A weed monitoring system using UAV-imagery and the Hough transform

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Note 1: Presentation as poster preferred.

Summary: *Usually, crops require the use of herbicides as a useful manner of controlling the quality and quantity of crop production. Although there are weed-free areas, the most common approach is to broadcast herbicides entirely over crop fields, resulting in a reduction of profits and increase in environmental risks. Recently, patch spraying has allowed the use of site-specific weed management, allowing precise and timely weed maps at very early phenological stage, either by ground sampling or remote analysis. Remote imagery from piloted planes and satellites are not suitable for this purpose given their low spatial and temporal resolutions, however, unmanned aerial vehicles (UAV) represent an excellent alternative. This paper presents a new classification framework for weed monitoring via UAV showing promising results and accurate generalisation in different scenarios.*

Keywords: *precision agriculture, sunflower crop, unmanned aerial vehicles, weed mapping, machine learning.*

Resumen: *Los cultivos precisan del uso de herbicidas para controlar la calidad y cantidad de producción. A pesar de que las malas hierbas se distribuyen en rodales, la práctica más extendida es la fumigación de herbicidas en todo el cultivo, resultando en un aumento del coste y de riesgos mediambientales. La pulvericación por parches ha dado lugar al auge de otras técnicas de manejo de malas hierbas, permitiendo su tratamiento en un estado fenológico temprano. Las imágenes remotas de aviones pilotados o satélites no son útiles en este caso debido a su baja resolución espacial y temporal. Sin embargo, este no es el caso de los vehículos aéreos no tripulados. Este artículo presenta un nuevo método para monitorización de malas hierbas usando este tipo de vehículos, mostrando resultados prometedores.*

Palabras clave: agricultura de precisión, cultivo de girasol, vehículos aéreos no tripulados, mapas de malas hierbas, aprendizaje automático.

INTRODUCTION

Precision agriculture referred to weed control is based on the design of early post-emergence site-specific control treatments according to weed coverage. The development of this type of methodologies has been motivated by the evident economical and environmental risks derived from over application of herbicides. In this sense, the recent inclusion of patch spraying in the treatment equipment has supported the feasibility of using site-specific weed management. Weed maps can be obtained either by ground sampling or by remote detection. However, in early growth stages, the spectral and appearance characteristics of crops and weeds are similar, thus imposing an additional handicap for the detection.

Previous works have mapped weeds at late growth stage (e.g. flowering) using piloted aircrafts or QuickBird satellite imagery. However, this technology can not be applied in early detection because of the poor spatial resolution of the data captured. Nonetheless, recently, a new aerial platform has joined the traditional ones, the Unmanned Aerial Vehicle (UAV), which represents a suitable option for this purpose.

In this paper, we study how to combine UAV imagery with a crop row detection method to improve the performance of the classification method, given the spectral similarities of crops and weeds at this phenological stage. Different sensors and flight altitudes are also compared in our experiments.

MATERIALS AND METHODS

This section exposes the studied area and the method used for the classification based on pixels performed in this paper.

2.1 Study area. The UAV system was tested in a sunflower field situated at the private farm La Monclova (Seville, southern Spain). The sunflower seeds were planted at the end of March 2014 at 6 kg ha−1 in rows 0.7m apart. The set of aerial images were collected on May 15th, just when post-emergence herbicide or other control techniques are recommended Several visits were periodically made to the field from crop sowing to monitor crop growth and weed emergence and, finally, to select the best moment to take the set of remote images. The sunflower was at the stage of 4-6 leaves unfolded. The weed plants had a similar size or, in some cases, were smaller than the crop plants. An experimental plot of 100 × 100m was delimited within the crop-field to perform the flights. A systematic on-ground sampling procedure was carried out the day of the UAV flights. The procedure consisted of placing 49 square white frames of 1 × 1m distributed regularly throughout the studied surface. Every frame was georeferenced with a GPS and photographed in order to compare on-ground weed infestation and output from image classification. These numbered cards were also utilised as artificial terrestrial targets (ATTs) to perform the imagery orthorectification and mosaicking process. In the course of the UAV flights, a barium sulphate standard spectralon panel (Labsphere Inc., North Sutton, NH, USA) of 1 × 1m was also placed in the middle of the field to calibrate the spectral data.

