Plant discrimination by Support Vector Machine classifier based on spectral reflectance

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1. Introduction

Weeds are one of the most challenging problems for farmers, threatening their ability to produce good-quality food cost-effectively (Oerke, 2006). Relying only on traditional chemical weed control not only imposes high financial pressure on farmers, but also has negative impacts on the environment, creating herbicide-resistant weeds and polluted soils (Owen, 2016; Ramsden et al., 2017; Strassemeyer et al., 2012; Deng et al., 2014; Fletcher and Reddy, 2016). Raymond et al. (2005) reported a new prototype capable of automatically detecting green plants (i.e., green-from-brown) and applying pesticides in real time. However, this system was incapable of discriminating weeds from crops (green-from-green). Askraba et al. (2016) reported real-time green-from-green discrimination sensors based on the use of a quad bike in conjunction with a spectral reflectance sensor. While this sensor demonstrated the concept of green-from-green discrimination, its accuracy was limited.

SVM is a machine learning technique that is typically used for object classification (Colgan et al., 2012; Guyon et al., 2002; Hernault et al., 2010; Ma and Guo, 2014; Wang et al., 2011). This technique has been proposed, but not implemented, as a promising tool for weed-plant discrimination (Lee et al., 2010).

In this paper, we propose the use of Support Vector Machines (SVMs) in conjunction with spectral reflectance measurements for the development of a high-accuracy plant discrimination sensor. In all experiments a weed sensor engine developed by Askraba et al. (2016) is used to collect the intensities of the laser beams reflected off vegetation and soil at three different wavelengths, and the Normalised Difference Vegetation Indices (NDVIs) are then calculated from these measured intensities. Two different investigations are carried out, namely: (1) a comparison between the accuracies of the weed detection methods based on the machine-learning-based Support Vector Machine (SVM) method and the conventional method of dual-NDVI-based plant discrimination (Symonds et al., 2015); (2) a comparison between the discrimination accuracies of the SVM method using as input the raw reflected laser beam intensities and the NDVI values.
2. Methodology

2.1. System description

2.1.1. Plant discrimination unit

Fig. 1 shows the layout of the spectral-reflectance-based Plant Discrimination Unit (PDU) that was used in the experiments to collect the intensities of the laser beams reflected off the investigated plants and background. The PDU was developed by Askraba et al. (Askraba et al., 2011; Symonds et al., 2015). PDU is photonic-based spectral reflectance system performing noncontact spectral reflectance measurements of plants and soil which is fully described by Arie (Paap, 2014).

The real-time Plant Discrimination Unit (PDU) shown in Fig. 1 comprised two sets of three-laser modules, two symmetric coated optical cavities, plus a linear array of high-speed photo detectors (a line-scan camera) and a motherboard housing six sub-modules including a laser driver, a central processing unit, a temperature controller, a board for a nozzle activator, a driver for the line-scan camera, and analogue and digital power supplies. The PDU unit was robustly boxed, using a rigid container and a light-weight dust shield, to overcome tough operational conditions including vibrations, shocks, and high temperatures (Symonds et al., 2015).

2.1.2. Vegetation illumination

Fig. 2 shows the schematic of the PDU layout and shows how laser beams illuminate the vegetation.

2.1.3. Beam generation

Each laser module used three 1 mm collimated laser beam sources including two red (635 nm and 685 nm) lasers and one near-infrared (785 nm). Two thin-film beam combiners were used in order to combine the laser beams, as described by Askraba, 2013. All lasers were aligned so that the beams emitted from the laser module were collinear, overlapped, and had identical polarisation directions.

The collimated laser beams emitted from each laser module were launched into an optical cavity. An optical cavity was used to generate multiple beams from a laser source in each side. The cavity was tilted by 23 degrees to cover a span of 490 mm. The top (back) of the optical cavity was coated with a reflective surface and the bottom (front) of the cavity was coated with a non-uniform transmissive surface (Askraba, 2013), so that all the beams emitted from the cavities had almost the same intensities (Symonds et al., 2015).

