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A semi-supervised system for weed mapping in sunflower crops using unmanned aerial vehicles and a crop row detection method

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ABSTRACT

This paper presents a system for weed mapping, using imagery provided by unmanned aerial vehicles (UAVs). Weed control in precision agriculture is based on the design of site-specific control treatments according to weed coverage. A key component is precise and timely weed maps, and one of the crucial steps is weed monitoring, by ground sampling or remote detection. Traditional remote platforms, such as piloted planes and satellites, are not suitable for early weed mapping, given their low spatial and temporal resolutions. Nonetheless, the ultra-high spatial resolution provided by UAVs can be an efficient alternative. The proposed method for weed mapping partitions the image and complements the spectral information with other sources of information. Apart from the well-known vegetation indexes, which are commonly used in precision agriculture, a method for crop row detection is proposed. Given that crops are always organised in rows, this kind of information simplifies the separation between weeds and crops. Finally, the system incorporates classification techniques for the characterisation of pixels as crop, soil and weed. Different machine learning paradigms are compared to identify the best performing strategies, including unsupervised, semi-supervised and supervised techniques. The experiments study the effect of the flight altitude and the sensor used. Our results show that an excellent performance is obtained using very few labelled data complemented with unlabelled data (semi-supervised approach), which motivates the use of weed maps to design site-specific weed control strategies just when farmers implement the early post-emergence weed control.

1. Introduction

Weeds are responsible for an approximate 35% reduction in potential global crop yields. Today, most farmers in the EU rely on synthetic herbicides as a useful tool for maintaining and ensuring the quality and quantity of crop production and allowing an efficacy of weed control of almost 75%. This involves both that actual yield losses due to weeds are around 9% being €3.334 M the cost of herbicides used, i.e. 41.5% of the total pesticides sales. This means by a 20 fold increase of herbicides from 1964 to 2004 [5,28]. Herbicides are usually broadcast over entire fields even though there are weed-free areas because weeds are usually spatially distributed in patches [20]. There are evident economical and environmental risks derived from over application, and to overcome this situation, patch spraying has supported the feasibility of using site-specific weed management (SSWM) based on weed coverage [30]. The cost of these herbicides usually accounts for 40% of the cost of all of the chemicals applied to agricultural land in Europe [5] and this economic factor together with environmental concerns have led to the creation of the European legislation on the sustainable use of pesticides, which includes guidelines for the reduction of these chemicals according to the weed infestation map [4,2]. A key component of SSWM is precise and timely weed maps for an appropriate early post-emergence weed control, and one of the crucial steps for weed mapping is weed monitoring [37], either by ground sampling or by remote detection and identification of weeds [33,16]. The remote sensing of weed canopies can significantly improve reliability compared to ground visits only whether the spectral and spatial resolutions of remote sensing equipment is sufficient for the detection of differences in spectral reflectance [39,23,24,15]. However, in early growth stages, the spectral and appearance characteristics of the crop and weeds are similar, thus imposing an additional handicap for the detection. Previous works have mapped weed at late growth stage (e.g. flowering) using

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piloted aircrafts or QuickBird satellite imagery [9,10]. However, this technology can not be applied in early detection because of the scarce spatial resolution of the data captured with these kind of platforms (pixel size around 50 cm and 2.6 m for piloted aircrafts and QuickBird satellite, respectively). In recent years, a new aerial platform has joined to the traditional ones, the unmanned aerial vehicle (UAV) [26]. Several investigations have demonstrated the advantages of the UAVs in comparison with airborne or satellite missions [22,25,44,32] regarding a minor cost and a higher flexibility in flight scheduling. These advantages make UAVs a proper tool to perform multi-temporal studies for crop and weed monitoring at early crop and weed phenological stage [42,41], which is a classic limitation of the traditional remote-sensed platforms. Another primary advantage of the UAV platforms is that flight route can be programmed at low altitude (e.g., <120 m), which allows the acquisition of highly overlapping ultra-high spatial resolution images (in the range of very few centimetres).

