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Plant discrimination by Support Vector Machine classifier based on spectral reflectance

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A B S T R A C T

Support Vector Machine (SVM) algorithms are developed for weed-crop discrimination and their accuracies are compared with a conventional data-aggregation method based on the evaluation of discrete Normalised Difference Vegetation Indices (NDVIs) at two different wavelengths. A testbed is especially built to collect the spectral reflectance properties of corn (as a crop) and silver beet (as a weed) at 635 nm, 685 nm, and 785 nm, at a speed of 7.2 km/h. Results show that the use of the Gaussian-kernel SVM method, in conjunction with either raw reflected intensities or NDVI values as inputs, provides better discrimination accuracy than that attained using the discrete NDVI-based aggregation algorithm. Experimental results carried out in laboratory conditions demonstrate that the developed Gaussian SVM algorithms can classify corn and silver beet with corn/silver-beet discrimination accuracies of 97%, whereas the maximum accuracy attained using the conventional NDVI-based method does not exceed 70%.

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., 2017). Automating weed control can play an important role in achieving viable weed management (LóPez-Granados, 2011; Slaughter et al., 2008). Most of the research carried out on automated weed-plant discrimination is based on the use of image recognition techniques (Aitkenhead et al., 2003; Burgos-Artizzu et al., 2011; Cope et al., 2012; Eddy et al., 2014; Hamuda et al., 2017). While image recognition by using typical cameras provide relatively high discrimination accuracies (> 90%), camera images are typically captured at visible wavelengths in the rage 300–700 nm. However, some of the key plant characteristics used in plant discrimination fall outside the visible range (Filella and Penuelas, 1994).

Plant discrimination based on the use of portable spectrometers for measuring the spectral reflectance properties of the illuminated vegetation has been investigated by different research groups (de Castro 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.

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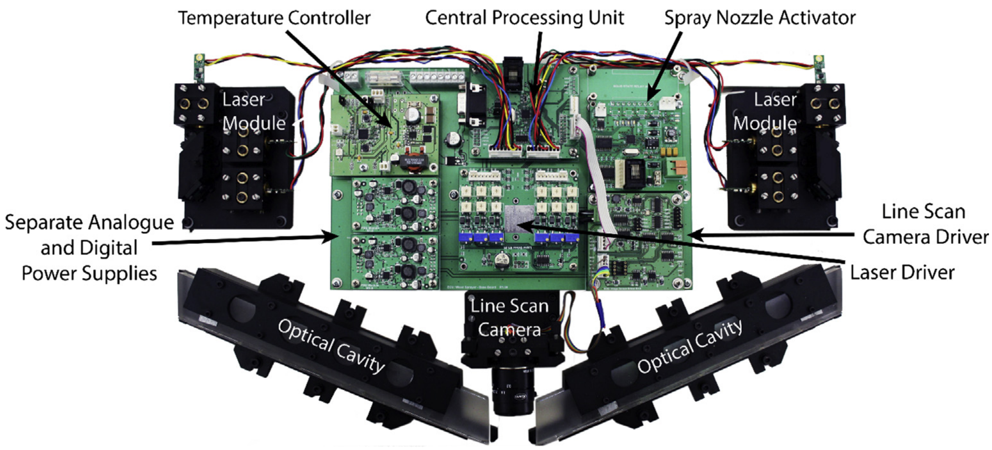

Fig. 1. A picture of the PDU developed for plant discrimination. The PDU has two sets of three-laser modules, two symmetric optical cavities, a line scan camera (which is an array of high-speed linear photo detectors), plus a motherboard comprising six daughter-boards, including a central processing unit, a laser driver, a temperature controller, a line scan camera driver, a spray nozzle activator, and analogue and digital power supplies.

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

[1] Festo: https://www.festo.com/cms/en-au_au/index.htm

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