OBJECT-BASED APPROACH FOR CROP ROW CHARACTERIZATION IN UAV IMAGES FOR SITE-SPECIFIC WEED MANAGEMENT

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ABSTRACT:

A list of color-infrared images captured from the new generation of remote platforms known as unmanned aerial vehicles (UAV), specifically a quadrotor, was tested for site-specific weed management applications. The aim was to identify and classify the crop rows within a maize crop-field, with the ultimate objective of distinguishing small weed seedlings at early stages for in-season site-specific herbicide treatment. An object-based image analysis (OBIA) procedure was developed by combining several scene, contextual, hierarchical and object-based features in a looping structure. The procedure integrates several features from the crop-field patterns: 1) field structure, such as field limits and row length, 2) crop patterns, such as row orientation and inter-row distance, and 3) plant (crop and weeds) characteristics, such as spectral properties (NDVI values) and plant dimensions; as well as 4) hierarchical relationships based on different segmentation scales, and 5) neighboring relationships based on distance, position and angle between objects. The algorithm identified and counted the rows with 100% accuracy in most of the images and the definition of the longitudinal border of the crop rows was successful with 90% of overall accuracy, comparing to on-ground measures of weed emergence.

1. INTRODUCTION

Site-specific weed management (SSWM) refers to the application of customising control treatments, mainly herbicides, only where weeds are located within the crop-field, using adequate doses according to weed density (Srinivasan, 2006). This technique generally uses new technologies to collect and process data from spatial information of the crop-field. Therefore, its efficient development somehow relies on the use of remote sensing technology, which is a major source to obtain crop information. In the context of SSWM, a remote image could be used to locate weed patches within the crop-field and, afterwards, to create herbicide application maps to be used by specific spraying machinery (López-Granados, 2011). This technology has been widely applied in agricultural studies and, in the case of SSWM, relevant results have been obtained in the mapping of weed patches in late growth stages (Peña-Barragán *et al*., 2007). Nevertheless, in many weed-crop systems, it is impossible to apply treatments in late phases due to the unavailability of herbicides or the toxicity of the existing ones. The optimal treatment is recommended for when the weeds and crop are in the seedling growth stage (early seasons). At this stage, some limitations of using remote imagery are usually attributed to: 1) insufficient imagery resolution for discriminating between bare soil and seedlings of crop and weeds, 2) early-stage weed and crop plants have similar spectra and a very similar appearance, and 3) the reflectance of the background soil interferes with detection.

Nowadays, these problems could be overcome by utilising the new generation of remote platforms known as unmanned aerial vehicles (UAV), whose potential lies on the fact that UAVs (*e.g.*, a quadrotor) can work on demand with great flexibility in critical moments according to each agronomic goal. In addition, they can operate at low altitudes and thus, capture images at a very-high spatial resolution (a few centimeters or milimeters), not feasible with conventional planes or satellites. This is crucial for discriminating between small weed and crop seedlings at early stages in the majority of fields. Together to the requirement of very high spatial resolution of the images, the other important aspect in this case is that a powerful procedure of image analysis is needed. At this growth stage, classification methods based only in pixel information are very limited due to the spectral similarities between weed and crop plants. To solve this limitation, object-based image analysis (OBIA) might be the only way to discriminate both classes. In this process, the definition of the row structure formed by the crop is essential for further identification of plants (crop and weeds), because relative position of every plant with reference to the rows might be the key feature to distinguish them (Burgos-Artizzu *et al*., 2009). The UAV technology has been adapted and utilised by diverse groups interested in agricultural investigation (Lelong *et al*., 2008; Berni *et al*., 2009) and only a few studies have reported the use of UAVs in assessing weed distribution or invasion of plants in rangeland monitoring (*e.g.*, Göktoğan *et al*., 2010; Laliberte *et al*. 2010).

Therefore, the objective of this research was to develop an OBIA procedure for the automatic definition of crop rows within a maize field in early-season, by combining the specific object-based and contextual features typical of this technology within a customized looping rule-set algorithm.

