Challenges of multi/hyper spectral images in precision agriculture applications

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Abstract. According to the CEMA, Agriculture 4.0 paves the way for the next evolution of farming consisting of unmanned operations and autonomous decision systems while Agriculture 5.0 will be based around robotics and (some form of) artificial intelligence. It is clear how Agriculture is experimenting a Copernican Revolution where multidisciplinarity is the engine of this revolution. In this context it is central the topic of Variable Rate Treatments (VRTs). A VRT application relies on prescription maps that are generated by considering the agronomist experience augmented with data sensed also by using advanced platform as Unmanned Aerial Vehicles (UAVs) or satellites. Prescription maps are usually implemented by tractors using Variable Rate Controllers (VRCs) that apply a given quantity of product on a given region. The typical operation is spraying nitrogen or weed treatment application over the agricultural field. The generation of a correct prescription map requires the definition of specific management zones that reflect areas and their status. The planning of agricultural tasks necessitates a deep knowledge of crop state, for example, an important but typical case is variable rate nitrogen fertilizer application. In this scenario multi-spectral images play a key role and today the technology is mature to be used also in real applications. Hyper-spectral imagery is still expensive and it is usually adopted for advanced research considering the complexity to acquire and post-process data. However multi and hyper spectral systems are changing the agriculture enabling complex analysis with ultra high spatial and spectral resolution.

1. Introduction
Over the last few years, agriculture is experiencing a sort of ”Copernican revolution” dictated by the use of high-performance technologies also supported by artificial intelligence. This is also underlined in the report of the European Committee of Agricultural Machinery Manufacturers’ Groups, which states that Agriculture 5.0 will be based on the use of robotic systems and artificial intelligence [1]. In this scenario, there is an ever increasing agrifood literacy of producers and consumers with references to the traceability of the supply chain and its environmental sustainability. It is clear that precision and sustainability are issues that are essential today. Precision consists in the optimal use of a resource with the objective of maximizing yield, minimizing costs and environmental impact. This complex optimization can be made possible if and only if man, machine and robots [2] work synergistically in measuring, evaluating, deciding and implementing prescriptions in a continuous cycle. This today can be achieved through multi-sensorial systems that operate at different spatial scales (where), temporal (when) and spectral (what) [3]. The centrality lies therefore in the data that by its nature in a scenario of Agriculture 4.0 / 5.0 becomes complex to manage both in terms of size and complexity of the
Figure 1. Processing of hyper/multi-spectral acquisition should consider different spatial, spectral and temporal scales considering also the complexity related to the data collection.

2. Main Challenges of Multi/Hyper Spectral Data

During last years multi-spectral and hyper-spectral sensors have been applied in Precision Agriculture applications [5]. The state-of-the-art technologies today acquire a hundreds of bands in the VISible (VIS), Near InfaRed (NIR) and Short Wave InfaRed (SWIR). Actually it is possible to mount these sensors also on ground/aerial ( unmanned) vehicles to precisely map fields and crops by identifying stress as nitrogen or water stress to derive custom and precise prescription maps that modern tractors are able to execute by using the Variable Rate Controller technology [3].

The high spatial and temporal resolutions require new approaches to process this huge amount of data [6]. It is also important to consider geometric and radiometric corrections in order to have useful data [7]. Radiometric correction plays a key role and several techniques are available with different pros and cons as radiometric target or real time incident light sensors [8]. Moreover ground and aerial sensors could be supported by satellite technologies that enable in some case weekly or daily updates [9, 10]. We performed several flights to collect multi/hyper-spectral cubes also developing new approaches to process data that include ground spectrometer and aerial sensors on different crops with different nitrogen and irrigation configuration in cooperation with the D3A Department of Universit Politecnica delle Marche. Figure 1 shows the approach that includes different spatial, spectral and temporal scales.

