AUTOMATIC REMOTE IMAGE PROCESSING FOR AGRICULTURE USES THROUGH SPECIFIC SOFTWARE

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ABSTRACT

Remote sensing could become an important and economically feasible tool for agriculture only if specific modules are developed to differentiate, isolate and process each parcel. A landscape scene is normally composed of many parcels with diverse cropping systems. Each cropping system (orchards, herbaceous) normally requires specific image processing software in order to analyse the targeted biotic factors, such as weeds or pathogens, or abiotic factors, such as nitrogen or water content, of interest. Furthermore, the characterization of such factors often needs managing multitemporal series of images. So that, the full use of remote images at agricultural landscape level requires: 1) to isolate each agriculture parcel; 2) to process it accordingly with the growing crop and the targeted factor; 3) managing both process for a multitemporal image series taken at the same area; 4) to automate all the previous mentioned steps, parcel by parcel and factor by factor; and 5) managing the outcome information to obtain a geo-referenced site-specific input prescription map.

The aim of this paper is to make general considerations to support the need to automate the remote images processing and to outline the contribution of our research group in the development of ENVI® add-on for this purpose, as follows: 1) AUGEO-2.0®, to increase the image georeferencing accuracy; 2) CAIR, calibration of multitemporal image series based on vegetative pseudo-invariant features. 3) CROPCLASS®, to isolate and assess individual agriculture plots before precision processing; 4) CLUAS®, for clustering and assessment orchards units; 5) SARI®, for sectioning and assessment images of annual/ herbaceous crops. 6) AMI, special module for the automatic management of the previous referred software. These modules are available for research purposes upon request.

Keywords: Precision agriculture, orchards, herbaceous crops, input prescription map, software

INTRODUCTION

There is a fierce competition between primary agriculture commodities suppliers in pricing, quality, health/ safety guarantee and environmental concern. Specifically precision agriculture can play more and more an important role in making easier, more economically feasible and environmentally safety the primary basic agricultural commodities production. By extension, remote sensing can contribute to make precision agriculture economically feasible.

Precision agriculture technology is based in sensors for assessing the spatial variability of both biotic (weeds, pathogens) and of abiotic factors (nutrients, water content) in agricultural parcels (López-Granados, 2011). In the short term proximal sensors transported on-ground machinery (herbicide sprayers, fertilizer applicators) shall likely become key tools to implement site-specific weed patches control or nutrients patches management, among others. Examples of this proximal sensor technology are the commercial development of site-specific nitrogen application in cereal (Raun et al., 2010) and of selective application of herbicide on weed patches (NTech Industries Com, 2011). However, in the medium-long term the use of remote sensors transported in satellites, conventional airplanes, and unmanned aerial vehicles (UAV) are likely to be more and more accepted as compared to proximal sensors. This could be due to the scale economy for the biotic/ abiotic variability assessment process, which can be consistently cheaper managing remote images of extensive agricultural areas. However this assumption could only be real if remote sensing for agricultural uses is more and more automated.

The aim of this paper is to make general considerations to support the need to automate the remote images processing and to outline the contributions of our research group to automate the remote image processing for agricultural, and particularly for precision agriculture.

GENERAL CONSIDERATIONS

Remotely-sensed images captured from satellites, conventional airplanes and unmanned aerial vehicles (UAV) can be used in precision agriculture. A clear advantage of satellite images are the large extension covered by each scene, typically 60 to 80 km^2. In addition the new satellite generations such as GeoEye-1 and Pleaides meet the spatial resolutions required for precision agriculture; these are about 1.6 m and 1.2 m in multispectral and 0.5 m in panchromatic, respectively. Revisit time is becoming relatively short, 3 to 5 days, which is an additional advantage when multitemporal image series are needed, an also a way to escape from cloudy days in temperate climatic areas.

The number of agricultural parcels contained in a typical satellite and airplane scenes of 80 km2 and 400 ha, assuming an agricultural surface/ total surface ratio of 90% and an average parcel size of 25 ha, will be around 288 and 16, respectively. Similarly, a UAV aircraft in just one day can take images covering a farm of about 200-300 ha. On the other hand, all the agricultural parcels of a satellite scene should, ideally, be used for site-specific management to bargain the

image acquisition and processing costs. Consequently, to extract the agro-environmental information from a remote image at competitive costs all preprocessing and site-specific processing steps should be automated as much as possible.