2. STUDY SITE AND UAV IMAGES

A set of aerial images were taken on a maize field located at Arganda del Rey (Madrid, Spain) in mid-May 2011, just when post-emergence herbicide or other control techniques are recommended. Maize field was naturally infested by *Amaranthus blitoides* (broad-leaved weed) and *Sorghum halepense* (grass weed). The maize was at the stage 4-6 leaves unfolded and the weeds had leaf sizes similar to maize leaves or smaller (Figure 1a). The images were collected with a 6-channel multispectral camera (mini-MCA, Tetracam, Inc., CA, USA) mounted in an UAV, model microdrone md4-1000 (microdrones GmbH, Siegen, Germany. CartoGalicia Company at Spain), provided with autonomous system for waypoint navigation (Figure 1b). The flight altitude was 30 m above ground level, yielding 16 images ha^{-1} of 2-cm spatial resolution. The channels were configured with independent bandpass filters (Andover Corporation, NH, USA) with center wavelengths at 530, 550, 570 (green region of the electromagnetic spectrum), 670 (red region), 700 and 800 nm (near-infrared region). The software PixelWrench2 was supplied with the camera to provide full camera control and image management, including the building of multi-band TIFs from RAW image sets (Figure 1c). A number of vegetation indices derived from different combinations of the six channels were evaluated in order to select the best one for the discrimination between vegetation and bare soil. After a preliminary analysis (data not shown), the normalized difference vegetation index (NDVI, eq. 1) was selected:

$$NDVI = \frac{NIR_{700} - R_{670}}{NIR_{700} + R_{670}} \quad (1)$$

Figure 1. a) In-field view of the study site, showing the maize crop rows and several weed plants; b) Unmanned aerial vehicle, type quadrotor, flying over the crop-field; c) Aerial image (color-infrared composition) collected by the UAV at 30 m altitude.

3. DESCRIPTION OF THE RULE-SET ALGORITHM

3.1 Work-flow

The OBIA procedure for the identification and classification of crop rows was developed by using the commercial software eCognition Developer 8 (Trimble GeoSpatial, Munich, Germany). The UAV images (*e.g.*, Figure 2a) were segmented into homogeneous multi-pixel objects using the multiresolution algorithm (Baatz and Schäpe, 2000). Two levels of segmentation were independently used throughout the procedure: 1) Level at scale 140, to defining the structure of the crop rows (Figure 2b), and 2) Level at scale 10, to generate the smaller objects within a crop row (Figure 2c). In both cases, the rest of the parameters involved in the segmentation were 0.9, 0.1, 0.5 and 0.5 for color, shape, smoothness and compactness, respectively. After segmentation, the general process tree is formed by the following steps:

1) Calculation of row orientation: This parameter was computed from the statistical value "mean of main-direction" of all the objects created at the initial segmentation at scale 140 and then saved as a scene variable for further use in the rule-set algorithm. A number of segmentation outputs were checked in a parallel study in order to determine the proper scale to define the row orientation within the studied field, concluding that no significant differences were between scales of 100 and 160. Next, the segmentation output is deleted to avoid influence in the subsequent bottom segmentation outputs.

2) Discrimination between objects of vegetation and bare-soil: The image was then segmented at scale 10 (objects smaller than vegetation plants) and the new objects were classified according to NDVI values. In this case, vegetation objects were attributed to NDVI ≥ 0.2, and bare-soil to NDVI < 0.2 (Figure 2d).

3) Definition of seed-objects: A customized merging operation was performed between vegetation-objects that fulfil the next rule: two candidate vegetation-objects are merged only if the length/width ratio of the target object increases after the merging. In this way, the new objects are only created lengthwise and following the shape of a crop row. Next, the first seed-object is selected for being the largest vegetation-object whose main-direction was the closest to the row orientation (Figure 2e).

4) Identification and classification of the first crop row: The seed-object grows in both directions by performing a looping merging process in which every candidate object is selected for having the angle to the seed-object closest to the row orientation angle as well as being right next to an extreme of the seed-object. The selected candidate object is then merged to the seed-object and the looping process follows until the end of the crop row in both directions (Figures 2f and 2g).

5) Identification and classification of the remaining crop rows: A looping process similar to points 3 and 4 was built to define one row after another. To avoid infinite looping, each row must be separated by a gap between each other (Figure 2h) defined by the crop planting distance (*e.g.*, 75±15cm in maize crops), which makes the algorithm to finish when the last row reaching the limits of the parcel (Figure 2i).

