WS01 B02

Deep Learning on Hyperspectral Data for Land Use and Vegetation Mapping

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Summary

Remote sensing technology is a remarkable tool to explore and to measure Earth's surface features. Total and ONERA set up a collaborative partnership named New Advanced Observation Method Integration (NAOMI) that aims at adapting and developing new remote sensing techniques specifically targeted for hydrocarbons exploration and environmental protection. In this context, we integrate deep learning for classification of hyperspectral data. To detect different land uses and materials in aerial hyperspectral images, neural networks prove themselves to be very efficient tools, as they are able to learn discriminant features that help classification performance.

Remote sensing technology is a remarkable tool to explore and to measure Earth's surface features. The ability to extract relevant information from recorded signals remains a challenging research topic. Total and ONERA set up a collaborative partnership named New Advanced Observation Method Integration (NAOMI) that aims at adapting and developing new remote sensing techniques specifically targeted for hydrocarbons exploration and environmental protection. The combination of state of the art vectors, sensors, and algorithms will enhance knowledge in applications such as detection and characterization of hydrocarbons and geological mapping. NAOMI research activities associate laboratory measurements, airborne acquisition campaigns and unique software development to acquire an essential understanding of the interaction between emitted signals and Earth's surface.

In this context, we integrate deep learning for classification of hyperspectral data. To detect different land uses and materials in aerial hyperspectral images, neural networks prove themselves to be very efficient tools, as they are able to learn discriminant features that help classification performance. This removes the need for band pre-processing and allows us to work directly with the hyperspectral cube. First, we introduce a baseline using fully connected networks to learn a mapping between the full pixel-wise spectrum and the semantic classes. For each pixel, this baseline classifier is able to predict a semantic class based on the training samples. Then, we integrate spatial context into the learning process using spatial-spectral convolutional neural networks (CNN). The CNN combines convolutions both in the 1D-spectral and 2D-spatial directions to classify each pixel using the neighbouring contextual data in the two domains. In this framework, one pixel will be classified not only by its spectrum, but also by its neighbours' spectrum. This increases spatial regularity and boosts overall accuracy. We validate our method on hyperspectral images acquired in the NAOMI collaboration.