Computers and Electronics in Agriculture 145 (2018) 153–160

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Evaluation of support vector machine and artificial neural networks in weed detection using shape features

Adel Bakhshipour[a], Abdolabbas Jafari[b,c,*]

[a] Department of Agricultural Mechanization Engineering, University of Guilan, Iran
[b] Biosystems Engineering Department, Shiraz University, Iran
[c] Lincoln Agritech Ltd., Lincoln University, New Zealand

ARTICLE INFO

Keywords:
Machine vision
Image processing
Pattern recognition
Weeding robot
Precision agriculture
Plant phenotype

ABSTRACT

Weed detection is still a challenging problem for robotic weed removal. Small tolerance between the cutting tine and main crop position requires highly precise discrimination of the weed against the main crop. Close similarities between the shape features of sugar beet and common weeds make it impossible to define an exclusive feature to be able to efficiently detect all the weeds with acceptable accuracy. Therefore in this study, it was tried to integrate several shape features to establish a pattern for each variety of the plants. To enable the vision system in the detection of the weeds based on their pattern, support vector machine and artificial neural networks were employed. Four species of common weeds in sugar beet fields were studied. Shape feature sets included Fourier descriptors and moment invariant features. Results showed that the overall classification accuracy of ANN was 92.92%, where 92.50% of weeds were correctly classified. Higher accuracies were obtained when the SVM was used as the classifier with an overall accuracy of 95.00% whereas 93.33% of weeds were correctly classified. Also, 93.33% and 96.67% of sugar beet plants were correctly classified by ANN and SVM respectively.

1. Introduction

One of the main obstacles discouraging farmers from growing sugar beet (*Beta vulgaris*) is the tedious job of weed removal which imposes a considerable cost to the cultivation. Weeding robots cannot come into reality unless highly precise weed detection is achievable. Research around weed detection is mostly followed in two ways including the use of machine vision as well as studying the spectral signature of weeds and main crops.

Weeds can be discriminated from the main crop in cases that their spectral reflectances are noticeably different (Eddy et al., 2014; Jinglei et al., 2017; Pantazi et al., 2016; Strothmann et al., 2017; Suzuki et al., 2008).

On the other hand, in the range of the visible spectrum, machine vision techniques have provided the chance to extract several features from the scene which can be used for object discriminations (Aitkenhead et al., 2003; Bosch et al., 2007; Guijarro et al., 2011; Montalvo et al., 2013; Pandey et al., 2016; Ribeiro et al., 2005; Tang et al., 2015; Van Evert et al., 2006; Yang et al., 2003; Zhang et al., 2014). These features can be categorised into three classes including colour, texture and shape features.

Colour features can be helpful when there is a considerable difference between the colour of weeds and main crop. The success rate of colour-based detection highly depends on the studied plants and their colour differences even if various colour spaces are used or compositions of colour components are tried (Hamuda et al., 2017; Jafari et al., 2006; Kazmi et al., 2015a; Zheng et al., 2017). Colour processing in YCrCb colour space assisted by a combination of the vertical projection and the linear scanning methods was applied by Tang et al. (2016) for weed detection under different illumination conditions. An accuracy of 92.5% was achieved.

Texture features of crop and weed patches are distinctive criteria in cases where leaves occlusion and overlapping of mature plants are problematic (Bakhshipour et al., 2017).

Shape features of individual leaf or whole plant are another source of information that can be extracted from the images to discriminate weeds from crops. High accuracy of detection can be expected if there is no occlusion or leaves overlapping (Kazmi et al., 2015b; Neto et al., 2006; Perez et al., 2000; Swain et al., 2011).

Due to close similarity of weeds and main crop, it is almost impossible to detect weeds by using a single feature. In these situations, pattern recognition methods such as Support Vector Machine (SVM)

* Corresponding author at: Biosystems Engineering Department, Shiraz University, Iran.
E-mail addresses: ajafari@shirazu.ac.ir, jafaria@lincolnagritech.co.nz (A. Jafari).

https://doi.org/10.1016/j.compag.2017.12.032
Received 25 January 2017; Received in revised form 20 December 2017; Accepted 22 December 2017

and Artificial Neural Networks (ANN) incorporate several features to make a decision about the admission of a plant in weed or crop group.

Deep neural networks perform well in image classification but they require very large amounts of data. Convolutional neural networks combined with k-means unsupervised feature learning as a pre-training process was used by Tang et al. (2017) for weed identification in soybean seedlings with an accuracy of 92.89%.

Support vector machine (SVM) is a supervised learning method based on modern statistical learning theory (Vapnik and Vapnik, 1998) that generates input-output mapping functions from a set of labelled training data (Wang, 2005). Classification of some aquatic weeds species by means of an SVM has represented a reasonable accuracy when a set of shape descriptors are used in the SVM (Pereira et al., 2012). SVM has also successfully achieved the classification of chilli and weeds in digital images taken from single plants (Ahmed et al., 2012).