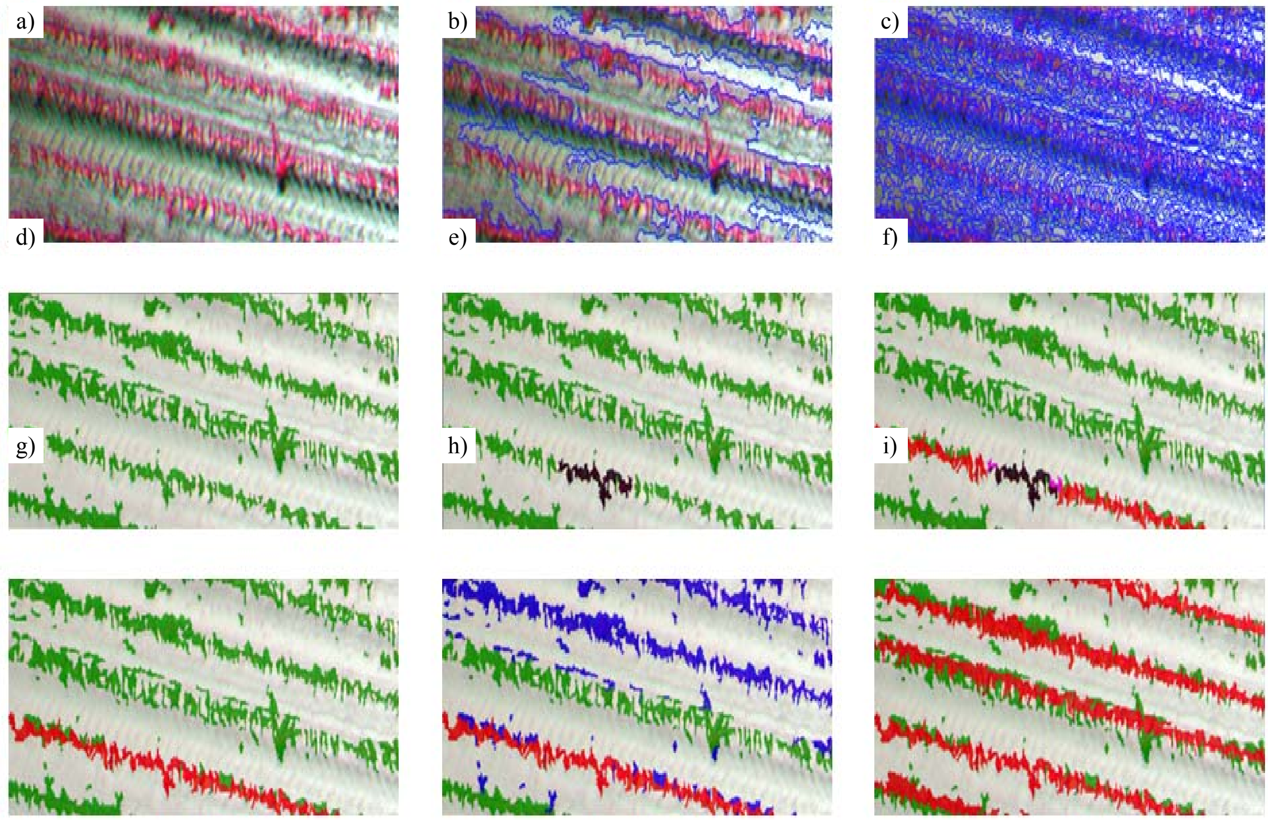

Figure 2. Partial view of the outputs from the rule-set algorithm at each step: a) original color-infrared image, b) segmentation at scale 140 to calculate row orientation, c) segmentation at scale 10 to define object size, d) classification of objects of vegetation (in green) and bare-soil (in white), e) selection of a seed-object (in black) belonging to a crop row, f) the crop row grows from the extreme of the seed-object and following the row orientation, g) the objects within the crop row are merged to create a single object (in red), h) the next crop rows (in green) must be located to a specific distance from the previous one, i) final classification, in which crop rows are in red, other vegetation objects (weeds) are in green and bare soil (inter-row spaces) are in white.