The embedded controller of the PDU employed a dsPIC33F microcontroller that controlled the lasers and image sensor and carried out the data processing needed to determine the spectral properties of the plants and the background soil. The distance between two adjacent laser beams was 15 mm and the gap between the two optical cavities was 34 mm. The total number of laser beams emerging from both cavities at one time was 30 beams (15 beams for each cavity). Each laser was driven by a constant current driver that controlled the power of each laser diode. The optical power for the 635 nm, 685 nm, and 785 nm lasers at the entrance to the optical cavity was set to 20 mW, 25 mW, and 15 mW, respectively. The line scan sensor recorded the intensities of the reflected beams. The line scan sensor was a Hamamatsu S9227-03 sensor, comprising an array of 512 photodiodes of size 250 × 10 µm. The analogue output voltage was converted to using a 10-bit analogue to digital converter (ADC).

2.1.4. Physical layout of the experiment

All the experimental data were collected using the custom-designed testing facility (referred herein as the ‘testbed’) shown in Fig. 3, which was built and installed at the Electron Science Research Institute (ESRI) by Festo, Western Australia.1

The testbed shown in Fig. 3 enabled data to be collected at speeds of up to 20 km/h with submillimetre accuracy. The PDU unit was placed (looking straight down (i.e. 90° from horizontal)) on a trolley which carried the PDU unit and moved it via a stepper motor. A laptop communicated via a router to control the stepper motor. Communication with the PDU was via Wi-Fi using the router, which enabled the speed of the PDU to be controlled, as illustrated in Fig. 3.

2.2. Data description

2.2.1. Data collection

Corn (Zea mays) leaves and broad silver beet (Beta vulgaris subsp.) leaves were used in the experiments to evaluate the performance of the developed algorithms. Data were selected representative to broad/narrow leaf combinations for the experiment. All data were captured on 6 March 2017, three weeks after germination for the corn leaves and four weeks after germination for the silver beet leaves. For each experimental run, three plants (grown in pots) were individually placed along the central area of the tray pots. In order to be able to generalise the results, training plants and testing plants were kept separately. The PDU was moved to capture the spectral reflectance data for each set of the three plants at a spatial resolution of 1 mm along the traveling speed of the PDU. The total number of scanned lines per run was 550. Data augmentation was achieved by randomly rotating the plants through ten different orientations.

2.2.2. NDVI calculation

The spatial profile of the detected beams was approximately Gaussian, and each beam occupied around 13 pixels, illustrated in Fig. 4 as peak region. Peak detection was performed to calculate the

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intensities of the reflected laser beams (Paap, 2014). The location of the peaks was recorded. Each peak existed in a region above the predetermined threshold. The starting and ending pixels of the region in which the peak exists were also recorded, as shown in Fig. 4.

Subsequently, the peak value was normalised with respect to the optical power of the incident beams emerging from the cavities, which were previously recorded by a Newport power meter, as follows (Paap, 2014):

\[ P_i = \frac{R_i}{D_i} \]  

(1)

where \( R_i \) is the measured peak of the reflected beam, \( D_i \) is the power of the laser beam emerging from the cavity.

The measured intensities of the laser beams reflected off the vegetation were used for the calculation of two different NDVIs, defined as

\[ NDVI_{635} = \frac{P_{685} - P_{635}}{P_{685} + P_{635}} \]  

(2)

\[ NDVI_{685} = \frac{P_{785} - P_{685}}{P_{785} + P_{685}} \]  

(3)

where, \( P_{685}, P_{635}, \) and \( P_{785} \) are the detected intensities of the 635 nm, 685 nm, and 785 nm laser beams reflected off the vegetation or background. It is clear from Eqs. (2) and (3) that the NDVIs represent the slope of the reflectance spectrum of a plant at two different wavelengths. The NDVI is typically a number between \(-1\) and \(1\). The intensities of
Since chlorophyll in plants exhibits high absorption properties in the red region and low absorption properties in the NIR region, measuring the NDVI around the red edge (i.e., between the visible and the near-infrared regions) enables the health status and key properties of the plants to be identified. Note that intense sunlight might influence the NDVI value, and hence, a shield is typically used to minimise the impact of atmospheric conditions in real-time weed detection runs.

