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An experimental comparison for the identification of weeds in sunflower crops via unmanned aerial vehicles and object-based analysis *

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Abstract. Weed control in precision agriculture refers to the design of site-specific control treatments according to weed coverage and it is very useful to minimise costs and environmental risks. The crucial component is to provide precise and timely weed maps via weed monitoring. This paper compares different approaches for weed mapping using imagery from Unmanned Aerial Vehicles in sunflower crops. We explore different alternatives, such as object-based analysis, which is a strategy that is spreading rapidly in the field of remote sensing. The usefulness of these approaches is tested by considering support vector machines, one of the most popular machine learning classifiers. The results show that the object-based analysis is more promising than the pixel-based one and demonstrate that both the features related to vegetation indexes and those related to the shape of the objects are meaningful for the problem.

Keywords: Unmanned Aerial Vehicles, Object-based Analysis, Weed mapping, Image segmentation, Support Vector Machines

1 Introduction

It is well-known that weeds are responsible for a large reduction in potential global crop yields (approximately a 35%). Because of this, nowadays, most farmers in the EU rely on synthetic herbicides as an useful tool for maintaining and ensuring the quality and quantity of crop production, which usually provides a weed control efficacy of 75%.

There are however very clear economical and environmental risks derived from over application, due to herbicides are applied to the whole field even when weeds are distributed in patches. The cost of these herbicides usually accounts for 40% of the cost of all of the chemicals applied to agricultural land in Europe [1] and this economic factor

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together with environmental concerns have led to the creation of the European legislation on the sustainable use of pesticides, which includes several specific guidelines for reduction of herbicides according to the weed coverage [2,3]. This has been possible because of the introduction of patch spraying in the machinery used, which has enabled the feasibility of site-specific weed management (SSWM) based on weed coverage. A key component of SSWM is to provide 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, either by ground sampling or by remote detection of weeds.

Nonetheless, in early growth stages, the spectral and appearance characteristics of both crops and weeds are similar, thus imposing additional difficulties for the detection. Most previous works have addressed this problem by mapping weeds at late growth stage (e.g. flowering) using piloted aircrafts or QuickBird satellite imagery [4,5]. However, this technology is not suitable in early detection because of the scarce spatial resolution that these kind of platforms provides (pixel size around 50cm and 2.6m for piloted aircrafts and QuickBird satellite, respectively). Recently, a new aerial platform has joined the traditional ones, known as the Unmanned Aerial Vehicle (UAV) [6]. Different studies have highlighted the advantages of UAVs over airborne or satellite equipment [7,8], specially a minor cost, a higher flexibility in flight scheduling and a better spacial resolution. These advantages make UAVs a proper tool to perform multi-temporal studies for crop and weed monitoring at early crop and weed phenological stage [9,10], which is a classic limitation of the traditional remote-sensed platforms.

In many cases, image information is represented by means of low-level features. However, a significant degree of abstraction can be achieved if an appropriate representation of the data is used [11,12]. In this sense, this paper compares different approaches to deal with the problem of weed mapping via remote sensing. These weed maps have to be provided timely, therefore, time is one of the factors to analyse in this study. This paper tries to approach some of the hypotheses and issues that have been identified when using a object-based analysis [11] of the images. Roughly speaking, object-based analysis is devoted to the division of remote sensing imagery into meaningful sets of pixels (known as objects) which are considered as similar based on some measure of homogeneity. The use of object-based analysis methods is spreading rapidly because of the advantages that have been seen when comparing this approximation to the common pixel-based approach. The first hypothesis that we try to validate in this study is whether an object-based analysis is the best option, and how large is the performance gap between such a method and a pixel-based approach. As a second hypothesis, we validate the use of histograms when using an object-based approach as opposed to the use of different statistical metrics. Finally, we also test different sets of features and training data, in order to analyse the usefulness of these features and the number of patterns needed to yield a reasonable performance. Note that although the base problem of this paper could be addressed from a binary classification point of view, crop detection is also a very important challenge for a wide range of applications, such as plant counting, detecting sowing failures or positioning the patch spraying equipment according to crop rows. To conduct this study, different datasets have been created (considering the previously mentioned hypotheses) and the results in each case are validated by the use of the well-known Support Vector Machine classifier.

