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Evaluation of hierarchical self-organising maps for weed mapping using UAS multispectral imagery

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ABSTRACT

Remote sensing has been used for species discrimination and for operational weed mapping. In the study presented here, the detection and mapping of *Silybum marianum* using a hierarchical self-organising map is reported. A multispectral camera (green-red-NIR) mounted on a fixed wing Unmanned Aircraft System (UAS) was used for the acquisition of high-resolution images of a pixel size of 0.1 m, resampled to 0.5 m. The Supervised Kohonen Network (SKN), Counter-propagation Artificial Neural Network (CP-ANN) and XY-Fusion network (XY-F) were used to identify the *S. marianum* among other vegetation in a field, with *Avena sterilis L.* being predominant. As input features to the classifiers, the three spectral bands of Red, Green, Near Infrared (NIR) and the texture layer were used. The *S. marianum* identification rates using SKN achieved an accuracy level of 98.64%, the CP-ANN achieved 98.87%, while XY-F was 98.64%. The results prove the feasibility of operational *S. marianum* mapping using hierarchical self-organising maps on multispectral UAS imagery.

1. Introduction

Mapping of weeds is the basis of site-specific weed management, which is of high importance to sustainable agriculture. Remote sensing and Unmanned Aircraft System (UASs) have been used in weed mapping for various precision agriculture applications (López-Granados et al., 2016). The detection of weeds using UASs equipped with multispectral cameras poses additional challenges compared to ground sensing (field spectroscopy with hand-held equipment and sensors mounted on ground vehicles), due to low spectral resolution. Torres-Sánchez et al. (2013) used a UAS equipped with a six-channel multispectral camera at altitudes of 30 m, 60 m and 100 m, providing narrow spectral (10 nm bandwidth) and high spatial (10–50 mm pixel^{-1}) resolutions. This study demonstrated that the discrimination performance was inversely dependent on the altitude. According to Hunt et al. (2005) and Woebbecke et al. (1995) the discrimination performance could be further enhanced by the use of either the Normalised Green-Red Difference Index (NGRDI) or the Excess Green index.

In order to achieve real-time recognition of target plants and to make use of specific applications of various management practices in a more efficient and precise way, RGB camera images acquired in oblique view and support vector machine architectures have been utilised (Tellaeche et al., 2011). It has further been established that weed species detection with sensors (Moshou et al., 2002) is crucial for the application of the necessary chemical herbicides at the correct spraying dosage. The discrimination between crops and weeds based on spectral leaf reflectance has been attempted in previous studies; for example, Borregaard et al. (2000) proved that it is possible to effectively discriminate between crop and plants as well as between weed species, while other researchers have reported identification accuracies as low as 31% in an effort to identify 10 weed species in a corn field by utilising One Class Classification algorithms. A hyperspectral camera mounted on a ground vehicle has been used for data acquisition (Pantazi et al., 2016). Further approaches aimed at weed recognition have been introduced, taking into account only the leaf size and shape analysis, such as the method proposed by Søgaard (2005) for automated machine vision, based on weed species classification via active shape modelling (ASM), which achieved an accuracy identification rate of between 65% and 90%. Moreover, it has been shown that spectral reflectance characteristics are sufficient to distinguish different weed species. Moshou et al. (2001) achieved the successful

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discrimination between maize crop and weeds with a correct classification rate of 96% for the maize and 90% for the weeds. Regarding the discrimination of sugar-beet from weeds in the same study, the accuracy rate was 98% and 97% respectively. Nevertheless, these results were aimed solely at crop - weed discrimination, not weed species recognition.

Kohonen (1982) introduced a neural network (NN); a tool which is capable of importing signals (x) that belong to a high-dimensional space by forming arbitrary dimension grids (Kohonen and Honkela (2007). Self-Organising Maps (SOMs) are one of the most prominent of the various Artificial Neural Networks (ANN) architectures presented in literature (Kohonen, 1988). Until recently, they were applied in varying fields and are currently one of the primary machine learning tools (Marini, 2009). Self-Organising Maps (SOMs) have the potential to handle problems in an unsupervised manner, independently targeting data.

Within agricultural research, unsupervised models have been modified to function in a supervised framework for the purposes of solving regression and classification problems. Methods including counter-propagation Artificial Neural Networks (CP-ANNs) have been developed, which provide additional features to SOMs, thus enabling the former to act as classifiers. In the CP-ANN architecture, an output layer is appended to the SOM layer (Zupan et al., 1995). Variants of CP-ANNs are Supervised Kohonen Networks (SKNs) and XY-fused Networks (XY-Fs) (Melssen et al., 2006) both of which act as classifiers.