### 2.2.3. Input structure

Since the aim of the research was to compare the discrimination accuracies of machine-learning SVM methods based on the use of Gaussian kernels with conventional NDVI-based discrimination methods, only the last beams emerging from the left and right cavities of the PDU (i.e., the central two beams) were considered for data collection. Note that it was possible to run both the SVM and dual-NDVI-based approaches with all the 15 beams in each side of the optical cavity, however, since we are focusing on proof-of-concept demonstration we selected the last beam (close to the cavity’s centre) of each cavity for data collection. These beams provide more reliable data since they are seen by the image sensor (placed between the optical cavities) at almost right angle, making their intensity measurements straightforward, whereas the accurate measurement of the intensities of the other beams require time-consuming calibration. The scanned span for each run was 550 mm, and the data was collected at 1 mm intervals.

Thirteen pixels were allocated for the calculation of the power of each detected laser beam. Since the laser beam typically has a Gaussian profile, the intensities of the reflected beams \( [P_{l,1}, P_{l,2}, \ldots, P_{l,13}] \) detected by the 13 pixels were different in values, with one pixel of the 13-pixel set exhibiting the highest photocurrent, which corresponds to the peak power of the laser beam. A peak detection algorithm was specially developed to determine the maximum photocurrent, which enabled the peak power value of the reflected laser beams to be calculated.

The SVM algorithm was trained and tested with an NDVI input (generated from the measured right and left beams), given by

\[
A_{\text{right,NDVI}} = \begin{bmatrix}
NDVI_{685,\text{right},1} & NDVI_{685,\text{right},2} & \ldots & NDVI_{685,\text{right},N}
\end{bmatrix}
\]

\[
A_{\text{left,NDVI}} = \begin{bmatrix}
NDVI_{685,\text{left},1} & NDVI_{685,\text{left},2} & \ldots & NDVI_{685,\text{left},N}
\end{bmatrix}
\]

The SVM algorithm was also trained and tested with raw data input, given by

\[
A_{\text{right,raw}} = \begin{bmatrix}
P_{685,\text{right},1} & P_{685,\text{right},2} & \ldots & P_{685,\text{right},N}
\end{bmatrix}
\]

\[
A_{\text{left,raw}} = \begin{bmatrix}
P_{685,\text{left},1} & P_{685,\text{left},2} & \ldots & P_{685,\text{left},N}
\end{bmatrix}
\]

where

\[
P_{\text{fl,1}} = [P_{l,1}, P_{l,2}, \ldots, P_{l,13}] \]

Fig. 5 shows the flowchart used to calculate the NDVI and raw data inputs.

Fig. 6(a and b) illustrates the partitioning of the data sets using NDVI and raw data, where blocks of 100-data-set are used to generate the Matlab*-based input structure of data.

### 2.3. Data analysis

Three 15-cm-diameter pots, containing either silver beet or corn plants, were distributed over a span of 550 mm. The size of the input data set for each scan was 550, corresponding to a spatial resolution of 1 mm. Since the material filling the gaps between the pots was soil (not green), data-set blocks that exhibited less than 15% green content (i.e., where the soil content was dominant) were discarded. This reduced the number of data-set blocks from 19 to between 7 and 12. Note that species were considered green when their NDVI values were in the range 400–800; otherwise, they were considered soil (Liu et al., 2014). Data augmentation was subsequently carried out by randomly rotating the plant pots in the test rig 10 times, thus increasing the input data-set blocks to 70–120. The data augmentation procedure used for training and testing the algorithm is illustrated in the flowchart in Fig. 7.

