Summary of Research Plan

Title: Machine Learning for Cloud Masking of Multispectral Satellite Images
PhD Student: Mateo García, Gonzalo
Advisor: Gómez Chova, Luis

Summary

Cloud masking of multispectral satellite images is a key primary task for analyzing and generating products based on Earth observation data. Traditionally, the problem of cloud masking has been tackled using tailored algorithms specifically designed for each independent satellite. We seek to explore the problem from a novel multisensor and multitemporal perspective: firstly, we want to design algorithms that easily exploit time series data for cloud detection; secondly, we wish to understand the extent to which machine learning models trained on a given satellite imagery can be applied to other data sets. By doing this, we want to increase the applicability of machine learning models for solving cloud detection problems.

1 Introduction and motivation

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: land use monitoring[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 multispectral 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.

1.1 Motivation for Cloud detection in Remote Sensing

The presence of clouds in multispectral images hampers the operational use of satellite data at a global scale since undetected clouds often cause a significant number of perturbations. Hence, cloud masking is one of the first important steps toward obtaining reliable image time series of the Earth's surface and the further derived products.

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 vegetation monitoring. For that reason, the European Space Agency (ESA) organized a dedicated Round Robin exercise to evaluate more advanced cloud detection schemes. We participated in this exercise with an approach based on neural networks, which results are published in [6, 7].

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 PhD Thesis proposal.

2 Methodology

Machine learning approaches to cloud masking have proven to be successful in many cases, such as Bayesian methods [8], fuzzy logic [9], neural networks [10], or kernel methods [11]. It is well known that these statistical approaches outperform threshold based approaches provided enough labeled data [6, 12, 13]. However, most satellites still rely on threshold based approaches for their operational algorithms. This is partly because threshold approaches are simpler to understand and to implement and machine learning approaches still have problems that limit their applicability on operational settings. In the following section we highlight some of these problems. These problems constitute the the research questions we plan to address in this Thesis.

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

3 Goals

1. **Effectively exploit the time dimension**. Time series cloud detection (i.e. using multiple collocated images from different acquisitions dates) has been disregarded in the literature due to the great amount of data and computational resources that it requires. In addition, supervised machine learning is practically impossible in this setting since it requires labelling the whole time series from many different locations. On the other hand, multiple-scene cloud masking is a fundamentally easier problem than single scene cloud masking since location of clouds within an image normally changes with time whereas the surface remains (more or less) stable.
2. **Effectively exploit the spatial dimension**. The most common approaches for cloud masking are pixel based. That is, each pixel is classified independently given its spectral signature. While this approach has advantages from a computational perspective it discards a great amount of information from the surrounding pixels. Convolutional neural networks (CNN) use a hierarchical stack of spatial convolutional filters to learn from surrounding pixels. CNNs have become one of the most promising methods for both general image classification tasks [14, 15] and image segmentation [16, 17]. 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, i.e. a previous custom feature extraction step is not required [18]. This capacity for extracting high level features make them capable of transferring learning representations from different domains [19, 20, 21].
3. **Find alternatives to apply supervised machine learning algorithms when we lack of (sufficient) labeled data**. Simultaneous collocated information about the presence of clouds within an image is usually not available or requires a great amount of manual labor. The recent success of convolutional neural networks are partly because of the proliferation of public big labeled datasets. Recently the NASA has released three manually labeled cloud masking datasets from Landsat 7 and Landsat 8 [22, 23, 24]. In addition we identified and generated other labeled datasets for MERIS[13], Sentinel 2[25], and Proba-V[26]. Using this datasets we can study transfer learning within different satellites. We believe this could greatly improve the applicability of machine learning based cloud detection on operational settings since the algorithms can be deployed even without any real image from the current satellite (and even before the satellite is launched).
4. **Exploit big datasets with kernel methods**. Kernel methods (KMs) have proven to be excellent modeling tools for nonlinear classification and regression problems [27, 11]. However, their application to EO data is hampered by their inability to exploit large training sets.
5. **Take advantage of the uncertainty estimations of machine learning models**. Recent work [28, 29] shows that it is possible to extract meaningful probabilistic information from standard CNN models. Is that information useful in the transfer learning setting?

4 Contributions

In this section we summarize the main contributions of the Thesis so far and how they relate to the aforementioned problems we seek to address. The purpose is to publish these studies as independent journal articles. Some of this contributions have already been presented as preliminary works in conferences.

- **Cloud masking in remote sensing image time series using the Google Earth Engine platform**. This contribution has been presented in preliminary works in [30, 26]. In this paper we will present a cloud detection and cloud removal algorithm that exploits previous collocated images and: 1) it takes advantage of the Google Earth Engine platform to overcome the computational limitations of time series cloud detection; 2) it is physically sensible; and 3) it is validated in the Landsat 8 Biome dataset[23] producing *state-of-the-art* results. We plan to submit this contribution to the special issue of the Google Earth Engine platform to be published in the Remote Sensing MDPI journal on July 2018.
- **Transfer learning with Convolutional Neural Networks for multispectral image cloud masking**. This seeks to be the main contribution of the Thesis. Firstly, in the conference works: [31, 32] we demonstrated that CNN for cloud masking of Proba-V satellite images outperformed both the operational Proba-V cloud detection model and the standard, pixel based machine learning approach presented in [7]. Secondly, the conference work [33] that will be presented this year in the IGARSS 2018 conference shows that CNNs trained on Landsat 8 data from the Biome dataset[23] and applied on Proba-V data outperform the current operational Proba-V cloud detection model. This model has the advantage that it does not use any real Proba-V image for training. In addition, if we fine tune this network with few Proba-V images it outperforms all previously mentioned works. We plan to extend this work using additional Landsat datasets [22, 24] for journal publication.
- **Optimizing kernel ridge regression for remote sensing problems**. This contribution is also a conference work that will be presented in IGARSS 2018 student contest [34]. Kernel methods have been really successful in remote sensing problems because of their ability to deal with high

dimensional non-linear data. However, they are computationally expensive to train when a large amount of samples are used. In this work, we modified the kernel ridge regression (KRR) training procedure to deal with large scale datasets. In addition, the basis functions (support vectors) in the reproducing kernel Hilbert space are defined as parameters to be also optimized during the training process.

