Contrail Recognition with Convolutional Neural Network and Contrail Parameterizations Evaluation

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Abstract
There is growing attention that the contrail by aviation may affect the earth’s energy balance and climate change. In this paper, we propose a novel approach, the convolutional neural network model termed ContrailMod, which can be used in contrail classification with Himawari-8 stationary satellite and outperforms the representative conventional algorithm contrail detection algorithm (CDA). We estimate the distribution of potential contrail formation using temperature and specific humidity from ECMWF reanalysis (ERA-Interim) in South China region. According to the convolutional neural network identification (CNNI) and artificial visual inspection (AVI), we adopt the contrail occurrence and persistence (COP) measured from Himawari-8 stationary satellite imagery to evaluate the potential contrail coverage (PCC) fractions of the ECMWF reanalysis data. There is a high correlation between contrail occurrence and persistence and potential contrail coverage. The correlation coefficient of convolutional neural network identification is close to artificial visual inspection, which illustrates that the parameterization is reliable by comparing the observation results and the actual reflection of contrail coverage in parameterization calculation of South China region.

(Citation: Zhang, G., J. Zhang, and J. Shang, 2018: Contrail recognition with convolutional neural network and contrail parameterizations evaluation. SOLA, 14, 132−137, doi:10.2151/sola.2018-023.)

1. Introduction
Cloud is an integral part of climate change (David et al. 2013; Liu et al. 2014). When the aircrafts fly in the atmosphere colder than −20°C, the air humidity approaches or reaches saturation, the contrail will appear in the relatively stable atmosphere. The special report of the Intergovernmental Panel on Climate Change (IPCC) estimates that the persistent contrails from aviation (IPCC 2013) brought a radiative forcing (RF) of about 0.01 Wm−2 for the year 2011. According to recent studies (Burkhardt and Kärcher 2011), the impact of contrail caused by aircraft on global warming is higher than the effects of aircraft CO2 emission on global warming.

Previous explorations about contrail detection mainly exploited the visual examination to detect contrails in ground-based and satellite images. For example, Bakan (1994) used a similar visual inspection method for AVHRR images to map contrail coverage over Europe. Degrand et al. (2000) manually calculated contrails on satellite images over the United States. These manual visual inspection methods for contrails are superior to surface-based observations, and they are time-consuming, subjective. To solve the inconvenience caused by the manual detection method, the researchers tried to develop an automatic computer algorithm to detect contrails from satellite images. Mannstein et al. (1999) proposed a computer algorithm contrail detection algorithm (CDA) to detect linear-shaped contrails on satellite images. Zhang et al. (2012) introduced an object-based classification method by combining both spatial and spectral information into the classification process. Although it distinguished contrails better than other methods, it is still very time-consuming.

During last decades, convolution neural networks (CNN) as one deep learning architecture which has achieved significant results in some fields such as face recognition and image classification (Krizhevsky et al. 2012). The CNN approach can learn more and more complex patterns and discriminant textures through a large number of pretrained and labeled datasets, which make it difficult to define and extract features by previous traditional methods (Lee et al. 1990). Although convolutional neural network has been proven in image classification with some remarkable results, few works evaluated their efficiency and accuracy of contrail classification in satellite. Thus, we propose an optimized convolutional neural network model ContrailMod for the satellite-based contrail classification, which improves the accuracy of contrail classification, and avoids the traditional dependence on many empirical classification mistakes.

Schmidt-Appleman criterion (SAC) reveals that contrails occur when the ambient air temperature is cooler than the threshold values, which depends on the flight level, ambient humidity and aircraft propulsion efficiency. According to the thermodynamic theory (Schmidt 1941; Appleman 1953; Schumann 1996), the formation of contrails needs the SAC function and suitable ambient atmospheric conditions, while the persistence of the contrail requires an ice-saturated atmosphere (Jensen et al. 1998). The coverage of global contrail can be calculated using the global atmosphere dataset (Sausen et al. 1998). Both direct and indirect estimates are qualitatively consistent. Sausen et al. (1998) used temperature and humidity from ECMWF reanalysis to estimate the potential formation and global scale orbital coverage using modified SAC with some additional cloud cover information.

Observations were then adjusted according to Bakan et al. (1994), with coverage 0.5% in the East Atlantic and Europe.

At present, contrail simulations in general circulation model are not only based on satellite observation, but also depend on the calculation of potential contrail coverage (PCC, Burkhardt et al. 2008). Potential contrail coverage (PCC) is a method of forming a contrail based on ambient atmospheric conditions. It evaluates the ability of one region to form a contrail, which consists of natural cirrus coverage parameters in the SAC. Previous explorations about contrail detection mainly exploited the visual examination and contrail detection algorithm to detect contrails with satellite images. In this paper, we use a novel approach, CNN model termed ContrailMod, for accurate contrail classification. Although the parameterization developed by Ponter et al. (2002) was used to calculate global contrail coverage, whether it has not yet been verified in South China. Hence, the goal of this paper is to evaluate contrail parameterization for South China region (102°E−122°E, 18°N−50°N). There are lots of aviation activities, where contrail occur with higher chance than other regions. So we choose South China as our research area (Liu 2013).