In agriculture, the information obtained from remote images is very diverse, and generally can be obtained by analyzing the whole scene and/or individualizing each parcel. For example, agricultural statistics such as classification and assessment of cropping systems and yield estimation can be achieved necessarily by multi-temporal image scene studies. In addition, for planning site specific agricultural operation such as herbicides, fertilizers or watering application at parcel level, necessarily parcel isolation is needed. To achieve any of these two approaches the geo-referenciation and calibration processes also need to be implemented. A general flowchart of remote image automation is shown in Fig. 1.

GEO-REFERENCIATION (AUGEO® Software)

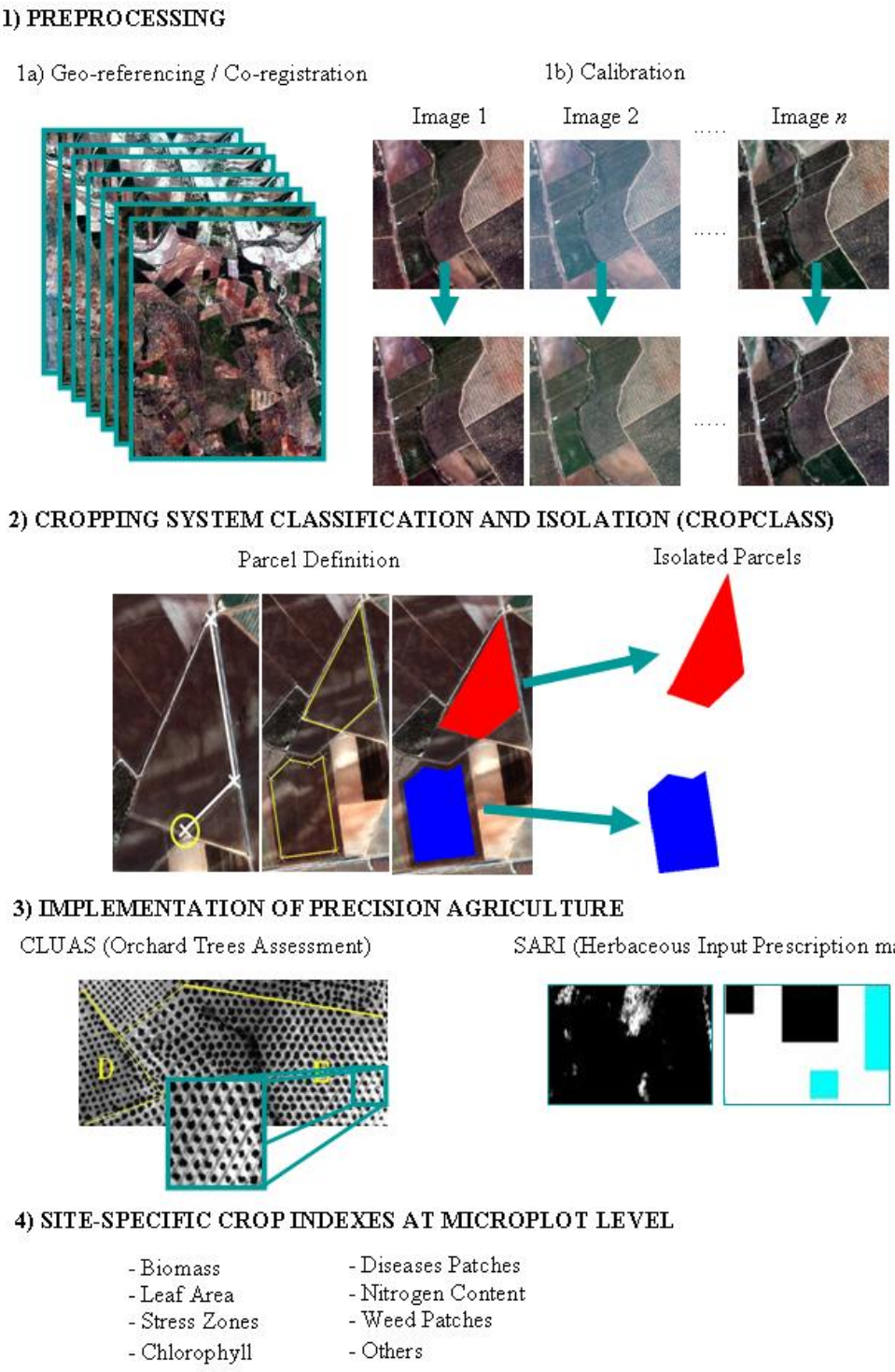
Precision agriculture requires high spatial resolution images, pixel size <1.0-1.5 m. As spatial resolution increase the position error estimated in pixels increase. Normally, satellite and airborne images are commercially provided with position errors not acceptable for precision agriculture (e.g. >5 to 10 m). Therefore a geo-referenciation process to improve/ decrease the position error is needed. Information on this matter and on the semi-automatic geo-referenciation AUGEO® system for geo-registration is described by García-Torres et al. (2012, in this conference) and Gomez-Candón et al., 2011).