### 2.4. Algorithms

SVM algorithms were applied to the NDVI values as well as the raw data to compare the performance of the dual-NDVI-based plant discrimination algorithm recently reported by Symonds et al. (2015).

#### 2.4.1. Dual-NDVI-based plant discrimination algorithm

The dual-NDVI-based plant discrimination algorithm has recently been used to classify green plants. It is based on measuring two NDVI
values at different wavelengths (NDVI_{635} and NDVI_{685}) and generating a scatter NDVI plot for each plant. Scatter plots generated by Symonds et al. have shown that for a particular green leaf, the NDVI values typically fall within a parallelogram region (Symonds et al., 2015), and that the discrimination of a plant A from a plant B is only possible when their NDVI parallelogram regions do not overlap. The boundaries of the parallelogram region for each plant are typically determined through trial and error (the criterion is based on minimising the false negatives). This trial-and-error approach is time consuming and generally inaccurate, because the calculation of the boundaries of the parallelogram region is user-dependent.

In this paper, we modify the approach for defining the boundaries of the parallelogram region by calculating the statistical properties of the NDVIs of the training data — namely, the mean values and standard deviations of the NDVI values, and by using linear regression to evaluate the slope of the parallelogram. To accurately evaluate the boundaries of the parallelogram region, all measured NDVI values that fell outside 400 and 800 (which corresponded to soil and non-green objects) were discarded. Fig. 8 graphically illustrates the steps used to define the boundaries of the parallelogram region for a plant. The coordinates of the centre of the parallelogram region are the mean values of NDVI_{635} and NDVI_{685}. The breadths of the parallelogram region are the standard deviations of NDVI_{635} and NDVI_{685}, and the slope is defined through linear regression.

2.4.2. Support Vector Machine (SVM) algorithm

Various pattern classifier types were considered for plant classification, including ANN. However, since the number of inputs in the experiments was limited to around 150 data in a 200-dimensional space, it was difficult to generalize an ANN with such a relatively-low number of inputs (Bousquet and Elisseeff, 2002; Hornik, 1991). SVM, in contrast to other pattern classifiers, enables classification with a low number of inputs, and hence, it was selected for this research investigation.

Support Vector Machine (SVM) is a suitable algorithm for binary classification. An SVM algorithm is based on defining a surface in a multi-dimensional input space and maximising the arithmetical margin between two input data sets [31]. In other words, SVM ideally finds the best hyperplane which can separate one class from another. The best hyperplane in ideal SVM means a hyperplane with maximum margin between each class. Margin in ideal hyperspace is defined as half of the utmost width parallel to the hyperplane that has no interior data in it. Hyperplane normally can separate many data but not all of them. Therefore, idea hyperspace does not usually exist. To solve this problem, the SVM uses soft margin with penalty parameter.

In here, a label was first given to each input data according to the type of data (e.g., corn or silver beet). Then, the testing and training datasets were separated. For the training datasets, they were shuffled randomly before training. The soft margin SVM algorithm was implemented in MATLAB Version 9.1.0.441655 (R2016b). The built-in Matlab function “fitcsvm” was applied to the shuffled training dataset.
The dual approach which is a standard procedure to solve the optimization problem is applied by using the *fitcsvm* function. Gaussian kernels were used and appropriately adjusted by auto scaling (using the Matlab heuristic procedure). Sequential Minimal Optimization (SMO) was used to solve the quadratic programming (QP) problem.

3. Results

The performances of all algorithms were compared by calculating, for each algorithm, a confusion matrix, which is a table showing the number of true positives and negatives as well as false positives and negatives after prediction.