Silybum marianum (milk thistle) is a weed responsible for major loss of crop yield and is also hard to eradicate. The presence of *S. marianum* in a field will negatively affect all crop cultivations. It is especially detrimental to the cultivation of cereal (Khan and Marwat, 2006) and leguminous crops (Parsons and Cuthbertson, 2001). It is also regarded as a problematic weed for the cultivation of ornamental species (Buxbaum et al., 1999). Khan et al. (2011) demonstrated the allelopathic effects of cold water extracts of *S. marianum* causing detrimental effects on germination percentage, germination time, germination index and seed vigor index on *Phaseolus vulgaris, Vigna radiata, Cicer arietinum*, and *Glycine* max. Approaches to managing this weed have usually involved herbicides like glyphosate, but they are expensive and have environmental consequences (Giesy et al., 2000). In addition, their excessive use led to pollution, degradation of ecosystems, and to resistance by some weeds (Powles, 2008). For this reason, it is important to map the extents and distribution of the weed's appearance, so as to define the appropriate site-specific weed management strategy.

In the current paper, the proposed hierarchical map classifiers are evaluated in a UAS-based mapping of the spatial distribution of *S. marianum*. Mapping of *S. marianum* was performed by using a fixed wing UAS, carrying a multispectral camera. The features that were used were constructed from the combination of spectral and textural information. Three hierarchical map classifiers including SKN, CP-ANN and XY-F were used to classify the data into *S. marianum* and other plants.

2. Materials and methods

2.1. Study area

The study was carried out at a 10.1 ha field situated in the area of Thessaloniki (40°34′14.3″N 22°59′42.6″E) (Fig. 1). The ground topography is approximately level and the elevation is 75 m. The area is mainly covered in graminaceous weeds, with large patches of *S. marianum*. Other weeds in the field include: *Avena sterilis* L., *Bromus sterilis* L., *Solanum elaeagnifolium* Cav, *Conium maculatum* L., *Cardaria draba* L. and *Rumex sp.* L. This field, previously cultivated with cereals, was abandoned in 1990 due to heavy infestation by S. marianum. Since 2006 it is part of a long-term experiment regarding biological control of S. marianum with smut fungi.

2.2. Datasets

The remote sensing imagery was obtained with a Canon S110 NIR camera (12 Mpixels) on board an eBee fixed wing UAS[1] on 19.05.2015, a clear day with mild wind (<3 m s^{-1}). The camera's spectral bands include green (560 nm, Full-Width Half-Maximum (FWHM): 50 nm), red (625 nm, FWHM: 90 nm) and near-infrared (850 nm, FWHM: 100 nm). The camera configuration was set to shutter priority mode and the shutter speed to 1:2000 s, while aperture and ISO sensitivity was set to automatic. Images were acquired in Raw format and then converted to JPEGs while accurate geotagging was applied to the EXIF out of the drone's flight log. The images were taken from a height of 115 m with 75% overlap and 70% sidelap, from 11:00 am to 12:00 pm, with a ground sampling distance of 0.04 m and with an image footprint of 160 m $\times$ 120 m. The collected 55 images were orthorectified in a mosaic using Pix4Dmapper Pro[2] software. The orthomosaic was generated using the Digital Surface Model (2.5D model) that comes from the 3D densified point cloud. Six GCPs were used for the creation of the orthomosaic. These were black and white markers positioned around the boundaries and within the field before the UAV image acquisition. Their location was recorded using an RTK-GPS (Spectra Precision SP80, horizontal accuracy 8 mm + 1 ppm). An estimate of the accuracy of the orthomosaic production was 2 pixels horizontal and 3 pixels vertical (RMSE). The image produced had a resolution of 0.1 m and was further rescaled to 0.5 m to avoid dealing with unwanted detail during pixel-based classification of very high resolution imagery, as explained in Tamouridou et al. (2016) (Fig. 1).

Texture was an additional information layer that was added to the orthomosaic. It was created from the NIR band of the UAS using the local variance algorithm with a moving window of 7 $\times$ 7 pixels. Local variance is described by the following equations:

$$Variance = \frac{\sum (x_{ij} - M)^2}{n - 1} \quad (1)$$

$$Mean = \frac{\sum x_{ij}}{n} \quad (2)$$

where xij is the digital number value of pixel (i,j), n represents the number of pixels in a window and M is the Mean of the moving window.

The outline of patches of *S. marianum* as well as of other vegetation were recorded *in-situ* on the day of the UAS image acquisition, using a Trimble GeoXH 2008 GPS with EGNOS correction and accuracy better than 0.3 m. The actual datasets used for the mapping consisted of the three spectral bands (R, G, NIR) and the texture layer. The recorded patches of known vegetation type were used as ground truth data for image classification, in order to train the classification algorithm and evaluate its performance. *S. marianum*, *C. maculatum* and *A. sterilis* have similar spectral profile in the visible spectrum and this has led to misclassification. When overlaid on the orthorectified UAS mosaic, this ground truth dataset comprised of 4745 pixels corresponding to *S. marianum* and 1434 pixels corresponding to other vegetation types. From the ground truth dataset, a calibration dataset was constructed, which consisted of 2868 pixels equally distributed between the class of *S. marianum* and the class of other vegetation. This calibration

[1] http://www.geosense.gr/en/ebee/.
[2] https://pix4d.com/.