On-board Efficient Hyperspectral Image Classification Using Convolutional Neural Networks on Reconfigurable Hardware

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ABSTRACT

On-board classification of hyperspectral images has become a challenging task for remote sensing. Hyperspectral sensors collect more and more information from Earth observation, and its analysis is essential for different areas and purposes.

Currently, convolutional neural networks (CNNs) are the most accurate technique for image classification, and several research have obtained promising results using them with hyperspectral images.

The aim of this research is to develop efficient solutions capable of processing hyperspectral images on-board at real-time. For its achievement, we will explore the use of CNNs and their optimization trough the development of specific hardware support, based on FPGAs.

KEYWORDS: Hyperspectral images; image classification; remote sensing; convolutional neural networks (CNNs); field programmable gate arrays (FPGAs); efficiency

1 Introduction

Classification of hyperspectral images from remote sensing is a complicated task, due to the enormous amount of information provided by the hyperspectral sensors. For instance, Copernicus project is an European initiative to gather information on a global scale, and their Sentinel satellites will deliver about 10 petabytes of data each year [Cop].

The use of convolutional neural networks (CNNs) is currently the best approach to classify images accurately, and some previous works have demonstrated that they can successfully cope with hyperspectral images [RGCV16, MKDD15]. However, CNNs are complex structures that perform many calculations, so it is usually needed to send data to Earth for its analysis, which requires a lot of time and bandwidth.

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The aim of this research is to explore the use of CNNs for remote sensing, and more specifically for pixel classification of hyperspectral images. *Our goal is to develop efficient solutions capable of processing hyperspectral images on-board at real-time*. To this end we have to focus not only in the accuracy achieved by the different CNNs, but also in optimizing their computational and energy requirements. We will explore different optimization techniques and develop specific hardware support to perform the computations efficiently.

Field Programmable Gate Arrays (FPGAs) have some interesting features that make them a great choice for our purpose. Hardware processing can be fast and efficient, and the possibility of reconfiguration is perfect for an on-board device.

2 Hyperspectral image classification

Hyperspectral images store information from multitude of wavelengths in different bands, so they provide more information about each pixel than a RGB image, as we can see in Figure 1.

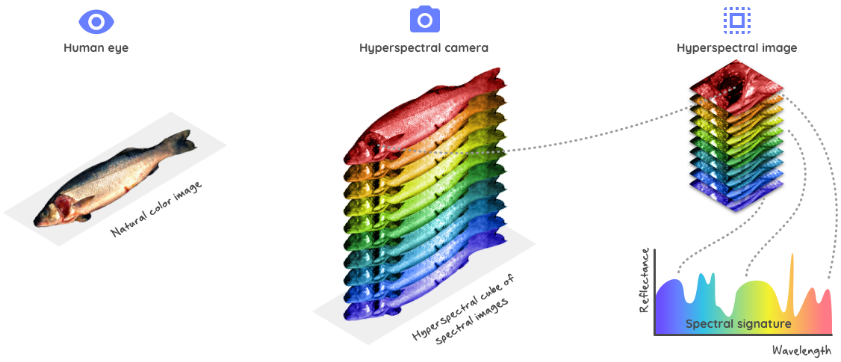

Figure 1: Explanation of hyperspectral images [con17].

Lately the Earth observation satellites are equipped with hyperspectral imaging sensors that produce a lot of information about the observed terrain, which leads us to the importance of automatic analysis and classification.

Detection of fires, monitoring of desertification or deforestation processes, land classification, biodiversity quantification, recognition of changes in certain ecosystems. These are just a few examples of its multiple applications.

3 Convolutional neural networks

CNNs are one of the most popular deep learning methods. In particular, they have proved its effectiveness for image recognition [Wik17a]. There are also several theses and paperworks dedicated to hyperspectral images classification using CNNs [RGCV16, MKDD15] with very promising results on accuracy.

The design of CNNs is inspired on the visual cortex behaviour, and its structure permits them to exploit the spatially local correlation between pixels. They are based on 3 dimensional neurons organized in layers connected between them [Wik17a].

Figure 2 shows the complete process of analysis. Each layer takes its entry, applies a convolution algorithm on it and then reduces partial results by pooling them. This new data set is the input of the next layer. After several processes of convolution and pooling, a fully connected neural network receives the data and generate the final output [Wik17a, RGCV16].

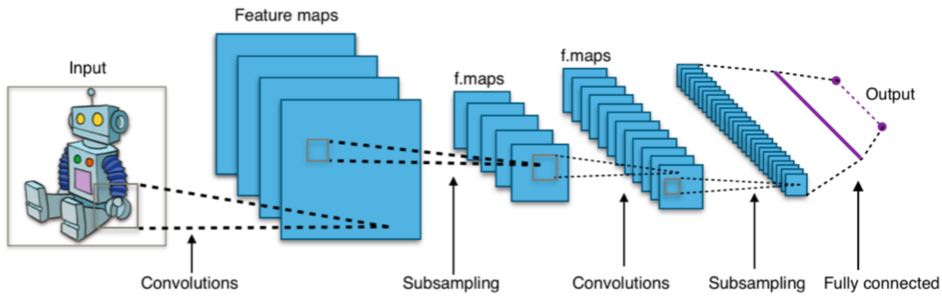

Figure 2: Typical CNN architecture [Wik17b].

4 Searching for efficiency: Field Programmable Gate Arrays

Reconfigurable hardware devices, and FPGAs in particular, combine hardware efficiency with the possibility of adding new functionalities or correcting design problems. In addition to flexibility, hardware reconfiguration also allows us to take advantage of parallelism. Moreover, they not only provided high performance, but also significant energy savings when compared to conventional processors. These characteristics make them very useful for remote sensing [GC12, p. 35-37, 54-56].

The doctoral thesis of Carlos González shows the possibility of using FPGAs for efficient classification of hyperspectral images, overpassing software solutions, with a scalable and platform-adaptable architecture [GC12, p. 159-161].

Taking into account the great results obtained by CNNs in the analysis of hyperspectral images, it is worth looking for an efficient CNN implementation in an FPGA. Some interesting proposal have been presented in other works [ORK+15, SJC+09], but we believe that there is a good margin for further optimizations by developing custom hardware for this specific task. The combination of low resources consumption, high performance, and the possibility of exploit parallelism are strong arguments for our purpose.

5 Conclussions

Considering the current features of hyperspectral sensors and the enormous amount of information they provide, the search for efficient on-board hyperspectral images classification techniques has lately become a major target in remote sensing.

The use of CNNs for images classification has proved to be the most accurate technique at the moment. Nevertheless, its great computational requirements make it difficult to use them for on-board processing.

Our work has two complementary objectives. On the one hand, the optimization of the computational and energy requirements of CNNs used for pixel classification of hyperspectral data, and, on the other hand, the development of specific hardware support compatible with the requirements of remote sensing.

The advantages that FPGAs bring us perfectly match both objectives. They combine great performance with low power consumption, and offer the physical characteristics necessary for their integration into satellites.

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