Today Satellites provide images with Ground Sampling Distance (GSD) that typically ranges from 0.5m to 1000m with a number of bands from 3 to 15-20 (in case of multispectral payloads) and some platform provides a worldwide coverage every 1-2 days. In this scenario precision agriculture gains the capability to monitor the trend of some vegetation index over time acting...
as a scouting service. In case of potential issues (i.e. area with a anomalous values of vegetation index) it could be possible to perform an acquisition by using an unmanned platforms that usually generate ultra high resolution images [11]. Satellites must be integrated by unmanned platforms [12] [13] in order to increase the spatial and also the spectral resolution. The use of unmanned vehicles as multi-rotor and fixed wing is quite common in precision agriculture [14, 15] even if the endurance and then the coverage are the main bottleneck. In particular hyper-spectral systems require low flight speed at altitude lower than 100m to avoid blurred images also considering that exposure time changes according to the detector technology. A complete field survey includes satellite and unmanned platform and also it is recommended to acquire ground data by using spectrometer [16]. The merging of data is a complex matter considering that each sensing platform has different techniques to provide calibrated data also considering that spectral configuration is not the same for all devices.

2.1. Calibration
The radiometric calibration is one of the most critical phase during the acquisition of multi/hyper-spectral images. This process enables the conversion from the Digital Number (DN) to a reflectance value. Recently this activity have been deeply studied with particular reference to Reflectance Mode Method, Linear-interpolation Method, Continuous Panel Method, Multi-band radiometer method [17, 18]. The calibration plays a key role to set-up the data processing in the right way [19, 20] also aided by in-situ calibration [21] for long term monitoring. If calibration is not properly performed then wrong results and then decisions could be generated as discussed in [22]. Moreover it is important to compensate changes in illumination mainly caused by clouds. In this case it is necessary to use incident light sensor to have properly calibrated data [23].

2.2. High resolution and noise reduction
Hyper-spectral linescan sensors require a complex post-processing to output co-registered hyper-spectral cubes. We developed algorithms to automate the detection of ground targets with well-known position and reflectance in order to facilitate the co-registration tasks since the sensor used was not equipped, for reasons of weight and cost, with a high precision and accuracy INS and GPS RTK. For each group of pixels and for each band we extract an histogram. Starting from this we isolate the response of the soil and the crop using the very high spatial resolution that reaches 1-2cm. Figure 2 shows an example of a histogram for a group of pixels for a given band. Systems have also been developed to perform a scouting by means of spectrometers mounted on board o low cost multi-rotor unmanned platform characterized by a very low spatial resolution, but at the same time with a very high spatial resolution [7].

From the analysis of the histograms for a given set of geographical areas that follow a given experimental scheme to induce nitrogen and water stress it is possible to extract complex vegetation indices that highlight the differences by extending indices such as NDVI and NDRE. The definition of these indices can then be used to identify the presence or absence of stress using data acquired with low-cost multi-spectral cameras with bands selected from the analysis of hyper-spectral data. We started from previous methods developed in the Land Use / Land Cover (LU / LC) presented in [10].

2.3. Soil vs Crop Segmentation
High and ultra-high resolution images (hyper or multi spectral) should be post-processed in order to remove the effect of soil that could generate wrong results during the data analysis. In this case it is necessary to mask out soil areas in order to evaluate only vegetation.

Typically the soil/crop segmentation is performed by using thresholding algorithms starting from vegetation indices such as Normalized Difference Vegetation Index (NDVI) that have
Figure 2. The histogram represents the reflectance dynamics (x-axis) for a group of pixels for a given band. It is possible to distinguish two contributions due in this example from soil and crop.

Figure 3. top-left: false colour image; top-right: DSM; bottom-left: extracted soil with algorithms as in [4]; bottom-right: extracted vegetation.

problems in grassland situations. In this situation it is necessary to use the Digital Surface Model (DSM) model in order to correctly discriminate between soil and crop in contexts such as vineyards. There have been several approaches such as CARSCAN and FANSCAN [4] that start from the DSM and then integrates the radiometric response if necessary to improve the overall quality (e.g. Figure 3).
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