Computers and Electronics in Agriculture 112 (2015) 10–19

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

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

Detecting creeping thistle in sugar beet fields using vegetation indices

Wajahat Kazmi [a,*], Francisco Jose Garcia-Ruiz [b,1], Jon Nielsen [b,1], Jesper Rasmussen [b,1], Hans Jørgen Andersen [a,2]

[a] Department of Architecture, Design and Media Technology, Aalborg University, Rendsburggade 14, Room: 5 353, 9000 Aalborg, Denmark
[b] Department of Plant and Environmental Sciences, Højbakkegård Allé 9, University of Copenhagen, 2630 Taastrup, Denmark

ARTICLE INFO

Article history:
Received 5 April 2014
Received in revised form 3 January 2015
Accepted 8 January 2015
Available online 4 February 2015

Keywords:
Weed detection
Precision agriculture
Vegetation index
Sugar beet
Thistle

ABSTRACT

In this article, we address the problem of thistle detection in sugar beet fields under natural, outdoor conditions. In our experiments, we used a commercial color camera and extracted vegetation indices from the images. A total of 474 field images of sugar beet and thistles were collected and divided into six different groups based on illumination, scale and age. The feature set was made up of 14 indices. Mahalanobis Distance (MD) and Linear Discriminant Analysis (LDA) were used to classify the species. Among the features, excess green (ExG), green minus blue (GB) and color index for vegetation extraction (CIVE) offered the highest average accuracy, above 90%. The feature set was reduced to four important indices following a PCA analysis, but the classification accuracy was similar to that obtained by only combining ExG and GB which was around 95%, still better than an individual index. Stepwise linear regression selected nine out of 14 features and offered the highest accuracy of 97%. The results of LDA and MD were fairly close, making them both equally preferable. Finally, the results were validated by annotating images containing both sugar beet and thistles using the trained classifiers. The validation experiments showed that sunlight followed by the size of the plant, which is related to its growth stage, are the two most important factors affecting the classification. In this study, the best results were achieved for images of young sugar beet (in the seventh week) under a shade.

1. Introduction

Weeds cause crop yield losses with a global average of 34% and which in certain cases, may exceed 70% (Monaco et al., 1981). They compete with crops for nutrients, water and light and therefore, their removal at an early stage is important for a higher crop production.

The most common tool for weed removal is blanket spraying of herbicides which raises environmental concerns. In order to reduce the amount of herbicides, knowledge of when and where to apply them is necessary which is provided by Integrated Weed Management (IWM) and Site Specific Weed Management (SSWM). IWM strives to reduce a weed population to an acceptable level while limiting the impact on the quality of soil, water and other natural resources below a threshold. It uses a combination of biological, mechanical and chemical tools to suppress the weed population at the most effective stages of its life cycle. IWM is complemented by SSWM which describes the techniques for controlling weeds according to their spatial variability in the field (Christensen et al., 2009; Lopez-Granadoz, 2011).

The concept of SSWM narrows the treatment to weed patches (Christensen and Heisel, 2003) or even down to plant scale (Ehsani et al., 2004). This requires sensing and perception technologies and therefore, machine vision is proving vital in agricultural automation.

Canadian or Creeping Thistle (*Cirsium Arvensis* (L.) Scop.) is an invasive perennial weed species that causes major yield loss to Sugar Beet (*Beta vulgaris*). Sugar beet is among the world's important crops, and in 2011 its estimated global production was around 278 million tonnes (FAOSTAT, 2011). Sugar beet industry in Denmark generated more than 137 million USD in 2011 and is becoming the seventh most valuable commodity of the country in terms of revenues (FAOSTAT, 2011). Creeping Thistle (thistle) is becoming increasingly frequent (Andreasen and Stryhn, 2012) and 5–6 plants/m^2 can halve the crop yield (Miller et al., 1994). Tyr and Veres (2012) graded thistles to be one of the two most dangerous perennial weeds for sugar beet stands in Slovak republic.

In order to apply SSWM for thistles, Danish projects such as ASETA (Kazmi et al., 2011) has investigated the utility of unmanned

* Corresponding author. Tel: +45 9940 8834.
E-mail addresses: wajahat.kazmi@outlook.com (W. Kazmi), fgr@agromapping.com (F.J. Garcia-Ruiz), jon@plen.ku.dk (J. Nielsen), jer@plen.ku.dk (J. Rasmussen), hja@create.aau.dk (H. Jørgen Andersen).
[1] Tel: +45 3533 3572.
[2] Tel.: +45 9940 8834.

http://dx.doi.org/10.1016/j.compag.2015.01.008
0168-1699/

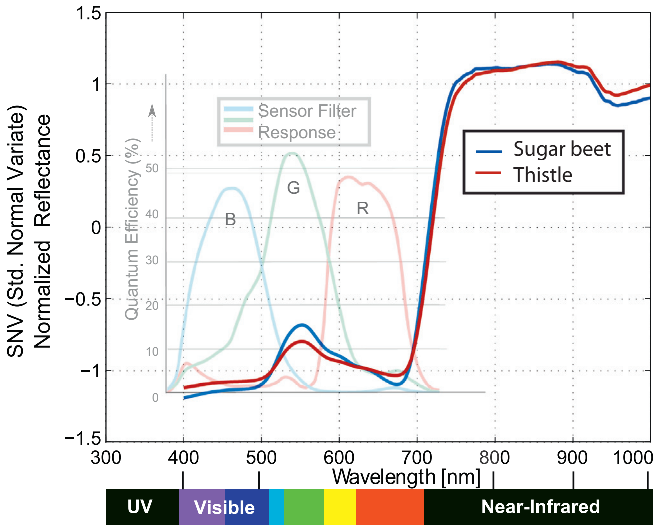


Fig. 1. Foreground: Spectral signature of Sugar beet and Creeping thistle recorded by Spectra Vista's GER 1500 spectroradiometer. It can be noted that the species have noticeable difference in violet, blue, green and red bands, while the discrimination in Near-Infrared band is also comparable. Background: Filter response of the Bumblebee XB3 camera (Quantum Efficiency curve of the ICX445 sensor) provided by Point Grey Research. Peak values: B(470 nm) = 46%, G(525 nm) = 53%, R(640 nm) = 48%, measured according to EMVA 1288 standard (Point Grey, 2013). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