The paper is organised as follows: Section II shows a description of the data acquisition stage; Section III describes the different approaches tested; Section IV presents the experimental study and analyses the results; and finally, Section V outlines some conclusions and future work.

2 Data acquisition and processing

The UAV system was tested in a sunflower field situated at the private farm La Monclova, in La Luisiana (Seville, southern Spain, coordinates 37.527N, 5.302W, datum WGS84). The set of aerial images were collected on May 15^{th} 2014, just when post-emergence herbicide or other control techniques are recommended in this crop. The sunflower was at the stage of 4-6 leaves unfolded [13]. The sunflower field was naturally infested by weeds and they 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. The coordinates of each corner of the flight area were collected using a global position system (GPS) to prepare the flight route in the mission-planning task.

2.1 UAV and sensor specifications

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 above-mentioned experimental crop-field. The flight route was programmed into the UAV software to allow the UAV to reach the programmed altitude and required degree of image overlapping for further mosaicking. The imagery was collected at the altitude of 30 meters. A low cost still camera, model Olympus PEN E-PM1 (Olympus Corporation, Tokyo, Japan) was used. At the moment of each shoot, the on-board computer system records a timestamp, the GPS location, the flight altitude, and vehicle principal axes (pitch, roll and heading). The Olympus camera acquires 12-megapixel images in true colour (R, G and B bands) with 8-bit radiometric resolution and is equipped with a 14-42 mm zoom lens. A sequence of 60% end or longitudinal lap and 30% side or lateral lap imagery was collected to cover the whole experimental sunflower field.

2.2 Image mosaicking

As said, different overlapped images were collected for this study to cover the whole experimental field. This is due to UAV images flying at low altitudes 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. As consequence, a large number of UAV images were acquired to cover the whole sunflower plot. A necessary step 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.

2.3 Object-based image analysis

Object-based image analysis (OBIA) can be said to be a sub-discipline of the research field of geographic information systems. OBIA is mainly devoted to divide remote sensing imagery into meaningful objects by assessing their characteristics. Objects are image regions derived by one or more criteria of homogeneity in one or more dimensions (i.e., characteristics of the feature space). Therefore, several advantages of objects over single pixels have been found [11]: objects can entail further information apart from the spectral characteristics (i.e., deviation of the values per band, shape, texture, relations with other objects, etc), the use of objects as basic units reduces the computational load of the classification method and also enables the user to consider more complex techniques (as the one proposed in this paper), and finally, that image objects could help to overcome the so called "salt and pepper effect".

The segmentation algorithm used in this case is the one presented in [14]. This method is based on the generation of spectrally similar units with a minimum object size. The procedure uses the well-known k-means clustering methodology [15] and a object-refining step (to avoid very small objects). The algorithm presents two key parameters: the number of clusters k, and the minimum object size. These parameters have been optimised using the Johnson and Xie method [16] for measuring segmentation quality.

The result of this procedure can be seen in Fig. 1 for a region of the experimental field. Note that each object has been represented in a colour (by averaging the spectral values of all the pixels of the object).

Fig. 1. The image on the left shows a region selected from the experimental field. The image on the right shows the output of the segmentation algorithm (note that objects have been plotted as regions with the same spectral information by measuring their spectral values).

2.4 Data labelling

To extract the data from the different classes we have randomly selected and labelled different objects until the total number per class was n (in this case, we chose $n = 100$). As said, the choice of these patterns was completely random. Therefore, depending on the results, these could indicate the necessity of developing more intelligent techniques for choosing the training patterns or validate the fact that a random selection represents a suitable choice in this case.