3.2 Crop-field features involved in the algorithm

The described procedure combines several scene, contextual, hierarchical and object-based features derived from the specific structure of the studied parcel and crop, as affected by the image object level (Figure 3).

1) Entire image level: The general crop-field structure was used to define the scene features "crop-orientation" (from the averaged main-direction of the objects segmented at scale 140) and "crop-row separation" (from the planting distance used by the farmer). Also, the image boundary defined the features "crop-row limits" and "crop-row length".

2) Image object level: The orientation (similar to crop-orientation defined at the entire image level), position (within the crop-row separation thresholds), shape (lengthwise) and size of the vegetation-objects were used to classify them as a seed-object belonging to a crop-row. Next, the relative position of every vegetation-object with reference to the crop-row was used to classify it as crop-row or weed.

3) Neighboring relationship: The distance between a crop-row and the candidate objects was used to merge the object to the crop-row (neighbor to the seed-object and within the crop-orientation angle) as well as if the vegetation-objects are classified as crop-row (if the distance to the crop-row is within the crop-row width) or otherwise as weed.

4) Hierarchical relationship: Every new crop row is submitted to a customized quality control based in the percentage of sub-objects (generated by a chessboard segmentation of the super-object formed by the crop row) belonging to vegetation (NDVI > 0.2).

5) Pixel level: Averaged NDVI values from pixels of every object defined the classification of the objects at the lower level as vegetation or bare soil.

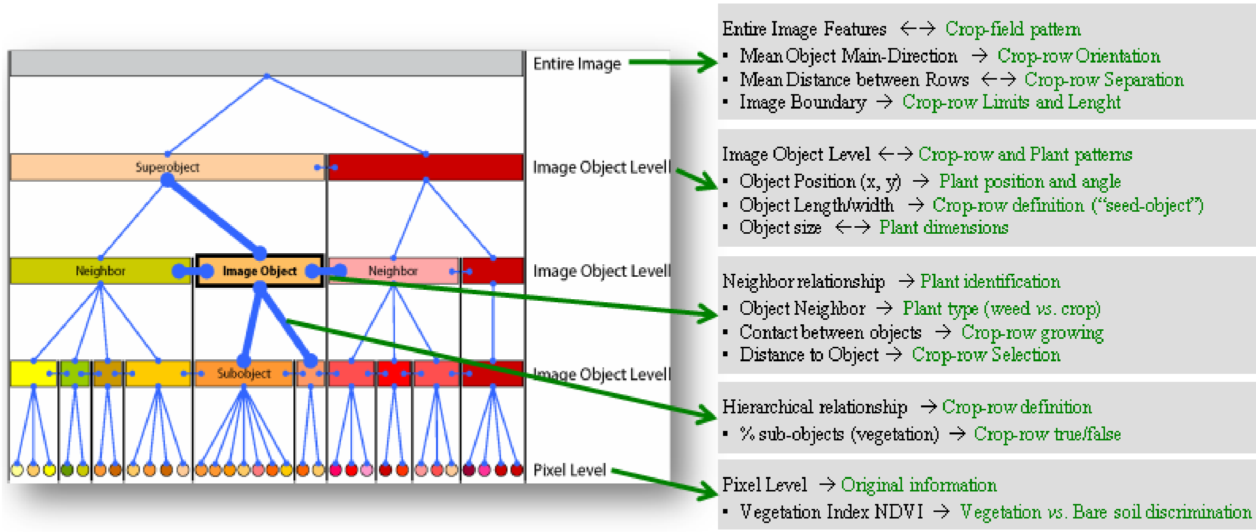

Figure 3. Field and crop features involved in the rule-set algorithm as affected by the image object scale (the figure in the left was extracted from Definiens Developer 7, User Guide)

4. EVALUATION OF THE METHODOLOGY

The rule-set algorithm was trained and developed in two of the aerial images and was tested in the rest of images. To evaluate the algorithm results, a systematic on-ground sampling procedure was carried out in the course of the UAV flight. The sampling consisted of placing 49 square white frames of 1x1 m distributed regularly throughout the studied surface (1.5 ha; Figure 4). Every frame was photographed and georeferenced to record on-ground data regarding to crop and weed cover in order to compare it with outputs from image classification.

