Research Statement: Transfer learning for Hyperspectral Image Cloud Masking

Gonzalo Mateo García

February 14, 2017

Summary

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

1 Introduction

Nowadays, monitoring and understanding the Earth's climate system is perhaps one of the main challenges in Science. Earth observation through remote sensing is an essential tool to study the processes occurring on the Earth surface and their interaction with the atmosphere. Earth monitoring using satellite images has been longtime applied in many societal, environmental and economical applications which include: monitor land usage, detect deforestation and invasive vegetation[1, 2], detect illegal logging, monitor surface water reservoirs [3, 4], estimating temperature or ocean salinity or post-catastrophe intervention among others.

New generation of Earth observation (EO) satellites such as Landsat-8, Sentinel-2, or Proba-V are providing vast amounts of data, in form of hyper spectral images, that could potentially help us to better understand and monitor our environment and its changes. In addition, private companies [1] are increasing the EO satellite landscape indicating that many new products and applications are about to come.

2 Motivation

However, the presence of clouds in hyperspectral images hampers the operational use of satellite data at a global scale since undetected clouds are an important source of error [5]. Hence, cloud masking is one of the first major steps to obtain reliable image time series of the Earth's surface.

Cloud masking is still an unsolved problem: Proba-V cloud detection round robin experiment[2] is a vivid example of it: the operational Proba-V algorithm based on static thresholds underperforms in many situations having a significant impact in a wide range of applications. For that reason, the European Spatial Agency (ESA) have organized a dedicated Round Robin exercise to evaluate more advanced cloud detection schemes. We participated on the exercise. (Final ESA evaluation is expected on March 2017).

As we see, proliferation of new satellites will need more and more the 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 want to face the cloud detection problem using machine learning techniques. We want to investigate the transfer capabilities of machine learning algorithms to work 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 proved to be successful in many cases, such as Bayesian methods [6], fuzzy logic [7], artificial neural networks [8], or kernel methods [9].

In the last years, convolutional neural networks (CNN) have become one of the most promising methods for both general image classification tasks [10, 11] and image segmentation [12, 13]. They have

[1] Planet Labs `https://www.planet.com/`

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

also been applied in the field of remote sensing for example in [14, 15]. Beyond the high classification accuracy shown in many problems, deep CNN present interesting properties for remote sensing image processing since they directly learn from the available data the most relevant spatial features for the given problem, i.e. a previous custom feature extraction step is not required [16]. This capacity to extract high level features make them capable to transfer learning representations from different domains [17, 18, 19].

4 Past and ongoing research

Contributions over the first year of the PhD program:

In [5] 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 surface using past images. Clouds were detected as abrupt changes in the time dimension. Experimental results on Landsat 8 satellite imagery[3] show that the proposed method is more accurate when confronted with *state-of-the-art* approaches used in operational settings.

As mencioned before, we worked with Proba-V hyperspectral images in the context of Proba-V cloud detection round robin experiment from the ESA. Proba-V satellite present 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 obtaining a good classification performance.

In [21] we applied for the first time a CNN for cloud detection. 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 cloud mask generated by a CNN model.

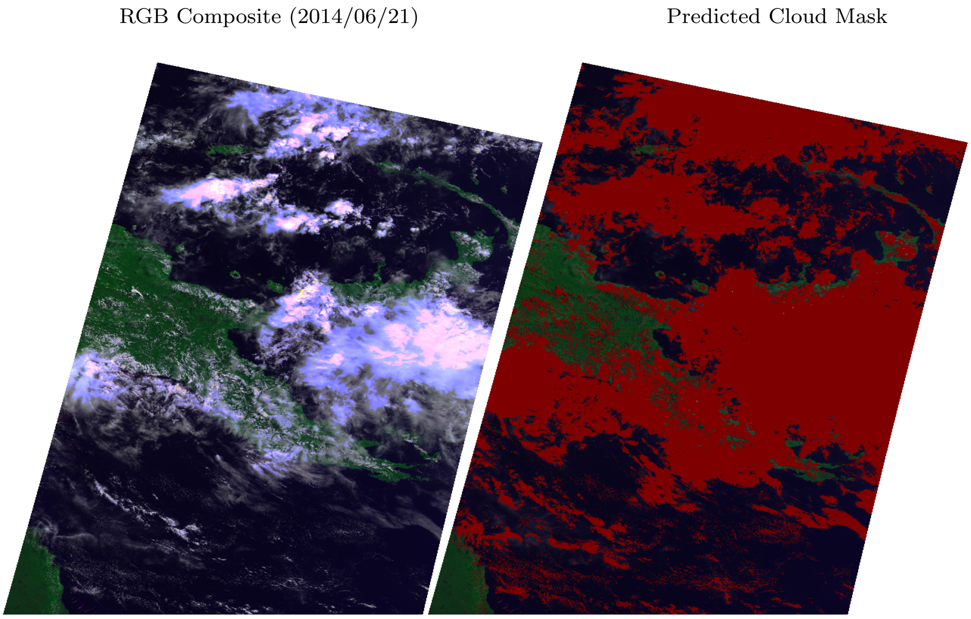

Figure 1: Example showing the RGB false color composite and the cloud mask obtained with a CNN model in a Proba-V satellite image over New Guinea island in the Pacific ocean.