3 Pattern classification

The goal in classification is to assign an input vector $\mathbf{x}$ to one of k classes (this label will be designed as y, where $y \in \mathcal{Y} = \{1, \ldots, k\}$), when considering an input space $\mathcal{X} \in \mathbb{R}^d$, where d is the data dimensionality. The training data are assumed to be generated from an i.i.d. $D = \{\mathbf{x}_i, y_i\}_{i=1}^N \in \mathcal{X} \times \mathcal{Y}$ from an unknown distribution $P(\mathbf{x}, y)$. Therefore, the objective in this type of problem is to find a prediction function $f : \mathcal{X} \rightarrow \mathcal{Y},\ f \in \mathcal{F}$ that minimises the expected loss or risk.

In this paper, we compare two different approximation for the problem of weed mapping by means of machine learning classifiers: pixel-based and object-based analysis.

3.1 Pixel-based approach

Concerning the pixel-based approximation, we propose two different approaches:

- Firstly, to extract the corresponding set of pixels from each labelled object. Each of these pixels will be considered as a new pattern. The label of the pixel will be the one associated to each object.
- Secondly, to reduce each object to a single pixel. To do so, we randomly select one of the pixels of the object.

The previous approaches would try to validate whether a pixel-based approach is suitable, and whether each object could be simplified by randomly choosing one of its components. In this case, only the spectral characteristics are used as input features for the model.

3.2 Object-based approaches

In relation to the object-based techniques, we present two different techniques depending on how the patterns are composed:

- Firstly, we would like to test the most common approximation for this type of problem, i.e., the simplification of each object by considering some specific statistical measures for the corresponding pixels. In this case, we consider the mean and standard deviation for each channel.
- Secondly, we propose to use histograms formed by the pixels of the object for each different channel. In this case, we simplify each histogram by grouping the elements into 25 different equally-spaced bins.

Features considered As stated before, OBIA methods present the advantage that they can entail further information apart from the spectral one. In this subsection, we will present the different features considered in this paper:

1. Spectral information: In this case we include the statistical metrics or the complete set of values via a histogram representation for each of the three channels (i.e., red, green and blue).
2. Information related to vegetation indexes: In our case, we consider the well-known Excess Green index [17]. We include two different sets of features in this case: vegetation indexes associated to the object itself, and vegetation indexes for the adjacent objects. For the latter case, we analyse the neighbouring objects to the one considered. Fig. 2 shows how we computed neighbouring objects, i.e. by selecting adjacent pixels and storing their object identifier. Then, we compute the mean vegetation index for each adjacent object identifier. Both sets of information (i.e. vegetation indexes for the pixels of the object itself and mean vegetation index of the adjacent objects) are included either by using the corresponding statistical features (mean and standard deviation) or the corresponding histograms.

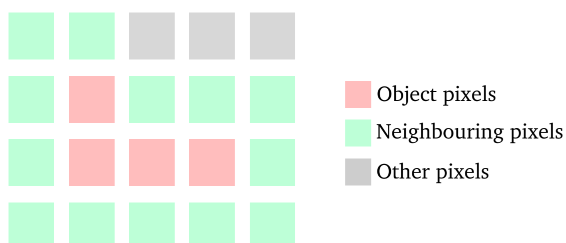

Fig. 2. Selection of adjacent pixels for one of the objects extracted.

3. Shape information: We include three basic features concerning the shape of the object. These characteristics are: the number of pixels that compose the object, the maximum number of pixels in a row, and the maximum number in a column.

Fig. 3 shows the different stages of the method proposed and the different options tested.

4 Experimental results

As previously introduced, three different cases are evaluated in this paper: Firstly, the use of pixels as basic units for classification, secondly, the use of objects, but not using the histogram information (only the mean and standard deviation), and, finally, the use of objects using the histograms.