5 Thesis schedule

Table 1 contains a detailed overview of the thesis schedule.

Milestones	2016-17	2017-18	2018-19
Literature review	x	x	
Papers:			
CNN for ProbaV	x	x	
Scaling KMs	x	x	
Transfer learning		x	
Transfer learning and uncertainty estimation			x
Toolboxes & databases		x	x
Stays			x
Conferences & Summer schools	x	x	x
Thesis writing		x	x

Figure 1: Thesis schedule

References

[1] 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.

[2] 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.

[3] 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.

[4] 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.

[5] 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.

[6] R. Q. Iannone, F. Niro, P. Goryl, S. Dransfeld, B. Hoersch, K. Stelzer, G. Kirches, M. Paperin, C. Brockmann, L. Gómez-Chova, G. Mateo-García, R. Preusker, J. Fischer, U. Amato, C. Serio, U. Gangkofner, B. Berthelot, M. D. Iordache, L. Bertels, E. Wolters, W. Dierckx, I. Benhadj, and E. Swinnen, "Proba-V cloud detection Round Robin: Validation results and recommendations," in *2017 9th International Workshop on the Analysis of Multitemporal Remote Sensing Images (MultiTemp)*, June 2017, pp. 1–8.

[7] L. Gómez-Chova, G. Mateo-García, J. Muñoz-Marí, and G. Camps-Valls, "Cloud detection machine learning algorithms for PROBA-V," in *2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, July 2017, pp. 2251–2254.

[8] 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.

[9] 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.

[10] 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.

[11] 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.

[12] M. Joseph Hughes and Daniel J. Hayes, "Automated Detection of Cloud and Cloud Shadow in Single-Date Landsat Imagery Using Neural Networks and Spatial Post-Processing," *Remote Sensing*, vol. 6, no. 6, pp. 4907–4926, May 2014.

[13] L. Gomez-Chova, G. Camps-Valls, J. Calpe-Maravilla, L. Guanter, and J. Moreno, "Cloud-Screening Algorithm for ENVISAT/MERIS Multispectral Images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 45, no. 12, pp. 4105–4118, Dec. 2007.

[14] 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.

[15] 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.

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

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

[18] 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.

[19] 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.

[20] 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.

[21] 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.

[22] U.S. Geological Survey, "L8 SPARCS Cloud Validation Masks," *U.S. Geological Survey*, , no. data release, 2016.

[23] U.S. Geological Survey, "L8 Biome Cloud Validation Masks," *U.S. Geological Survey*, , no. data release, 2016.

[24] U.S. Geological Survey, "L7 Irish Cloud Validation Masks," *U.S. Geological Survey*, , no. data release, 2016.

[25] André Hollstein, Karl Segl, Luis Guanter, Maximilian Brell, and Marta Enesco, "Ready-to-Use Methods for the Detection of Clouds, Cirrus, Snow, Shadow, Water and Clear Sky Pixels in Sentinel-2 MSI Images," *Remote Sensing*, vol. 8, no. 8, pp. 666, Aug. 2016.

[26] 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, Jan. 2017.

[27] G. Camps-Valls, J. Muñoz-Marí and, L. Gómez-Chova, L. Guanter, and X. Calbet, "Nonlinear Statistical Retrieval of Atmospheric Profiles From MetOp-IASI and MTG-IRS Infrared Sounding Data," *IEEE Trans. on Geoscience and Remote Sensing*, vol. 50, no. 5, pp. 1759–1769, May 2012.

[28] Alex Kendall and Yarin Gal, "What Uncertainties Do We Need in Bayesian Deep Learning for Computer Vision?," in *Advances in Neural Information Processing Systems 30 (NIPS)*, 2017.

[29] Michael Kampffmeyer, Arnt-Børre Salberg, and Robert Jenssen, "Urban Land Cover Classification with Missing Data Using Deep Convolutional Neural Networks," *arXiv:1709.07383 [cs]*, Sept. 2017, arXiv: 1709.07383.

[30] G. Mateo-García, J. Muñoz-Marí, and L. Gómez-Chova, "Cloud detection on the Google Earth engine platform," in *2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, July 2017, pp. 1942–1945.

[31] G. Mateo-García, L. Gómez-Chova, and G. Camps-Valls, "Convolutional neural networks for multispectral image cloud masking," in *2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, July 2017, pp. 2255–2258.

[32] Gonzalo Mateo-García, Luis Gómez-Chova, Jordi Muñoz-Marí, and Gustau Camps-Valls, "Advances in statistical cloud screening: the Proba-V case study," in *Vth International Symposium: Recent Advances in Quantitative Remote Sensing, Sept 2017, (RAQRS)*, Sept. 2017.

[33] Gonzalo Mateo-García and Luis Gómez-Chova, "Convolutional Neural Networks for Cloud Screening: Transfer learning from Landsat-8 to Proba-V," in *2018 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, July 2018.

[34] Gonzalo Mateo-García, Valero Laparra, and Luis Gómez-Chova, "Optimizing kernel ridge regression for remote sensing problems," in *2018 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, July 2018.

Advisor: Luis Gómez Chova **PhD Student**: Gonzalo Mateo García