maximum widths, perimeter, and area of each ship track. Ship tracks with lengths less than 10 km and 1-km pixels less than 50 are excluded from the training database. In the current nighttime database, a total of 1,500 ship tracks are carefully identified from 3 months of MODIS nighttime granules in the northeast Pacific off the coast of California. Prior to training, each image is normalized using $BTD' = (BTD - \overline{BTD})/\sigma_{BTD}$, so that the input variable has zero mean and unit variance.

3. Model architecture and training

3.1 model architecture

The deep neural network model is trying to solve a mapping problem from input, a BTD image, to a binary mask image where a ship-track pixel has a value of one and zero elsewhere. We use a fully convolutional network with skip connections architecture (Long et al., 2014; Ronneberger et al., 2015). In this architecture, the model encodes the input image through a series of convolutional layers into lower resolution images, the contracting path, and then decodes it back into a full resolution mask image, the expansive path. The contracting path follows a typical convolutional network architecture consisting of two application of 3x3 convolution layers in each step. Each convolutional layer is followed by a rectified linear unit activation and a batch normalization layer. Finally, a step is finished with a max-pooling layer to down-sample the image resolution. Four steps are stacked in the contracting path. The expansive path is nearly the reverse of the contracting path with an up-convolution layer replacing the max-pooling layer to up-sample the image. A skip connection that connects each corresponding contracting and expansive step at the same depth. The final expansive step produces a binary image with the same size as the input. We explore parameter space of the neural network to search for the most promising models. The parameters we probed include the number of features in a layer, the depth of the model and activation functions.

3.2 data augmentation

Each full-size training image is broken into patches of 64x64 small images to increase the training sample size as well as to get high enough ratio of number of ship-track pixels over non-ship-track pixels. The training data is further augmented by rotating and flipping each 64x64 image to increase the robustness of the model. Our goal is to increase the training sample size enough to obtain a robust model and we will test if model outputs can be stitched back together to produce full size mask images.

3.3 training

The input BTD training data and corresponding manually labeled ship-track masks were used to train a model with the Adam optimization algorithm (Kingma & Ba, 2014). The model was trained on a K40m graphical processing unit (GPU) with a batch size of 64. The soft Dice was used as our loss function:

$$D = 1 - 2 \sum_{pixels} y_{true} y_{pred} / (\sum_{pixels} y_{true}^2 + \sum_{pixels} y_{pred}^2),$$

where y_{true} and y_{pred} are manually-labeled mask and model predicted values. We trained the model until the loss stabilized, something that was usually achieved within about 150 epochs. After training, we measured the model's error statistics using the intersection over union (IOU),

$$IOU = \frac{1}{N} \sum_1^N Y_{pred} \cap Y_{true} / Y_{pred} \cup Y_{true},$$

where N is the number of training images. An IOU of 100% means the predicted values match exactly the 'ground' truth. Any mis-match between the prediction and ground truth will result in a decrease in IOU. Our best performing model achieve an IOU of 91%. As we will discuss later, the 9% mismatch may not be purely model error since the human classifier may also fail to identify true ship track pixels. Therefore, the calculated IOU value may represent a lower bound of the true IOU.

4. Results and discussion

4.1 A few example patches

Figure 2 shows four examples to illustrate model performance. Results from three different models are accompanied by the raw BTM images as well as the human-labelled ship-track mask images. Even at 64x64 scales, the BTM can clearly capture the expected ship-track features under ideal conditions where single-layered, overcast stratocumulus clouds overlay the emitting ships. On many occasions, the low stratocumulus clouds are overlapped by high cirrus (Yuan & Oreopoulos, 2013) whose BTM signature is distinct from that of low clouds; in other cases, the stratocumulus fields do not form a homogeneous deck, but are rather made up of broken clouds. Under these non-ideal conditions, the models can still correctly identify ship-tracks. The models generally perform well for different shapes of ship-tracks which can be straight lines or wavy curves, and may even intersect each other. Furthermore, model three not only identifies ship-track pixels that are labelled by human experts, but also picks out those that have relatively weak signatures and are missed by human experts. This indicates that the trained model can generalize well, i.e. the model does not simply memorize the training data, but indeed learns the features characterizing a ship-track pixel. It is clear that the model does not simply determine a threshold value to distinguish ship-track from other pixels. This is particularly clear in example patch number four of Figure 2. Despite the noisy nature of the scene, model three successfully finds the ship-track feature and avoids the small dark patches in the same scene. This is indeed a challenging scene as evidenced by the other two models struggling to find any ship-track feature at all or misclassifying regular pixels as ship-tracks. Model three in Figure 2 was actually selected as our production model given its superior performance under a range of conditions.