![NDVI block partitioning](image1)

![Raw data block partitioning](image2)

Fig. 6. (a) NDVI-set block partitioning, and (b) Raw data set block portioning. Partitioning into 100-data-set block is used to generate Matlab®-based input structure of data.
3.1. Comparison of dual-NDVI-based plant discrimination and SVM algorithms with NDVI inputs

A set of 100 dual-NDVI sets (corresponding to a linear distance of 100 mm) was used in conjunction with the dual-NDVI-based plant discrimination algorithm for the classification of corn and silver beet. For this algorithm, the discrimination of plant X from plant Y was based on the following criteria: After generating the scatter plot, if the data counts falling within the parallelogram region of plant X exceed those falling within the parallelogram region of plant Y, then the detected plant is X. Otherwise, the detected plant is Y.

On the other hand, for the Gaussian SVM classifier, 100 consecutive dual-NDVI measurements were used as input during training, and a hyper-sphere for non-probabilistic binary classification was formed. Tables 1 and 2 show the confusion matrices for the dual-NDVI-based plant discrimination and SVM algorithms.

In all tables, the following terminology is used: True Positive (TP) for a plant that was correctly identified as a crop (corn); True Negative (TN) for a plant that was correctly not recognised as a crop (silver beet); False Positive (FP) for a plant incorrectly identified as a crop, False Negative (FN) for a plant incorrectly not recognised as a crop.

Note that for algorithm training, out of the 190 augmented data-set blocks, 73 data-set blocks exhibited more than 15% green content for corn, and 74 data-set blocks exhibited more than 15% green content for silver beet. On the other hand, for algorithm testing, out of the 190 augmented data-set blocks, 115 and 73 data-set blocks exhibited more that 15% green content for corn and silver beet, respectively. Therefore, in order to compare the accuracies of the algorithms, 73 data-set blocks were selected for both training and testing.

It is obvious from Tables 1 and 2 that while both algorithms produced almost similar numbers of true positives and false negatives, the Gaussian-kernel SVM algorithm predicted less false positives (10) and higher true negatives (63) than the dual-NDVI-based plant discrimination algorithm (39 and 34, respectively). Tables 1 and 2 also show that out of the 146 data-set blocks (73 for corn and 73 for silver beet), the dual-NDVI-based plant discrimination algorithm predicted 96 as corn and 50 as silver beet, whereas the SVM algorithm predicted 82 as corn and 64 as silver beet.

The sensitivity, specificity, precision and accuracy of a discrimination algorithm are as following (Fawcett, 2006)

\[ \text{Sensitivity} = \frac{TP}{(TP + FN)} \]  
\[ \text{Specificity} = \frac{TN}{(TN + FP)} \]  
\[ \text{Precision} = \frac{TP}{(TP + FP)} \]  
\[ \text{Accuracy} = \frac{TP + TN}{(TP + FP + TN + FN)} \]

Fig. 9 shows the sensitivities, specificities, precisions and accuracies attained using the dual-NDVI-based plant discrimination and SVM algorithms. The third column in Fig. 9 shows the improvements that are calculated according to the following formula:

\[ \frac{\text{Second algorithm metric} - \text{First algorithm metric}}{\text{First algorithm metric}} \times 100 \]
Gaussian SVM with NDVI data and 70 as silver beet (all correctly). SVM algorithm predicted 76 as corn (73 correctly and 3 incorrectly) that out of the 146 test data sets (73 for corn and 73 for silver beet), the algorithm, obtained using raw data as input. It is obvious from Table 3 input data. The third column in Fig. 10 shows the improvements, that is accuracies of the Gaussian-kernel SVM algorithm, for both raw and NDVI Eqs. (4) and (5). Table 3 shows the confusion matrix for the SVM algorithm, signifcant improvements in sensitivity (85%), precision (43%) and accuracy (31%).