2.1 UAV flights, sensors and image preprocessing. A quadrocopter platform with vertical take-off and landing, model md4-1000 (microdrones GmbH, Siegen, Germany), was used to collect the set of aerial images over the experimental crop-field (for different altitudes). The whole UAV system consists of the vehicle, the radio control transmitter, a ground station with the software for mission planning and flight control and a telemetry system. Three persons were employed for the secure use of the UAV: a radio control pilot, a ground station operator and a visual observer. Two sensors with different spectral and spatial resolutions were separately mounted on the UAV to be tested in this experiment: a still point-and-shoot camera, model Olympus PEN E-PM1 (Olympus Corporation, Tokyo, Japan), and a six-band multispectral camera, model Tetracam mini-MCA-6 (Tetracam Inc., Chatsworth, CA, USA). The Olympus camera acquires 12-megapixel images in true colour (Red, R; Green, G; and Blue, B, bands) with 8-bit radiometric resolution and is equipped with a 14-42mm zoom lens. The camera's sensor is 4, 032 × 63, 024 pixels. The mini-MCA-6 is a lightweight multispectral sensor composed of six individual digital channels arranged in a 263 array. Each channel has a focal length of 9.6mm and a 1.3 megapixel (1, 280 × 61, 024 pixels). The camera has user configurable band pass filters (Andover Corporation, Salem, NH, USA) of 10-nm full-width at half-maximum and centre wavelengths at B (450 nm), G (530 nm), R (670 and 700 nm), R edge (740 nm) and near-infrared (NIR, 780 nm). These bandwidth filters were selected across the visible and NIR regions with regard to well-known biophysical indices developed for vegetation monitoring (J. Kelcey & A. Lucieer, 2012). Different overlapped images were collected for this study to cover all of the experimental field. This is due to UAV images flying at low altitudes (according to Spanish regulation maximum altitude is 120m for UAV < 25kg) that can not cover the whole field, and this causes the need to take a sequence of multiple overlapped (end-lap or lateral-lap and side-lap or longitudinal-lap) images. One of the crucial steps of the image analysis procedure developed in this paper is the combination of these individual images via a process of image orthorectification and mosaicking. The Agisoft Photoscan Professional Edition (Agisoft LLC, St. Petersburg, Russia) software was employed for this task.

2.2 Applied method. The classification method developed in this paper is based on the well-known Support Vector Machine paradigm (SVM), a machine learning classifier that has been widely used for remote sensing (G. Mountrakis et al., 2011). Machine learning classifiers receive a set of training data and construct a model based on these patterns in order to generalise over new unseen data. The first step of the classification process is therefore the selection of a training set. In this case, we consider a very small set of data, in order to alleviate the user intervenction and analyse the capabilities of the method in such a situation. More specifically, we have selected a square of 10x10 pixels for each class (soil, weed and crop) for each image considered in the experiments.

The next step of the classification process is to decide the data features to include. The most straight-forward idea would be to use the spectral information of each pixel. This is our first option for the experiments. However, other information could be included as well. In this case, we consider the use of the Hough transform for crop row detection (R. O. Duda and P. E. Hart, 1972). This is motivated by the fact that usually, in early growth stages, the spectral and appearance characteristics of crops and weeds are similar. However, crops are distributed in rows and this information could be then of interest to train a classification model.

The Hough transform is usually computed over binary images. Two vegetation indexes have been selected for this purpose: the excess green vegetation index (ExG) (D. M. Woebbecke et al., 1995) for the Olympus camera and the normalised difference vegetation index (NDVI) (A. A. Gitelson et al., 2002) for the Tetracam sensor. A thresholding step using the Otsu's algorithm (N. Otsu, 1979), was applied to binarise these indexes. After detecting the crop rows, a different threshold was computed to obtain a buffer for these crop rows. This buffer was obtained through the use of the ROC curve. After this step, we would have a binary image that indicates whether each pixel belongs or not to a crop row. The new characteristic included in the processing is simply the multiplication of the vegetation index and this feature indicating the belonging to crop rows. This new proposed characteristic would differentiate between pixels that lie inside the crop rows (also considering the vegetation index of these) and outside the crop rows.

RESULTS AND DISCUSSION

The experiment in this paper is mainly intended to test the difference in performance using the proposed feature based on the Hough transform, as well as to analyse the impact of the flight height and sensor used.