IMAGE CALIBRATION (CAIR Software)

Herbaceous cropping systems are typically variant features in the landscape and consequently any vegetative indexes which describe it vary with time. Similarly, multitemporal images series is needed for the assessment of the targeted biotic/ abiotic factor occurring in the cropping systems. On the other hand remote sensing observations are usually instantaneous and are affected by many factors such as atmosphere conditions, sun angle, viewing angle, while the soil and plant–atmosphere system changes dynamically (Yoshio Inoue, 2003). Therefore, multitemporal images of the same area need to be calibrated to enable comparisons between images.

The QUAC and FLAASH are atmospheric correction modules of ENVI image processing software (ENVI/ EXCELIS, 2012). QUAC (Quick Atmospheric Correction) is on-the-fly method for use in real time data processing and determine parameters directly from the information contained in the scene using the observed pixel spectra. FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) is a physic-based correction method, allowing the user to define all parameters that influence atmospheric absorption and scattering such as

Fig. 1. Tentative flowchart of semi-automatic image processing for precision agriculture



relative solar position, atmospheric, aerosol, and scattering models, and visibility parameters, and more. The advantage of QUAC is that is in-scene approach easily implemented, while FLAASH, need to use very diverse atmospheric ancillary parameter and therefore data is highly tunable by the image expert.

On the other hand, we are developing a new calibration method of multitemporal images, so called CAIR, based on pseudo-invariant vegetative features (VPIF), such as dense riparian trees patches or citrus orchards, CAIR is based in the following assumptions a) the light reflectance would be constant in VPIF throughout the vegetative growing season if solar and atmospheric conditions are even, not changeable; and b) In a multitemporal images series the band spectral data and vegetative index of any image could be transformed through band linear equations to provide similar vegetative indexes in VPIF to the other image (so called reference image).

Working with a multitemporal series of Geo-Eye-1 our preliminary data on VPIF show that FLAASH provide better, more accurate calibration as compared to QUAC (data not published), and that CAIR could also being considered a quick and accurate calibration methods to calibrate multitemporal images for cropping systems comparison.

PARCELS CLASSIFICATION AND ISOLATION (CROPCLASS® **Software*)***

Remote sensing either alone or in combination with ground surveys, has been used to determine crop area, and it is playing an increasingly important role in delivering accurate and timely information regarding the location and area of major crop types (Ozdogan, 2010). Maps of cropland distribution are usually generated by image classification of critical period images or multiple remotely sensed data through the growing season (Lobel & Asner, 2004; Fritz & al. 2010).

We have developed an ENVI add-on/ software, so called CROPCLASS, that first isolate each agriculture parcel (Figure 2 and 3) (García-Torres et al, 2011a and b). and then classified it. The advantage of this method is to treat each parcel separately, avoiding the pixel mixing boundaries effect, and at the same time as a preliminary step to implement additional modules for site specific strategies. CROPCLASS can be implemented to multitemporal scenes of the same geographical area to separate and classifying the cropping system each parcel, normally using decision trees as the statistical approach. The semi-automatic parcel separation achieved by CROPCLASS is a necessary preliminary step to implement specific software for within-parcel assessment the targeted biotic/ abiotic agri-environment factor in the previously classified cropping system.

PRECISION CROP MANAGEMENT (CLUAS® and SARI® Software)

Both add-on/ software has been designed to assess targeted factors in agricultural parcels, CLUAS of orchards and SARI of herbaceous crop. SARI can also provide input prescription maps. The development and some tentative application

of the mentioned software have been previously described (García-Torres et. al., 2008 and 2009; Gómez-Candón et al. 2011a & b).

FINAL COMMENTS

The implementation of precision agriculture is important to support environmental and economic features. Furthermore, remote sensing could become a key technology for precision agriculture. The need to automate remote image processing for agricultural studies seems obvious to enable the use remote sensing technology economically feasible. In this paper we have just mentioned a few add-on, among many others which can be developed, intending to contribute to automate remote image processing for agricultural use.

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