3.2. SVM classifier performance comparison using NDVI and raw input data

In this section, we focus on the improvement in the performance of the SVM algorithm when raw data, rather than NDVI data, was used as input. The intensities of the beams reflected off the investigated vegetation (raw data) and the corresponding NDVI values were stored in an input data structure. This enabled (i) training of the SVM algorithm with input raw as well as NDVI data and (ii) testing it to assess its performance for both raw and NDVI input data. Note that the raw data sets are given by Eqs. (6)–(8), whereas the NDVI data sets are given by Eqs. (4) and (5). Table 3 shows the confusion matrix for the SVM algorithm, obtained using raw data as input. It is obvious from Table 3 that out of the 146 test data sets (73 for corn and 73 for silver beet), the SVM algorithm predicted 76 as corn (73 correctly and 3 incorrectly) and 70 as silver beet (all correctly).

Fig. 10 shows the sensitivities, specificities, precisions, and accuracies of the Gaussian-kernel SVM algorithm, for both raw and NDVI input data. The third column in Fig. 10 shows the improvements, that is calculated according to the Eq. (13). It is clear from Fig. 10 that by using raw data, rather than NDVI data, as the input for the SVM algorithm, significant improvements in sensitivity (11%), specificity (13%), precision (22%), and accuracy (20%) are achieved.

4. Discussion

The main finding of the current study was that using the Gaussian SVM algorithm with NDVI values as inputs enables significant improvements in specificity, precision, and accuracy compared to the conventional dual-NDVI-based plant discrimination algorithm (even when the boundaries of the plant-scattering plot parallelograms were defined automatically, based on measuring the means and standard deviations of the NDVI values). A possible explanation for this is as follows: Both the dual-NDVI-based plant discrimination and the Gaussian SVM algorithms use a set of 200 data for input (100 for the NDVI_{635} and 100 for the NDVI_{685}). However, for the dual-NDVI-based algorithm, the NDVI_{635} and NDVI_{685} values are defined independently in a two-dimensional space, and plant identification is based on aggregating the 100 readings for each NDVI value. In contrast, the SVM algorithm considers a set of 200 inputs in a 200-dimensional space. This enables better plant classification, since the correlation between the patterns of the NDVI values can be evaluated while the SVM is being trained and tested.

In addition, the number of input data per set for the NDVI-based SVM algorithm was 200, while that for the raw-data-based SVM algorithm was 7800 (200 data sets × 13 intensities per laser source × 3 laser sources). Having a space with a larger number of dimensions helps the SVM algorithm to be trained with more data patterns.

Note that, unlike hyperspectral imaging, the novel approach presented in this paper is based on using the reflected intensities of only three lasers of different wavelengths, in conjunction with the SVM algorithm for corn and silver-beet classification. Thus, this approach particularly results in (i) fewer data in comparison to hyperspectral techniques and (ii) a faster processing time, which is essential in real-time applications and (iii) a plant classification accuracy of 97%, which is higher than that attained using a conventional algorithm based on dual-NDVI calculation.

5. Conclusion

Algorithms based on Support Vector Machine (SVM) learning with NDVI and raw data inputs were developed and their weed-crop discrimination performances were evaluated and compared with a conventional plant discrimination algorithm based on the measurement of discrete NDVIs and the use of data aggregation. Data was collected by measuring the spectral reflectance properties of corn (as a crop) and silver beet (as a weed) at 635 nm, 685 nm, and 785 nm. The results of this work show that the discrimination performance of the Gaussian-kernel SVM algorithm, with either raw reflected intensities or NDVI values being used as inputs, provides better discrimination accuracy than the conventional discrete NDVI-based aggregation algorithm. Experimental results, carried out in laboratory conditions, demonstrated that the Gaussian SVM algorithms can classify corn from silver beet with corn/silver-beet discrimination accuracy of 97%, whereas the maximum accuracy attained using the conventional NDVI-based method does not exceed 70%. The key scientific contribution of this paper was the demonstration of the ability of the SVM algorithm to classify broad-leaved (silver beet) and narrow-leaved (corn) plants with high accuracy by generating a set of 100 raw reflected intensities. The application of machine learning techniques for plant classification...
opens the way for new techniques for weed management and precision agriculture.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.compag.2018.03.026.

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