2. Materials and methods

2.1 Materials

a. Himawari-8 AHI measurements
Himawari-8 is the 8th Himawari geostationary weather satellites operated by the Japan Meteorological Agency. The Advanced
Himawari Imager (AHI) has 16 channels with different central wavelengths. We choose the infrared channel 13 and channel 15 with brightness temperature difference (BTD) images to study contrails (Mannstein et al. 1999), as shown in Table 1. The AHI can complete full-disk measurements every 10 min, and the observations of Japan areas can be acquired every 2.5 min.

b. ECMWF data
We use the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis data (ERA-Interim) for the current study, and ERA-Interim is the latest global atmospheric reanalysis data since 1979. In order to be consistent with the Himawari-8 satellite observation time, we consider the spring of 2017 (Mar, Apr, May). Monthly temperature, specific humidity, ice water content have been considered in our research. The horizontal resolution of the data we used is 1° × 1°, and we choose vertical 400 to 150 hPa levels, which cover the most altitudes of aircraft activities.

2.2 Methods
a. CNNs-based contrail detection method
Here, we also propose an optimized convolutional neural network ContrailMod, which evolves from an improvement of Alexie (Krizhevsky et al. 2012), and has a strong ability to learn characteristics of contrail representations. As shown in Fig. 1a, the ContrailMod architecture consists of 3 convolutional layers and 1 fully-connected layer. Compared with previous works (Szegedy et al. 2016), the architecture of ContrailMod takes a series of fixed size Himawari-8 satellite sub-images as input, and handles a series of labels prediction as output, which indicates the probability of each category. Because the contrail features are difficult to extract, the third and fourth convolutional layers are directly connected. At the same time, we will lose to the fifth and sixth fully connected layers (Srivastava et al. 2014). Finally, the complete connected layer and softmax activation generate the distribution of 3 output probability classes for each category. The entire network contains 5 layers, which is trained from scratch. We use the Stochastic Gradient Descent optimizer (Tsuruoka et al. 2009) with the default parameter.

b. Artificial visual inspection
In the experiments, we investigate the Himawari-8 satellite images of spring 2017 (March, April, May) in statistical analysis. We choose 30 min as a statistical time scale after a significant amount of observation analysis, as introduced in (Zhang et al. 2017). In the previous studies (Duda et al. 2004), they used commercial flight data to analyze contrail occurrence fraction. But this method did not consider the contrail spreading and persistence, and their observation samples were insufficiency. Thus considering the process of contrails persistence and spreading, we use contrail occurrence and persistence (COP) to characterize the contrail coverage (Zhang et al. 2017). The contrail occurrence and persistence is the rate between the number of sub-grid that contain identified contrails and total number of sub-grid, this example is (8+6+5+3)/64 = 0.34375, as shown in Fig. 1b. The experiments of artificial visual inspection (AVI) are based on the joint efforts of the research team's partners and spend a month identifying contrails visually in satellite images and cross-checking each other. Therefore, AVI method represents the best accuracy and can be used as a benchmark.

c. Contrail parameterization
If the Schmidt-Appleman criterion is satisfied and the ambient air is relative to the over saturation of the ice rather than the water (Schmidt 1941; Appleman 1953), the contrails can persist. When persistent, contrails can develop into contrail cirrus eventually losing their line shape. The potential contrail coverage is a method of forming a contrail based on ambient atmospheric conditions. In order to identify the regions where persistent contrails can exist we should calculate PCC based on physical variables monthly temperature T, specific humidity q, ice water content IWC. Therefore, in this paper, we use the potential contrail coverage parameterization method developed by Ponter et al. (2002).
3. Results

3.1 Convolutional neural network identification (CNNI)

We introduce two scenes of the Himawari-8 images with different time scales, which represent different samples to evaluate the proposed contrail detection method. Figure 2 shows the identification results of the CNNI with the different samples. We distinguish between areas with contrails and non-contrails in scenes. The red areas are classified as contrails, and the rest of areas are classified as non-contrails in right panels. The blue areas are the CNNI's segmentation results for the samples, and they are divided into several parts and disconnected from each other. Some mis-detection occurred as labeled with the black cycle. As indicated in the green cycle, there are some false alarms about contrails. The detection efficiency is affected by the amount of data, while the CNNI will miss some small visible contrails and contrails of contrail-cirrus overlap. Overall, the CNNI results are acceptable and reduce a lot of workloads. We also employ the artificial visual inspection to calculate the contrail occurrence and persistence fraction.