The parameters associated to the SVM classification method and the Hough transform have been cross-validated using a 5-fold procedure. For the evaluation of the results 32 frames of ground truth have been considered for each image. For each frame, the approximate percentage of soil, crop and weed number of pixels has been computed. These percentages will be compared to the ones obtained. In order to evaluate and compare the performance, the Mean Average Error (MAE) is used. The measure is equivalent to the general mean deviation from the expected percentages computed differently for each class. In this case, we only consider the deviation obtained for the weed class.

Table 1 shows the results obtained for the experiments considered. Several conclusions can be drawn in this case. Firstly, it can be seen that the flight altitude is an important factor to consider, being the results at 100m worst than the ones at 30m. Secondly, it can be seen that the inclusion of the proposed feature helps to improve the results in all the cases considered. Moreover, the results for each camera do not differ to a great extent, although Tetracam seems to be better suited for greater altitudes. It is also noticeable the good synergy presented by the use of the Tetracam sensor and the proposed feature. However, in this case, the authors consider that the use of the Olympus camera could be more interesting, given the greater cost of the Tetracam sensor. Finally, the general tendency of the results (a deviation of 3% from the original weed percentages) indicates that the use of this approach and the inclusion of very few training information lead to promising results for this crop. This can also be appreciated analysing the results presented in Figure 1.

Table nº1. Mean MAE results obtained for two sensors, two flight altitudes and two different approaches. Recall that MAE is to be minimised.

	Camera and flight altitude			
	Olympus		**Tetracam**	
Features	**30m**	**100m**	**30m**	**100m**
Spectral features	0.037	0.252	0.053	0.172
Spectral features + proposed feature	0.032	0.138	0.039	0.042

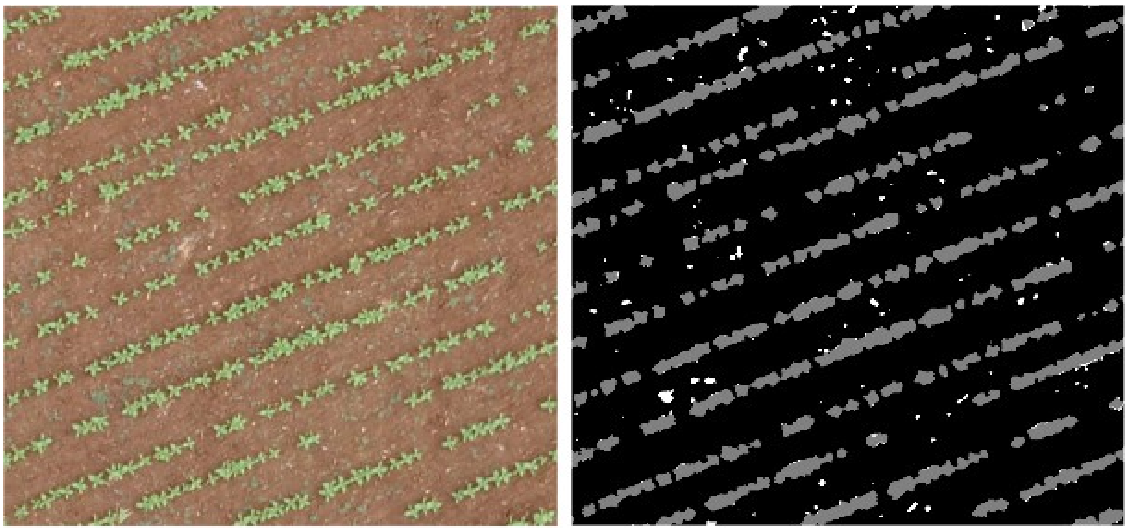

Figure nº1. The image in the left part shows a selected part of the experimental field at 30m; the figure on the right shows the classification results obtained by the procedure proposed

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CONCLUSIONS

This paper has explored the use of UAV-imagery for the purpose of weed monitoring in sunflower crops. The proposal of this paper is to complement a well-known classification technique with a crop row detection method. This is based on the assumption that the classification method will benefit from the crop row information, given that the spectral and appearance characteristics of crops and weeds are similar. The results show that such an approach leads to promising results in all the cases considered (two different cameras and flight altitudes), therefore opening a future line of research using the Hough transfrom for UAV-imagery.

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