It is interesting to note the architecture difference among models we explored. The main difference between model 3 and the other two is the depth of the neural network and the number of features in each convolutional layer. Model 1 has six layers in the contracting path with each convolutional layer with 32 features. Model 2 has the same number of contracting layers but with each having more features than model 1. Model 3 has the eight contracting layers with each convolutional layer having double the number of features every other layer. The number of features increases from 64 to 512 and back down to 64 again. Simply adding more layers and features do not necessarily makes the model perform better all the time, which will be discussed in the discussion section.

4.2 Application of the model to full granules

Figure 1 shows an example of model performance on a full MODIS granule which was not part of the training dataset. This is created by first breaking the full BTM granule into 64x64 patches, applying the model to each patch, and finally stitching the patches back together in their original order to recover the original large granule mask image. We chose this granule as an example because it contains multiple ship-tracks of different length, shape, relative position etc., making it a good test case for evaluating the model's performance on unseen data.

The model's performance holds well upon close inspection. A cluster of ship-tracks in the upper-left corner of the granule is identified by the model with high accuracy according to our inspection. All the parallel and intersecting ship-tracks are extensively and accurately found. This part of the image is covered mostly by overcast stratocumulus clouds with few overlapping cirrus, the bright white features in the image. Clouds on the right side of the image are more complex because the low clouds are more broken and overlapped by cirrus which creates large contrast in the BTM data. The model seems to handle these situations rather well and is able to find ship-tracks that are embedded in low clouds even if they are partially overlapped by cirrus. It is remarkable that the model even picks out two long, parallel ship-tracks that are broken by a high cirrus cloud. The lower left corner of the image contains low clouds that are more broken and where multiple patches of dark pixels are interspersed with brighter pixels in an arrangement that can resemble ship-tracks. Demonstrating its skill, the model correctly rejects them as non-ship-track pixels probably because of their none ship-track-like shapes. The good performance by the model on this and other large granules gives us confidence that our deep neural network-based method is viable for automatic detection of ship-track features in large datasets.

4.3 Application of the model to a large dataset

Given the model's performance on individual granules and its IOU metric, we applied the model more extensively to one year of MODIS granules covering the oceanic region off the Californian coast which is a busy with ship traffics and covered by semi-permanent stratocumulus decks (Figure 3).

In total, we find 70,338 ship-tracks of various lengths and shapes in the box outlined in Figure 3. This is an order of magnitude higher than the previous highest number of ship-tracks recorded in a single study in past literature which is about 4,200 (Segrin et al., 2007). For each ship-track, we record the total number of pixels it consists of, its length, and its perimeter in addition to the position of each ship-track pixel. For this region, the most common width of a ship-track is about 10-20 pixels the most common length is about 60-80 pixels. Still, much longer ship-tracks, e.g. 200-300 pixels long, are also occasionally found.

Figure 3 shows maps of the number of ship-track pixels and ship-track density that results from the model processing thousands of MODIS granules. The geographic distribution of the ratio between numbers of ship-track pixels and MODIS low cloud pixels is very similar to what is expected from the distribution of ship traffic for this region. For example, the ratio is high over regions that extend from Northern Pacific just south of Alaska all the way to the California and Canadian coast. Overall this mirrors the large fleet of ships running between Asia and the Americas. There are roughly three local maxima in ship-track pixel number and in the ratio of ship-track to total low cloud pixel number. The first one extends from south of Alaska to the ports of Vancouver, Seattle and Portland corresponding to ships that go through one strait of the Aleutian Islands. This route is more clearly visible in the map of ratios. The second local maximum originates from the

southern part of the same large band in the Northern Pacific, turns southeastward and runs nearly parallel to the coast line. This is traffic to the ports of Los Angeles, San Francisco and to the ports of Central and South America. The third maximum runs very close to the coast line, representing local shipping traffic between the ports of California, Oregon and Washington. Even though ship-tracks can be twisted and advected after they have formed due to cloud movement, it is striking that the major shipping routes expected in this region can still be identified using MODIS data. Our results are powerful demonstrations of the deep neural network model's skill to capture the distribution of real ship traffic via ship tracks.