We evaluate all the proposals by considering the multiclass version of the Support Vector Classifier (SVC) [18]. For the case of classifying all pixels of the objects, we

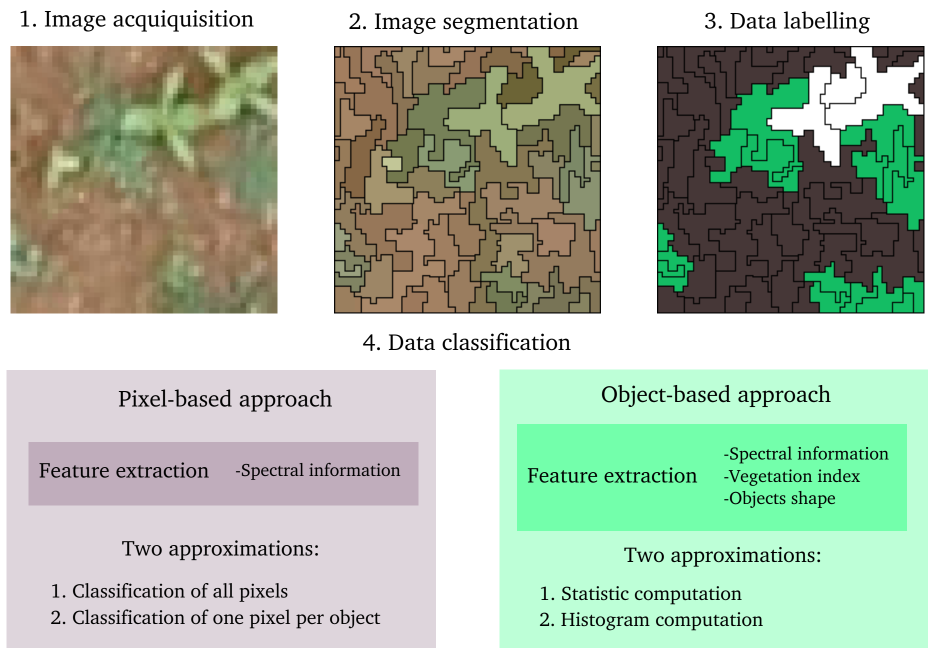

Fig. 3. Different stages for the tested methods.

used the linear version of SVC given the large amount of patterns (around $15,000$ training patterns, which makes unfeasible the use of the nonlinear SVC).

The results have been reported in terms of three metrics for measuring the performance of a classifier: 1) the well-known accuracy, *Acc*, which corresponds to the correct classification rate, 2) the Minimum Sensitivity ($MS = \min\{S_1,\ldots,S_k\}$), where S_i is the sensitivity for the class $\mathcal{C}_i$ (ratio of correctly classified patterns considering only this class), and 3) the computational time of the classification method in seconds. The measure considered during hyperparameter selection was *Acc*.

A stratified 10-fold technique was performed, where the results were taken as the mean and standard deviation of the selected measures over the 10 test sets. For all nonlinear methods, the standard Gaussian kernel was used. In this case, the kernel width was selected within the values $\{10^{-3}, 10^{-2}, \ldots, 10^{3}\}$, as well as the cost parameter of SVC, by means of a nested 5-fold procedure applied to the training set.

4.1 Results

The results of the experiments are shown in Table 1. Different conclusions can be drawn from this table. Firstly, concerning the pixel-based approach, the random selection of a pixel per object presents a poorer performance, probably because the selected pixel does not represent enough information about the object. Moreover, it can be seen that a simple pixel approach leads to reasonable performance (even when a linear algorithm is being used), although the computational cost is very high. Note that, the time recorded is that needed to train the model using a small portion of the experimental field. Therefore, the increase of 5 seconds to 1100 seconds is very important and could result in an intractable algorithm. However, we can appreciate the superiority in terms of performance of the object-based approach over the pixel-based one for all the metrics selected. In this sense, it can be seen that the use of statistical metrics is sufficient for obtaining very competitive results (being these results better than the one obtained by the use of histograms). Finally, the combination of the different sets of features improves the results to a great extent and results in a very promising classification of the data, while still maintaining a low computational cost.