The combination of machine learning and UAVs for precision agriculture, although showing good synergy in a few previous works [31,45,18], is still an emerging research area mostly undeveloped. Usually, the most popular choice for defining a weed mapping system based on UAV-imagery is undoubtedly the use of manually defined rule sets [32,34] (based on pixel dissimilarity, pixel location or vegetation indexes), which has indeed led to very promising results. However, remote sensing and more specifically precision agriculture could benefit to a great extent from the use of supervised learning methods. Until now these methods have been mostly used with on-ground images in proximal sensing presenting great potential [38,23,6], which has motivated further research in this line. Proximal sensing can be said to present some limitations that make its use difficult in practice [6]. Firstly, this analysis is usually performed in real-time, resulting then in other series of concerns (e.g. computational resource limitations). Another factor contributing to this is the vibration of the equipment and changes of luminosity, which could jeopardize the correct classification of the data if the system is not robust enough. Opposed to this, remote sensing analysis would have to be performed prior to the broadcasting, but it could be useful to estimate *a priori* the quantity of herbicide and to optimise the field path to follow, notwithstanding that the image analysis step would be in general more simple. It is now, when the existing issues of UAVs have been mastered, such as route planning and others, and the cost of such platforms is affordable, that this technology is ready to use. In this sense, machine learning and image segmentation are suitable technologies for this task, given the large amount of previous research and the applicability of these techniques. Because of this, studies combining these two areas are starting to emerge in remote sensing [31,45]. Until now, the works in the literature have studied the feasibility and limitations of such an approach, proposing new methods for weed or vegetation fraction mapping and testing them in a wide variety of situations. These methods have shown great promise in detecting weeds between crop rows [32,41,40], but the identification of weeds within crop rows still remained an open challenge. The main difference between the proposal and the rest of studies is the analysis and use of a wide variety of machine learning techniques and the combination of these with a flexible crop row detection algorithm, which results in a robust and accurate method able to distinguish both weeds outside and within crop rows. Up to our knowledge, this is the first occasion where the information concerning crop rows is used in conjunction with the spectral features as input characteristics for a classifier.

In this paper, a new system is proposed for weed mapping in sunflower crops. The objective is to alleviate the problem of crop and weed spectral similarity, therefore allowing a proper identification of weeds in a crop (sunflower, in this case). This crop was selected because it is the most important annual oilseed crop in southern Europe and the Black Sea region, with over 5 Mha grown annually [1], of which 0.8 Mha are in Spain [3] and consequently weed control operations account for a significant proportion of production costs. Ideally, the process of weed mapping should be performed timely and accurately to directly provide the farmer with a treatment map for early post-emergence. However, the direct generation of this treatment map is tricky when no prior information is provided and when the lighting settings and spectral properties of the different fields to study differ. Nowadays, with the current technology, the output of the proposed algorithm could be used to provide different treatments: a binary apply/not apply herbicides to weed infested field section (if one kind of weeds is present, e.g. grass weeds) or the application of different herbicides (e.g. to control broadleaved, grass or resistant weeds). These treatment maps will be afterwards given to a specific software which will be part of a treatment equipment in order to properly apply the chemicals. Moreover, the detection of crops could also be useful for plant counting or to position the equipment according to crop rows.

The system proposed in this work uses the imagery of the field provided by the UAV and relies on very little information provided by the user: a set of labelled patches for each class and the set of parameters for the different algorithms. The methodology is based on the following steps: partition of the experimental field into different subimages, computation of vegetation indexes and binarisation of these, detection of crop rows and, finally, training of a classification model for the data provided. The main novelty of the methodology is the detection of crop rows based on the Hough transform (HT) [12] using imagery from UAVs (note that the Hough transform has been widely used with on-ground studies [38], but not with remote sensing imagery, for which and under our knowledge has only been used once in vineyard crop detection [8]). The HT information proves to be a very good way to differentiate crop from weed pixels presenting similar spectral information.

On the other hand, the proposal tries to minimise the amount of information provided by the user and, at the same time, to obtain the maximum benefit from it. Most traditional machine learning approaches learn a discriminant function from a set of labelled data. However, labelled examples are usually expensive and time-consuming to obtain, as opposed to unlabelled data. This issue is indeed of serious concern for applications which require that the processing is performed in a limited time, such as the problem considered in this paper. In this direction, the paper explores how to perform this study with a simple a priori analysis of the UAV-captured images and how to optimise all the parameters of the method automatically. The second novelty of this work is the comparison of three machine learning paradigms (unsupervised, semi-supervised and supervised learning) to study the influence of labelled and unlabelled examples in the quality of the classifiers obtained.

The objectives of the proposed system can be summarised in the following two: (1) to study how to combine UAV imagery with a crop row detection method, in such a way that the performance can be improved; and (2) to analyse the potential of different machine learning methods in the development of an algorithm using the minimum information possible, in order to provide a mostly unsupervised analysis which could be used easily in other real field scenarios. Different sensors and flight altitudes are also compared to study the influence of both factors. As far as the authors of this paper are concerned, this is the first approach to weed mapping via UAV imagery which combines spectral information with the HT [12] and analyses the performance of a wide range of different machine learning methods.

The paper is organised as follows: Section 2 shows a description of the data acquisition and the weed mapping system proposed in this work; Section 3 describes the experimental study and analyses