Research Statement: Transfer Learning for Hyperspectral Image Cloud Masking

Gonzalo Mateo García

Summary

Cloud masking for hyperspectral earth observation images is a key primary task in analyzing and building products based on earth surface satellite data. Traditionally, the problem of cloud masking has been tackled using tailored algorithms specifically designed for each satellite. Inspired by the success of deep learning using pretrained networks, in this we seek to explore the problem from a novel multisensor perspective: we hope to understand the extent to which networks trained on one satellite can be applied to others. By doing this, we hope to improve model detection accuracy in a multimodal scenario where multitemporal and mutisensor entities coexists.

1 Introduction

Monitoring and understanding the Earth's climate system is one of the main challenges in science today. Earth observation through remote sensing is an essential tool for studying the processes occurring on the Earth's surface and their interaction with the atmosphere. Earth monitoring using satellite images has long been applied in many societal, environmental and economical applications including: monitoring land usage[1], detecting deforestation and invasive vegetation[2, 3], detecting illegal logging, monitoring surface water reservoirs [4, 5], estimating temperature or ocean salinity or post-catastrophe intervention among others.

A new generation of Earth observation (EO) satellites such as Landsat-8, Sentinel-2 and Proba-V is providing vast amounts of data in the form of hyper spectral images, which could potentially help us to better understand and monitor our environment and its changes. In addition, private companies are widening the EO satellite landscape, thus indicating that many new products and applications are on their way.

2 Motivation

The presence of clouds in hyperspectral images hampers the operational use of satellite data at a global scale since undetected clouds often cause a significant number of errors [6]. Hence, cloud masking is one of the first important steps toward obtaining reliable image time series of the Earth's surface.

Cloud masking is still an unsolved problem: the Proba-V cloud detection round robin experiment[1] is a vivid example of this. The operational Proba-V algorithm based on static thresholds underperforms in many situations causing a significant impact on a wide range of applications. For that reason, the European Spatial Agency (ESA) has organized a dedicated Round Robin exercise to evaluate more advanced cloud detection schemes. We participated in this exercise. (Final ESA evaluation is expected on March 2017).

As we see, proliferation of new satellites will need further development of algorithms and methodologies to systematically transfer knowledge from previous satellites to new instruments. This fact has been scarcely explored and will be the main issue of this proposal.

3 Project description

In this PhD thesis we seek to deal with the cloud detection problem using machine learning techniques. We want to investigate the transfer capabilities of machine learning algorithms working under multiple sensors. This will hopefully ease the process of developing new cloud detection algorithms for upcoming satellites.

Machine learning approaches to cloud masking have proven to be successful in many cases, such as Bayesian methods [7], fuzzy logic [8], neural networks [9], or kernel methods [10].

In recent years, convolutional neural networks (CNN) have become one of the most promising methods for both general image classification tasks [11, 12] and image segmentation [13, 14]. They have also been applied in the field of remote sensing for example in [15, 1]. Beyond the high classification accuracy shown in many problems, deep CNN present interesting properties for remote sensing image processing since they learn the most relevant spatial features for the given problem directly from the available data,

[1] `https://earth.esa.int/web/sppa/activities/instrument-characterization-studies/pv-cdrr`

i.e. a previous custom feature extraction step is not required [16]. This capacity for extracting high level features make them capable of transferring learning representations from different domains [17, 18, 19].

4 Past and ongoing research

Contributions over the first year of the PhD program:

In [6] we exploited the time dimension by casting the cloud detection problem as an unsupervised change detection problem. We designed an algorithm to accurately estimate the Earth's surface using past images. Clouds were detected as abrupt changes in the time dimension. Experimental results on Landsat 8 satellite imagery[2] show that the proposed method is more accurate when confronted with *state-of-the-art* approaches used in operational settings.

As mentioned earlier, we worked with Proba-V hyperspectral images in the context of ESA's Proba-V cloud detection round robin experiment. Proba-V satellite presents a limited amount of spectral bands (Blue, Red, NIR and SWIR) which makes cloud detection particularly challenging. In this work [20], we applied traditional feature extraction methods and *state-of-the-art* classifiers to obtain good classification results.

In [21] we applied CNN for cloud detection for the first time. Experimental results with Proba-V data improved classification accuracy. This suggests that CNN are a promising alternative for solving cloud masking problems. Figure 1 is an example of a cloud mask generated by a CNN model.

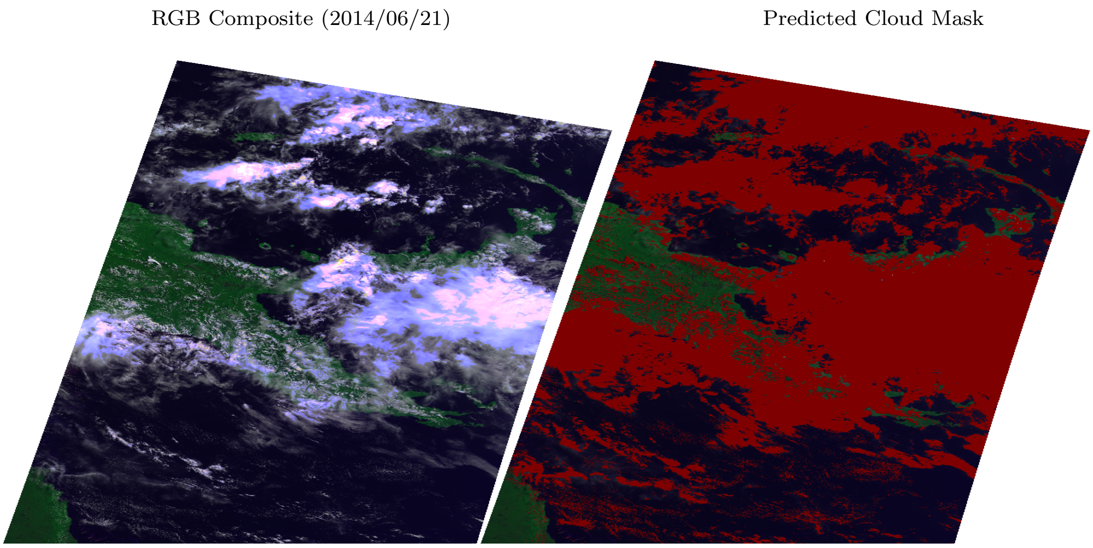

Figure 1: Example showing the RGB false color composite and the cloud mask obtained with a CNN model in a Proba-V satellite image over New Guinea island in the Pacific ocean.

5 Forthcoming steps

During the last 2 years of the PhD thesis we plan to extend the CNN approach to:

- Find a common *feature domain* to project data from different sensors. This could be done using a pretrained network from an unrelated task, from a remote sensing task or from an specific cloud detection task such as the Proba-V CNN. Afterwards a simple classifier can be trained. If we find a good *feature domain*, it is expected that classification will generalize well even using few labeled examples.
- Another research direction will be to extend the concept of convolution from the *spatial* to the *temporal* and *spectral* domain. Hyperspectral images present high correlation in the spectral domain. 2D convolutions, through weight sharing, were specifically designed to take advantage of high spatial correlation. We will study the applicability of 3D convolutions which include the spatial and spectral domains.

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