aerial and ground vehicles equipped with advanced imaging sensors. Multi-spectral aerial imaging for the detection of weed patches was investigated as the plant canopies of both sugar beet and thistle show a separation in the spectral response (Fig. 1).

However, to coordinate the aerial detection with subsequent spot treatment, a ground vehicle equipped with a close range imaging system may also be necessary. This is particularly useful for low density patches or single weed plants which are difficult to identify from aerial or satellite platforms (Backes and Jacobi, 2006).

The reduced soil impact, carbon footprint and required human resource for the unmanned ground vehicles (UGV) are making them increasingly famous as a future weed removal technology (another example is European project RHEA (2011)). UGVs can even deploy short range intense lasers to destroy unwanted plants and therefore can completely avoid the use of chemicals (Mathiassen et al., 2006). But for any such scheme to be successful, a sensing system capable of efficiently detecting weeds must be available.

State-of-the-art smart imaging sensors can be highly expensive. This may be affordable with aerial platforms, since fewer aerial vehicles can serve a large field area. But in order to apply timely treatment, several UGVs may be required as the ground vehicles have restricted mobility given the structure and the spread of the plantation inside the fields. Imaging sensors for UGVs must therefore be kept economical and weed detection real-time for a field deployable system.

1.1. Background

For machine vision based weed detection, color vegetation analysis is perhaps the most efficient way. Raw RGB channels and extracted vegetation indices have been widely used, primarily, for vegetation detection against background (Meyer and Neto, 2008; Golzarian et al., 2012).

Extensive work has been done in exploiting vegetation indices for crop/weed classification. Tosaka et al. (1998) used color information to separate vegetation from background and then thinned out the vegetation to identify sugar beet plants with 55–78% accuracy. El-Faki et al. (2000b) used several color indices to classify three weed species competing each wheat and soyabean. They collected data both outdoor under sunlight and indoor under artificial lighting and achieved an accuracy of 54.9% for soyabean and 62.2% for wheat. Jafari et al. (2006) used stepwise discriminant analysis on the R, G and B color channels for sugar beet and seven types of weeds. They processed the sunlit and shadow datasets separately. The individual weed Correct Classification Rates (CCR) ranged from 79% to 89% producing overall accuracy of 88%. Nieuwenhuizen et al. (2007) used ExG and RB (Red–Blue) index to detect volunteer potato plants among sugar beet, obtaining 49% and 97% accuracy for data from two different fields.

Color indices can be scaled down to pixel classification, but the limiting factor is the separation among the subject plant species in the reflected wavelengths. When the separation is not enough, shape features are used after background subtraction (Pérez et al., 2000), or a combination of color and shape features such as Golzarian and Frick (2011) combined color indices with Waddle Disk Ratio (WDR) which is a measure of roundness of the leaf. Their system was able to classify green house grown wheat from ryegrass and brome grass with an accuracy of 88% and 85% respectively. Åstrand and Baerveldt (2002) used average and standard deviation of the three color channels combined with shape features such as elongation, compactness and perimeter, etc. to detect weeds in sugar beet fields using neural network classifiers.

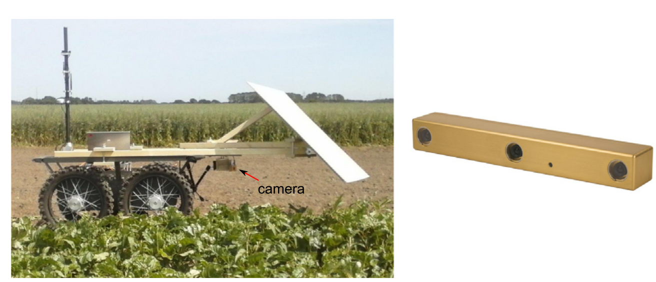
Approaches for sugar beet so far adopted in literature either do not address thistles (Jafari et al., 2006) or else include them among other weed species and use shape features (Åstrand and Baerveldt, 2002; Sogaard, 2005). Other approaches employ multi-spectral imaging extending from visible to Infrared wavelengths (Feyaerts et al., 1999; Backes and Jacobi, 2006; Vrindts et al., 2002).

1.2. Objective

As can be observed in Fig. 1, there is a noticeable separation between thistle and sugar beet in the blue, green and red spectra. Therefore, the objective in this article is to present a system that can accurately and efficiently detect thistles in sugar beet fields down to plant scale using only vegetation indices thus avoiding shape features which require occlusion detection or segmentation of plant organs (stems or leaves).

2. Materials and methods

Color (RGB) images were acquired using Point Grey's Bumblebee XB3 (Fig. 2(b)). The camera uses three Sony ICX445 1/3″ progressive scan CCD's. One of the three cams were used at the image resolutions and corresponding GSDs (Ground Sample Dis-



(a) RobuRoc 4 (b) Bumblebee XB3

Fig. 2. Equipment: The unmanned ground vehicle (UGV) and the color camera used in the experiments. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)