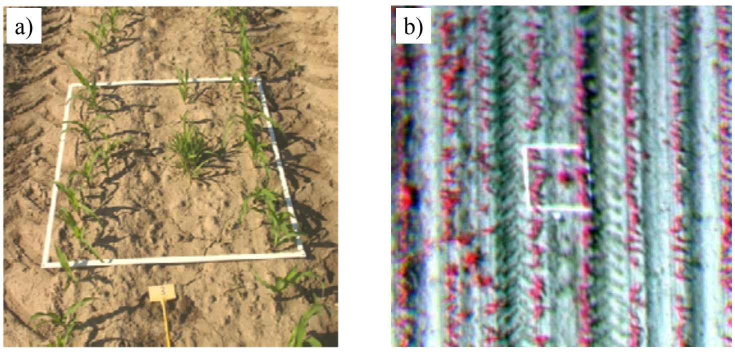

Figure 4. Example of a 1x1 m frame used in the ground-truth sampling: a) On-ground photography, and b) UAV image.

The algorithm identified and counted the rows with 100% accuracy in most of the images and only made minor errors in the extremes of some images because the short size of these rows. The definition of the longitudinal border of the crop rows was successful with 90% of overall accuracy, based on the results obtained in the selected frames. This process is strongly affected by the presence of weed plants very close or within the crop rows. Therefore, weed discrimination was higher than 95% effective in the frames with low weed infestation, but decreased to lower accuracies in the frames with moderate or high weed infestation (preliminary results, analysis still in progress). The figure 5 shows an example of the final classification output.

5. CONCLUSION

An effective and robust OBIA procedure has been developed for the identification and classification of crop rows in a maize field in early season. The task is complex because spectral properties and general appearance of weed and crop plants are very similar at this growth stage, plus the difficulties of variability and changing conditions in natural crop-fields. The rule-set algorithm was designed by combining several scene, contextual, hierarchical and object-based features in a looping structure, reporting very satisfactory results in the identification of the crop rows in most cases. These results showed that this procedure might be very useful for a further discrimination and classification of small weed and crop plants. Once detecting crop rows, next work will be to discriminate weed seedlings in the early season for site-specific weed management strategies.

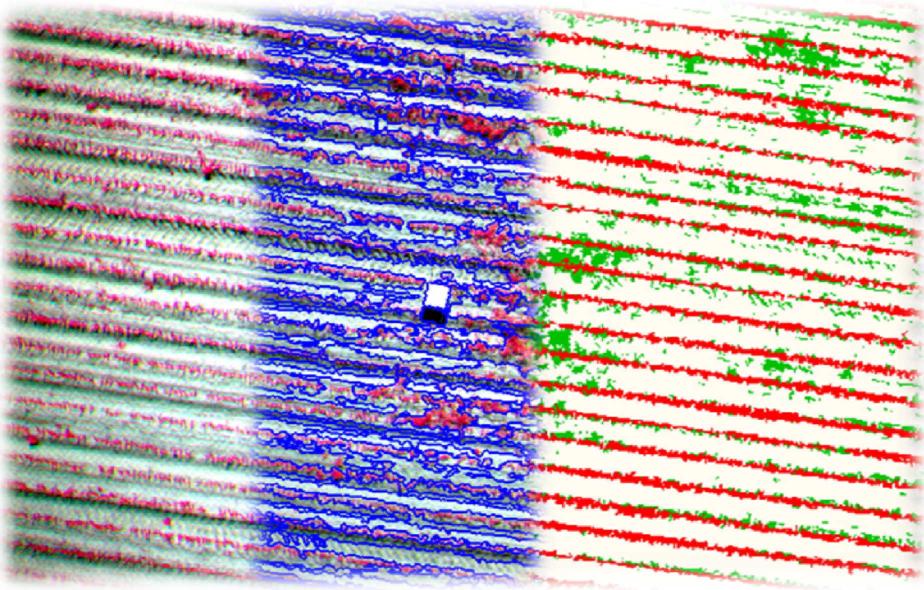

Figure 5. General scheme of the OBIA procedure, showing the original UAV image (in the left), the segmentation process (in the middle), and the classification output (in the right) with crop rows in red, weed patches in green and bare soil in white.

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