The ratio of ship-track pixel to MODIS liquid cloud pixel numbers has strong geographic variability as shown in Figure 3, with a range from below 1% to above 10%. This wide range results from the combination of specific shipping route locations and the local low cloud properties. Regions dominated by broken cumulus clouds are not expected to produce noticeable ship-tracks because the low cloud fraction is too small. Similarly, a region seldomly visited by ships will not contain many ship-tracks regardless of low cloud fraction. Over such regions, ship-track pixels occupy 1.75% of low cloud coverage on average. We note that this direct calculation represents a lower bound of the influence of ship exhausts on low clouds because old ship-tracks may persist longer but get diffused. These aged ship tracks continue to exhibit modified low cloud properties, but have become undetectable by the model because they have lost their distinctive ship-track features. Based on the numbers from this extensive analysis, we surmise that ship-tracks can have significant impact on low cloud properties on regional scales.

5. Summary

5.1 Discussion

Despite its overall good performance, the current version of the model can still be improved. For example, it used only BTD. It is possible to include other inputs such as cloud height and cloud phase, additional information which would increase the robustness of the model. Furthermore, in this study we train the model with 64x64 image patches. Larger images may contain potentially richer contextual information and given enough training samples a model trained on larger images could perform better. We experimented with 128x128 images and while the preliminary results are encouraging, increased input image size likely requires more training data. Also, the current model relies on the BTD between the 3.7 μm and 11 μm channels, which works best during nighttime. Daytime ship-tracks may be detectable using the same model, but trained on a combination of shortwave infrared (e.g. 2.1 μm) and visible channels. Finally, our training data is dominated by overcast stratocumulus cloud scenes. A possible extension would include cases of ship-tracks in other marine boundary layer cloud regimes. Future work will explore these avenues.

In this paper, we found a working model that can reasonably handle various challenging situations. We mainly tested models with different depths and number of features in each layer. Simply increasing the complexity of the model, e.g. increasing depth or number of features, does not necessarily help the model to generalize because complex models with limited training data may overfit and not generalize well. The model we adopt strikes the balance between complexity and generalizability given the training data we have. However, the parameter space we explored is not comprehensive enough. Future work may carry out a systemic exploration of the parameter space and get a better understanding of the model behavior, which requires computing resources we do not have right now and is left for another study.

Our technique can substantially increase the scale of detecting and analyzing ship-tracks in satellite imagery. Despite limited application of the model, we have already found more ship-tracks than all previous studies combined by several times. Furthermore, the model can be applied to data from other instruments than MODIS such as the Advanced Very High-Resolution Radiometer, the Visible Infrared Imaging Radiometer Suite, the Advanced Baseline Imager (ABI). Such application will further expand sampling opportunities and help us advance our understanding of aerosol-cloud interactions in marine low clouds using ship-tracks as natural experiments and may allow us to utilize ship-tracks for other studies such as monitoring ship pollution and trade.

5.2 Conclusion

We developed a method to train deep neural networks to find ship-tracks in nighttime satellite data. Several model configurations were tested before settling on the one we considered best for wide-scale application. The model generalizes well to unseen data and learns meaningful features to even detect ship-tracks missed by human experts. The best performing model achieves an IOU of 91%. Application of the model to small patches works well in practice based on manual inspections of results from large granules. Application of the model to one year of MODIS data to the Pacific Ocean region off coast of California shows that the model realistically captures the patterns of shipping routes. This is the first time a high-resolution map of ship-track distributions was created automatically. It revealed a wider than previously thought presence of ship-tracks over oceanic regions frequented by ships and suggested that low clouds are strongly affected by the emissions of shipping exhausts at regional scales. The availability of such data will enable the study of aerosol-cloud interactions at a large-scale and narrow the uncertainty associated with aerosol indirect effect.

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Fig 3: maps of MODIS liquid cloud fraction, number of ship-track pixels, and the ratio off the coast of California in 2010. Probability distributions of ship-track width and length are also shown.

