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Detection of transverse cirrus bands in satellite imagery using deep learning☆

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ABSTRACT

We demonstrate the viability of using a convolutional neural network (CNN) for facial recognition of meteorological phenomena in satellite imagery. Transfer learning was used to fine tune the widely used VGG-16 network architecture and allow the network to successfully detect (94% accuracy) the presence of transverse cirrus bands (TCBs) in NASA MODIS and VIIRS satellite browse imagery. The CNN exhibited better performance compared to a random forest classifier (84% accuracy) and was further validated by applying it to NASA satellite browse imagery in order to create a multi-year (2013–2015) global heat map of TCB occurrence. The annual heat map shows spatial patterns that are consistent with known mechanisms for the generation of TCBs, providing confidence in the CNN classifications. Our study shows that CNNs are well suited for meteorological phenomena detection due to their generalization capabilities and strong performance. An immediate application of our work intends to enable phenomena-based search of big satellite imagery databases. With additional modifications, the CNN could be utilized for other applications such as providing situational awareness to operational forecasters or developing phenomena specific climatologies.

1. Introduction

Automated detection of meteorological phenomena in satellite and radar observations is important for both research and applications. For example, pattern recognition algorithms are operationally utilized to detect tornadic signatures in radar data (Mitchell et al., 1998) and for estimating tropical cyclone intensity from satellite imagery (Bankert and Tag, 2002). In research studies, phenomena detection is utilized to compile climatology of meteorological features. Such climatologies are used to investigate a variety of aspects related to meteorological phenomena, including their relationship to large scale environmental conditions, forcing factors, and influence of climate variability on trends in occurrence of the phenomena (Mohr and Zipser, 1996; Morel and Senesi, 2002; Gray and Dacre, 2006; Rife et al., 2010; Berry et al., 2011). Most detection algorithms currently utilized for such purposes are rule-based and phenomena-specific. Development of rules relies on domain expertise, often leveraging features identified by scientists involved in phenomena specific research.

Recent advances in deep learning have enabled development of neural networks that are capable of solving complex pattern recognition issues. Image classification using convolutional neural networks (CNNs) (LeCun et al., 1989) is one such example. Unlike prior work on the use of neural networks for specific phenomena detection tasks such as cloud classification (Bankert, 1994; Azimi-Sadjadi et al., 1996; Tian et al., 1999), CNNs are less reliant on domain expertise and offer a generalized approach to meteorological phenomena detection. Further, CNN algorithms are able to utilize accelerated computing capabilities offered by graphical processing units (GPU), resulting in 40 times reduction in network training time. In addition, transfer learning–a technique where a CNN that was pre-trained for general image classification is re-trained for a specific task (such as detection of transverse cirrus bands)–helps to reduce the time necessary for training the network while also reducing the number of images required to properly train the network.

We test the feasibility of utilizing a CNN as a generalized framework for phenomena detection by training a CNN to detect complex meteorological features–namely, transverse cirrus bands (TCBs) (Fig. 1a–c)–in NASA Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) browse imagery. Although this browse imagery contains only a small subset (three out of 36 spectral channels) of the MODIS spectral information,