Despite similarities between ANN and SVM in pattern recognition, some differences are experienced in their performance, convergence, and getting stuck in local minima. Their achievement depends on the complexity of the cases and regulated parameters of the classifier. Since there is not a persistent preference for choosing one of the two classifiers, besides a small enhancement in the accuracy of weed detection can be of great importance for a weeding robot, both classifiers were assessed in this study. Therefore the main objective of this study was to evaluate the accuracy of SVM and ANN in discrimination between weeds and sugar beet based on shape features extracted from images.

2. Material and methods

The project had four main parts namely image acquisition, image segmentation, feature extraction and plant classification which are distinctly described below:

2.1. Image acquisition

Digital images used in this project were provided from experimental sugar beet fields of Shiraz University. To use the shape characteristics of plants for weed detection, it was necessary to take the images at early growth stages so that the overlaps of individual plants were negligible. Images used in this study were taken at 4-leaf stage of plant growth which was the beginning of critical weed control period. The camera was positioned at the height of 0.5 m above the crop row and images were captured with a resolution of 960 × 1280 pixels. A shelter was used on top of the image acquisition setup to exclude the direct sunlight and let the scene to be illuminated just by diffused light. In total, 50 images were taken to collect the five plant species including sugar beet and four common weeds in the sugar beet fields namely Pigweed (*Amaranthus chlorostachys*), Lambsquarters (*Chenopodium album*), Hare's-ear mustard (*Conringia orientalis*) and Turnip weed (*Rapistrum rugosum*) (Fig. 1). Since images were acquired from normal growth condition in the field, several plants appeared in each image. Therefore in the next step, from these collections of images, some parts were cropped to comprise just a single plant. Five sets of the plants were collected so that each set included 120 images which produced 600 (=5 × 120) images in total.

2.2. Image segmentation

The captured RGB images were transferred to the computer to be processed using image processing toolbox of MATLAB software (R2013a, The Mathworks, USA).

Combinations of RGB colour components have proved their potential in segmentation of vegetation from soil (Gée et al., 2008; Guijarro et al., 2011; Meyer and Neto, 2008; Ribeiro et al., 2005) Therefore in this project, three indices were generated as linear combinations of Red (R), Green (G) and Blue (B) colour components to be used for greenness detection (Table 1).

By applying optimal thresholds on Excessive Green (EXG) and Green Minus Red (GMR) in RGB colour space, as well as the green colour difference (Cg) in YCrCb colour space (Bulanon et al., 2002), the green regions inside the images were detected and primary binary images resulted. These binary images were used in the main weed detection algorithm and will be described in section 2.5.

2.3. Feature extraction

In this study, the possibility of discrimination of weeds from sugar beet using three sets of shape features has been investigated. Shape factors and moment invariants as region-based features and Fourier descriptors as boundary based features were extracted from images and were evaluated.

The flowchart in Fig. 2 shows the steps of extracting the shape features and introducing them to the classifiers. The samples were binarized (Fig. 3) and three sets of shape-based features including shape factors, moment invariant features and boundary Fourier descriptors were extracted.

2.3.1. Shape factors

Shape factors are dimensionless numerical values calculated based on at least two simple shape measures, which makes them independent to object orientation, translation and scale (Gościewska and Frejlichowski, 2015). These features may provide useful information for morphological description of plants.

Primary shape features namely Area, Perimeter and Major and Minor axis length values of each plant were extracted from binary images and four shape factors were calculated using Eqs. (1)–(4) (Shouche et al., 2001):

$$ShapeFactor1 = \frac{4{\cdot}\pi{\cdot}Area}{Perimater^2} \tag{1}$$

$$ShapeFactor2 = \frac{Major\ axis\ length}{Area} \tag{2}$$

$$ShapeFactor3 = \frac{Area}{Major\ axis\ length^3} \tag{3}$$

$$ShapeFactor4 = \frac{4{\cdot}Area}{\pi{\cdot}Major\ axis\ length{\cdot}Minor\ axis\ length} \tag{4}$$

2.3.2. Moment invariant features

Moment invariants are functions created based on the information of both the shape boundary and its interior region (Hu, 1962). These normalised functions are independent of geometric translation, scaling, or rotation (Wong et al., 2007). This makes moment invariant features to be insensitive to particular deformations whereas they provide higher discrimination power to differentiate among objects of different classes (Zulkifli et al., 2011). Assuming the function $f(x, y)$ as the image of a plant (where x, y are pixel coordinates); the discrete form of a 2-dimensional moment of the $f(M_{p,q})$ is calculated using Eq. (5) (Keyes and Winstanley, 2001):

$$M_{p,q} = \sum_x \sum_y x^p y^q f(x,y) \quad p,q = 0,1,2,3,... \tag{5}$$

Note that, since the features were calculated for a binary image, then $f(x, y)$ was '1' for plant pixels and '0' for the background. To be invariant to translation, the coordinates of object centroid $(\bar{x},\bar{y})$ were included and the central moment $(\mu_{p,q})$ can be defined as Equation (6) (Wong et al., 2007):

$$\mu_{p,q} = \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q f(x,y) \quad p,q = 0,1,2,3,... \tag{6}$$

To be independent of scale changes, the moments were normalised using Eq. (7):