5 Forthcoming steps

During the last 2 years of the PhD thesis we planned 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 a the Proba-V CNN. Afterwards a simple classifier can be trained. If we find a good *feature domain*, it is expected that classification generalizes 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 presents high correlation in the spectral domain, 2 dimension CNN, through weight sharing, were specifically designed to take advantage of high spatial correlation. Applying a 3D convolution to include the spectral domain or even a 4D convolution taking into account the time axes will be considered.

[3] http://isp.uv.es/projects/cdc/GEE_cloud_detection_results.html

References

[1] M. C. Hansen, P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend, "High-resolution global maps of 21st-century forest cover change," *Science*, vol. 342, no. 6160, pp. 850–853, 2013.

[2] Janice Ser Huay Lee, Serge Wich, Atiek Widayati, and Lian Pin Koh, "Detecting industrial oil palm plantations on landsat images with google earth engine," *Remote Sensing Applications: Society and Environment*, vol. 4, pp. 219 – 224, 2016.

[3] Jean-François Pekel, Andrew Cottam, Noel Gorelick, and Alan S. Belward, "High-resolution mapping of global surface water and its long-term changes," *Nature*, vol. 540, no. 7633, pp. 418–422, Dec 2016, Letter.

[4] Amee K. Thakkar, Venkappayya R. Desai, Ajay Patel, and Madhukar B. Potdar, "Impact assessment of watershed management programmes on land use/land cover dynamics using remote sensing and gis," *Remote Sensing Applications: Society and Environment*, vol. 5, pp. 1 – 15, 2017.

[5] Luis Gómez-Chova, Julia Amorós-López, Gonzalo Mateo-García, Jordi Muñoz-Marí, and Gustau Camps-Valls, "Cloud masking and removal in remote sensing image time series," *Journal of Applied Remote Sensing*, vol. 11, no. 1, pp. 015005, 2017.

[6] F. Murtagh, D. Barreto, and J. Marcello, "Decision Boundaries Using Bayes Factors: The Case of Cloud Masks," *IEEE Trans. on Geoscience and Remote Sensing*, vol. 41, no. 12, pp. 2952–2958, Dec 2003.

[7] A. Ghosh, N.R. Pal, and J. Das, "A fuzzy rule based approach to cloud cover estimation," *Remote Sensing of Environment*, vol. 100, pp. 531–549, 2006.

[8] José Antonio Torres Arriaza, Francisco Guindos Rojas, Mercedes Peralta López, and Manuel Cantón, "An Automatic Cloud-Masking System Using Backpro. Neural Nets for AVHRR Scenes," *IEEE Trans. on Geoscience and Remote Sensing*, vol. 41, no. 4, pp. 826–831, Apr 2003.

[9] L. Gómez-Chova, G. Camps-Valls, L. Bruzzone, and J. Calpe-Maravilla, "Mean map kernel methods for semisupervised cloud classification," *IEEE Trans. on Geoscience and Remote Sensing*, vol. 48, no. 1, pp. 207–220, Jan. 2010.

[10] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in Neural Information Processing Systems 25*, F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, Eds., pp. 1097–1105. Curran Associates, Inc., 2012.

[11] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *2016 IEEE Conf. on Computer Vision and Patt. Recognition (CVPR)*, June 2016, pp. 770–778.

[12] Jonathan Long, Evan Shelhamer, and Trevor Darrell, "Fully convolutional networks for semantic segmentation," *CoRR*, vol. abs/1411.4038, 2014.

[13] Fisher Yu and Vladlen Koltun, "Multi-scale context aggregation by dilated convolutions," *CoRR*, vol. abs/1511.07122, 2015.

[14] Martin Längkvist, Andrey Kiselev, Marjan Alirezaie, Amy Loutfi, Xiaofeng Li, Raad A Saleh, and Prasad S Thenkabail, "Classification and segmentation of satellite orthoimagery using convolutional neural networks," 2016.

[15] Marco Castelluccio, Giovanni Poggi, Carlo Sansone, and Luisa Verdoliva, "Land use classification in remote sensing images by convolutional neural networks," *CoRR*, vol. abs/1508.00092, 2015.

[16] A. Romero, C. Gatta, and G. Camps-Valls, "Unsupervised deep feature extraction for remote sensing image classification," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 54, no. 3, pp. 1349–1362, March 2016.

[17] Fan Hu, Gui-Song Xia, Jingwen Hu, and Liangpei Zhang, "Transferring deep convolutional neural networks for the scene classification of high-resolution remote sensing imagery," *Remote Sensing*, vol. 7, no. 11, pp. 14680, 2015.

[18] Andre Esteva, Brett Kuprel, Roberto A. Novoa, Justin Ko, Susan M. Swetter, Helen M. Blau, and Sebastian Thrun, "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, vol. 542, no. 7639, pp. 115–118, Feb 2017, Letter.

[19] Otávio Augusto Bizetto Penatti, Keiller Nogueira, and Jefersson Alex dos Santos, "Do deep features generalize from everyday objects to remote sensing and aerial scenes domains?," in *CVPR Workshops*, 2015.

[20] Luis Gomez-Chova, Gonzalo Mateo-Garcia, and Gustau Camps-Valls, "Cloud detection machine learning algorithms for PROBA-V," in *IGARSS 2017. IEEE 2017 International Geoscience and Remote Sensing Symposium.*, submitted.

[21] Gonzalo Mateo-Garcia, Luis Gomez-Chova, and Gustau Camps-Valls, "Convolutional neural networks for multispectral image cloud masking," in *IGARSS 2017. IEEE 2017 International Geoscience and Remote Sensing Symposium.*, submitted.