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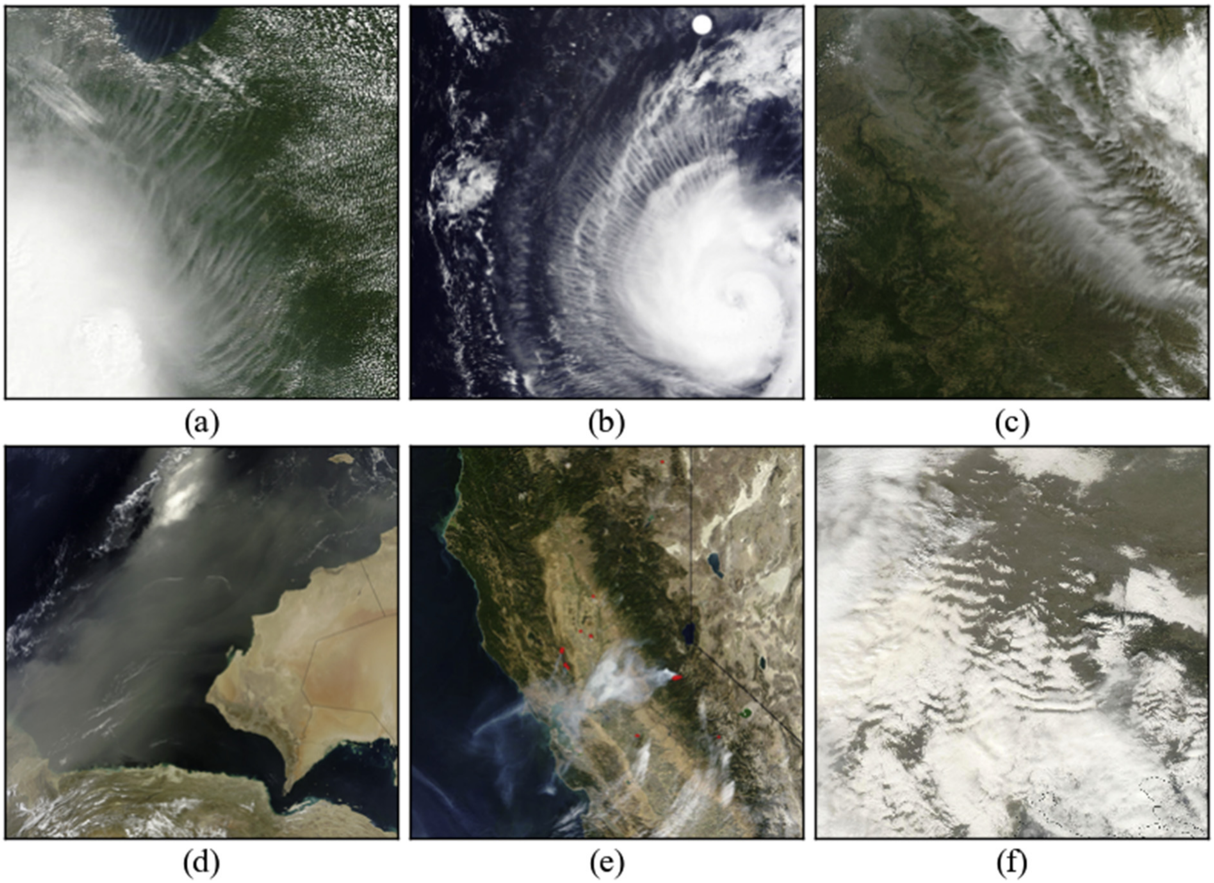

Fig. 1. Examples of images used for training (a-c shows examples of images with TCBs; d-f shows examples of scenes images without transverse bandsTCBs).

we propose that the morphological characteristics associated with the TCBs are unique enough to enable detection by CNNs. Identifying TCBs in satellite imagery is challenging since they closely resemble cloud features associated with atmospheric gravity waves and horizontal convective rolls (HCRs).

TCBs are ice clouds with very characteristic morphology and often form in association with other weather phenomena such as mesoscale convective systems (MCS), tropical cyclones, and jet streaks (Knox et al., 2010). The physical processes that are important to the formation of TCBs are not well understood, yet these processes are important for the analysis of clear air turbulence (CAT) using meteorological fields (Knox et al., 2010). Analysis of long term climatology of TCBs and co-occurring environmental conditions are key to developing such an understanding. Due to human limitations associated with manual analysis of satellite imagery, only a short-term climatological analysis has been available to researchers (Lenz et al., 2009). This limitation is only one of the important motivations for the development of automated detection of TCBs in satellite imagery.

Furthermore, because TCBs are often associated with CAT, aviation forecasters have used them as a proxy for CAT in satellite imagery (Ellrod, 1989). Analysis by Lenz et al. (2009) throughout a four-month period over the United States found that nearly every case of TCBs was associated with light turbulence and slightly less than half of those cases were further associated with moderate or greater turbulence. Thus, automated detection of TCBs has substantial operational utility in aviation weather forecasting.

In this study, we demonstrate for the first time (to the best of our knowledge) the feasibility of automated detection of TCBs in satellite imagery by using deep learning. Another unique aspect of this approach is the use of both spectral and morphological information for the detection of meteorological phenomena.

The subsequent sections are organized as follows: Section 2 provides deep learning theory and background information on CNNs; Section 3 discusses the network architecture and the training and testing data; Section 4 illuminates the results and presents a proof of concept; and Section 5 concludes with a result synthesis discussion.

2. Theory and background

Many cloud detection techniques employ algorithms that use time and seasonal-dependent thresholds (Jedlovec et al., 2008; Hagolle et al., 2010; Zhu et al., 2015). These particular methodologies use spatial analysis techniques to detect the contrast between reflected energy from clouds and surrounding surfaces in order to determine the extent of cloud cover in satellite imagery. This approach, however, struggles when the sun is at a low angle or when the surrounding surfaces are highly reflective (for example, in snowy or icy areas) (Jedlovec, 2009). Therefore, the task of identifying TCBs within a satellite image requires a more detailed process in order to capture the features of the image as a whole. Analyzing details within an image is precisely the type of task for which deep neural networks, particularly CNNs, have excelled. Not only do CNNs garner impressive results, but these types of neural networks also generalize very well across very different datasets (Penatti et al., 2015).

2.1. Convolutional neural networks

CNNs, like traditional neural networks, are made up of neurons with learnable weights and biases. The main difference between a CNN and a traditional neural network is that a CNN performs convolution on the input image rather than general matrix multiplication. CNNs are useful for image classification because the network is able to learn