Table 1. *Acc*, *MS* and time results obtained for the different settings and sets of input features considered.

Dataset	Characteristics	*Acc*	*MS*	Time
Pixel-based analysis				
One pixel per object	Spectral	87.33 ± 8.29	76.00 ± 14.30	$\mathbf{4.53 \pm 0.02}$
All pixels	Spectral	90.89 ± 0.77	84.56 ± 1.76	1122.01 ± 299.37
Object-based analysis				
Statistical metrics	Spectral	93.33 ± 3.51	86.00 ± 5.16	4.66 ± 0.04
Statistical metrics	Spectral + VI	$\mathit{94.33 \pm 3.87}$	$\mathit{89.00 \pm 5.68}$	4.86 ± 0.02
Statistical metrics	Spectral + VI + Shape	$\mathbf{96.33 \pm 3.67}$	$\mathbf{93.00 \pm 6.75}$	5.03 ± 0.06
Histograms	Spectral	92.67 ± 5.62	87.00 ± 8.23	6.73 ± 0.04
Histograms	Spectral + VI	93.00 ± 5.54	85.00 ± 11.79	6.98 ± 0.04
Histograms	Spectral + VI + Shape	92.67 ± 5.62	85.00 ± 12.69	6.90 ± 0.06

The best results are highlighted in bold face and the second ones in italics.

In relation to the number of patterns used for training the model, it can be seen that the use of only 90 patterns per class (corresponding to the 9 training folds of the 10-fold experimental design) seems to be sufficient in this case. Nonetheless, it would be interesting to analyse how the model would change when providing a lower number of training patterns. We performed an additional experiment using a 2-fold stratified technique, instead of the previously used 10-fold approach (implying 50 patterns per class for training the model, instead of 90). The results for *Acc* and *MS* for the method based on the computation of the statistical metrics using the three sets of information are the following: 94.33 ± 0.47 in terms of *Acc* and 92.00 ± 0.00 in terms of *MS*. This is representative of the fact that the model can be trained accurately without much training information.

Fig. 4 shows the results obtained for the best performing method for a region of the experimental field. From this figure, it can be seen that the method performs reasonably identifying most crop and weed pixels. However, the methodology proposed classifies some soil pixels as crops (pixels that could be associated to imperfections on the ground such as rocks). This motivates the use of a more intelligent and thorough technique for selecting the objects to be labelled (e.g. objects that significantly differ in the spectral histogram from the rest).

Fig. 4. Representation of the different steps for the procedure considered: image acquisition, segmentation of the image, and, finally, classification.

5 Conclusions and future work

This paper explores different classification alternatives to the problem of weed detection via Unmanned Aerial Vehicles in sunflower crops. More specifically, we have compared two common approaches (object-based analysis versus pixel-based analysis) and studied the influence of different data features and training samples in the performance of the classifier.

There are several conclusions that can be extracted from this work. It can be seen that an object-based analysis is more suitable than a pixel-based approach for the application considered. Firstly, because of the better performance, and secondly because of the decrease of the computational time. Moreover, the use of other features, such as the information about the vegetation indexes or the shape of the objects, is meaningful and leads to better results. It has also been seen that the use of a small training sample (in this case, 90 patterns per class) is sufficient to yield a reasonable performance. However, there are still some issues that prevail and that will be considered in future studies. Firstly, it could be interesting to analyse which statistical metrics are the best to provide enough information for properly identifying weeds. Another issue is which data features are the best combination for this specific problem (e.g. texture features have not been studied in this case). Furthermore, it could be very useful to analyse if a specific technique for histogram classification (such as the histogram intersection kernel [12]) leads to better results. Finally, a method for selecting the most dissimilar patterns could be proposed, in order to be able to create more robust training samples.

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