3.2 Plots of the contrail occurrence and persistence fraction

Figures 3a, 3b, and 3c illustrate the statistical COP fraction according to artificial visual inspection (AVI), contrail detection algorithm (CDA) and convolutional neural network identification (CNNI) respectively. The CNNI field gives the COP distribution in South China, which is similar to the overall COP distribution in the AVI field, but the COP values in the artificial visual inspection field are significantly higher than that in the CNNI field. In our experiments, CNNI and AVI have maximum value distribution characteristics in the Pearl River Delta, Yunnan and Taiwan Straits, while the other large value area is near by Dongsha Islands. The smallest value appears around Fujian and Jiangxi province. Figure 3e shows that the AVI with a similar distribution in the CNNI and AVI fields has a wider value. Because AVI has more ability to detect the irregular shape of the contrail than CNNI. From Figs. 3d and 3e, the CNNI we proposed is superior to the representative traditional algorithm CDA.

The ContrailMod architecture can be divided into convolutional layers and fully-connected layers. They can refine the characteristics of contrails and gradually extract and train the models. However, for some small visible contrails, CNNI performs not so good. In the face of complicated contrails, even if the model trains sample satellite images many times, there are few learning and useful response. Therefore, some small visible contrails are missing and some complicated contrails cannot be identified by CNNI resulting in COP by CNNI method ranges between 0 and 0.4. The reason of COP by AVI ranges from 0 to 0.7 is that we can identify and capture small contrails with our eyes patiently. We find AVI has higher accuracy than CNNI, but convolutional neural network identification can reduce a lot of workloads.

In Table 2, we illustrate the contrail occurrence and persistence fraction at different local times in South China. It can be noted that the observed seasonal contrail occurrence and persistence using artificial visual inspection during day and night is approximately equal.

3.3 Potential contrail coverage (PCC)

Figure 4 shows the PCC simulated by parameterization in South China. Firstly, 150 hPa, 175 hPa, 200 hPa have higher potential contrail coverage. Secondly, larger value areas of PCC are in parts of Taiwan, Hainan, Yunnan and South China Sea. Smaller value areas locate in Fujian and Jiangxi. Finally, we find out the southern PCC is higher than north.

Fig. 2. The results of the convolutional neural network identification. (left panels) are Himawari-8 satellite sub-images; (center panels) are segmentation results for the samples; (right panels) are contrail identification results. The areas formed by blue lines are segmentation result including contrails and non-contrails, the areas formed by red lines represent contrails. (a) date and local time is 2017/3/10, 03:30 in the early morning. Spatial extent is 104°E−105°E, 26°N−27°N, about 111 × 111 km. (b) date and local time is 2017/4/6, 11:00 at noon. Spatial extent is 116°E−117°E, 23°N−24°N, about 111 × 111 km. (black cycle: misdetection and green cycle: false alarm).
3.4 Correlation of the contrail occurrence and persistence fraction and potential contrail coverage

The above calculation about COP and PCC in South China, and the parameterization needs to be verified through observation. Figure 5 shows the COP fraction versus the mean of PCC values. Figures 5a and 5b show the relationship between COP and PCC for CNNI and for AVI, respectively. The correlation coefficient between COP and PCC for CNNI is 0.58, while the correlation coefficient between COP and PCC for AVI is 0.66. There is a high correlation between COP and PCC, and the correlation coefficient of CNNI is close to AVI which illustrates that the parameterization is reliable by comparing the observation results with the actual reflection of contrail coverage in parameterization calculation in South China.

Table 2. Seasonal contrail occurrence and persistence using artificial visual inspection for different times of day (local time). Himawari-8 observations in South China

| Time   | 8:00 | 11:00 | 14:00 | 17:00 | 20:00 | 23:00 | 2:00 | 5:00 |
|--------|------|-------|-------|-------|-------|-------|------|------|
| COP    | 0.3195 | 0.3504 | 0.3423 | 0.3258 | 0.3752 | 0.2944 | 0.3661 | 0.3324 |

4. Conclusion and prospect

This paper propose a deep learning model ContrailMod for contrails classification, which outperforms the representative conventional algorithm contrail detection algorithm (CDA), relying on texture, structure, and shape feature simultaneously. According to the convolutional neural network identification (CNNI) and artificial visual inspection (AVI), the novel index contrail occurrence and persistence (COP) measured from Himawari-8 stationary satellite imagery is compared with potential contrail coverage (PCC) fractions computed with the ECMWF reanalysis data. It is found that there is a high correlation between contrail occurrence and persistence and potential contrail coverage, and the correla-
The parameterization is reliable by comparing the observation results and the actual reflection of contrail coverage in parameterization calculation in South China. The comparison between the parameterization calculated and observed contrail data is promising. It shows that the valuable issues in the field of contrail research can be found, such as, improved parameterization or validation of the remote sensing techniques. The evaluation of contrail observations against parameterization calculated data could significantly improve our understanding of contrail effects on climate change.
Acknowledgements

This work was supported by National Natural Science Foundation of China (Award IDs: 41775008; 61702275), National Science Foundation of Jiangsu Province (Grant No. BK20150931) and Priority Academic Program Development of Jiangsu Higher Education Institutions (PAPD). This paper is also a contribution (no. 227) to the ESMC of NUIST.

Edited by: H. Iwabuchi

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