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Assessment of an inter-row weed infestation rate on simulated agronomic images

G. Jones [a], Ch. Gée [a,*], F. Truchetet [b]

[a] ENESAD/DSI/LGAP 'Laboratoire en Génie des Agroéquipements et des Procédés', 21 Bld Olivier de Serres, 21800 Quétigny, France
[b] UMR 5158 uB-CNRS, Le2i, 12 rue de la Fonderie, 71200 Le Creusot, France

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ABSTRACT

We present a robust and automatic method for evaluating the accuracy of Crop/Weed discrimination algorithms. The proposed method is based on simulated agronomic images and a Crop/inter-row Weed discrimination algorithm can be divided into the two following steps. Firstly a crop row detection (Hough transform) is performed from the identification of the crop line vanishing point taking the opportunity of the perspective geometry of the scene. Afterwards, the discrimination between crop and weeds is done by a region-based segmentation method using a blob-colouring analysis and an inter-row Weed Infestation Rate (WIR) can be estimated. We propose to test and validate the robustness of this method on simulated images with perspective.

To simulate photos taken from a virtual camera, a pinhole camera model is used and the field is modelled according to the spatial periodicity distribution of crop seedlings and the spatial distribution of weed species based on stochastic processes (Poisson process, Neyman–Scott aggregative process or a mixture of both).

For each simulated image, the comparison between the initial inter-row WIR and the detected inter-row WIR informs us about the errors made by the algorithm. A pixel classification between the two classes – Crop and Weed – is performed in order to identify misclassification errors. This comparison demonstrates an accuracy of better than 85% is possible for inter-row weed detection.

1. Introduction

During the 1970s, the highlighting of the heterogeneity of agronomical characteristics in fields led to the development of precision agriculture. One field of research is the regulation of herbicide spraying (Robert, 1999) and its uses must be led by new weed strategies based on site-specific weed management. Recent technological developments include 'real-time' robotic systems that have become commercial systems like DetectSpray (Felton and McCloy, 1992) or Weedseeker (Felton, 1995). Nevertheless, as data processing is usually very basic, these systems discriminate only between vegetation (either crops or weeds) and background (soil, rocks and residues). These devices spray only on vegetation (crop and weeds) detected and identified by their spectral properties using photodetectors (Hopper et al., 1976; Haggar et al., 1983). However, the spectral approach to identify plants is questionable. Indeed, although there is clear discrimination between monocotyledons and dicotyledons (Vrindts, 2000; Gée et al., 2004, 2006a), the discrimination between weed species and crop in-field reflectance measurements needs to be improved (Bossu et al., 2005). Therefore, image-processing technologies for plant discrimination have been extensively investigated to specifically spray weed patches. Nevertheless, few machine vision systems have led to real-time applications and most are devoted to a specific task and usually at low operation speeds (Lee et al., 1999; Blasco et al., 2002; Søogard and Heisel, 2002). Many Crop/Weed discrimination studies have investigated segmentation of colour images (Lu et al., 2001; Nieuwenhuizen et al., 2007; Langner et al., 2006), shape (Franz et al., 1991; Woebbecke et al., 1995) features analysis (Hague et al., 2006; Watchareeruetai et al., 2006), Gabor filter (Tian et al., 1999; Vioix et al., 2002), Hough Transform (Hemming and Rath, 2002; Fontaine and Crowe, 2006; Gée et al., 2006b; Rao and Ji, 2008) and blob-colouring analysis (Bossu et al., 2006a) or texture (Zang and Chaisattapagon, 1995) analysis. Many authors implementing these image-processing algorithms for Crop/Weed discrimination usually test and discuss the limits of their algorithms but do not clearly report assessment of their methods. This is understandable given that usually the image processing methods are tried on in-field images. It is unreliable and difficult to compare such results to a ground truth from manual counting of weed density in the field corresponding to the field of view of the vision system. For instance, Onyango and Marchant (2005) developed a segmentation algorithm to separate

* *Corresponding author.* Tel.: +33 3 80 77 27 71; fax: +33 3 80 77 28 16.
E-mail address: c.gee@enesad.fr (Ch. Gée).

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crop rows from weeds. Applying a Crop/Weed competition model and comparing to algorithm results, they studied the consequences of misclassification errors of the image-processing algorithm (to classify pixels either as Crop or Weed) on the estimated yield of cabbage crops.

The aim of the present study is twofold. Firstly, a simulation of agronomic images composed of crop and weed to assess the Crop/Weed discrimination image processing is presented. Different spatial distributions of weed species in a crop field are developed to generate the virtual field. They are based on stochastic processes of three types: a Poisson process, a Neyman–Scott aggregative process and a mixture of both. We show that proper use of these processes leads to realistic weed plant distributions as observed in real crop fields. Secondly, an algorithm for discrimination between crop and inter-row weeds based on spatial location of plants was implemented. The detection of crop rows in the field uses the Hough Transform with a region-based segmentation analysis for discrimination between crop and weed plants. This allows an automatic inter-row Weed Infestation Rate ($dWIR_{inter}$) extraction, estimated from perspective wide-view images. The method is particularly well adapted to perspective images and is dedicated to cereal crops. Particular attention is paid to these kind of perspective images, since our laboratory is developing a real-time precision sprayer, based on machine vision fastened to the front of a tractor with an R_X angle of 70° from the vertical axis, thus implying perspective effects (Bossu et al., 2006b).

The double aim is achieved considering that the first herbicide treatments in a season are at an early growth stage of plants when WIR in the crop field is low. This justifies use of the Poisson stochastic process, although complemented by the Neyman–Scott aggregative process to generate the virtual field.

The originality of this study is testing and validating algorithms' effectiveness using simulated agronomic images that model the spatial distribution of weed species in a crop field by stochastic processes.

These objectives were accomplished in different steps: (1) collection of a database of simulated images in many different situations (different weed pressures, different weed spatial distributions, etc.); (2) extraction of an inter-row WIR by image processing (Hough Transform and blob-colouring analysis) and comparison with the initial inter-row WIR ($iWIR_{inter}$); (3) classification of each pixel for a Crop/Weed discrimination; and (4) evaluation of the accuracy of the algorithm. The discussion is devoted to the analysis of the accuracy of these algorithms for simulated images.

2. Materials: image database

A database of simulated images was used to test and validate the image-processing algorithm developed for Crop/Weed discrimination in perspective agronomic images.

As explained in the introduction, the modelling of perspective agronomic images was divided into two steps: (1) simulation of a crop field with invasive weed species based on the spatial distribution models of plants (*i.e.* crop and weed) population, and (2) construction of a virtual photograph of the crop field, depending on the intrinsic and extrinsic parameters of the virtual camera (*i.e.* pinhole camera model). Different input parameters are required to characterise simulated images (Table 1).

Crop and weeds are represented by patterns created from real plants, for a more realistic scene two different types of patterns were created: one for monocotyledons and one for dicotyledons. Their distributions in the field are explained as follows.

Table 1
Initial parameters used for simulation.

Parameters	Values
The spacing-row and the type of the crop	18 cm for wheat
	12 cm for barley
	45 cm for sunflower
The weed spatial distribution	(a) Poisson law
	(b) Neyman–Scott process
	(c) A mixture of both
Global weed density	[0; 45] % of the global vegetation density
Crop density	Depending on the size of the field
Camera parameters	CCD dimension: 7 mm × 5.28 mm
	Focal length: 16 mm
	Rotation: $R_X = 70°$, $R_Y = R_Z = 0°$
	Translation: $T_x = T_y = 0$, $H = T_z = 1$ m

2.1. Crop field simulation

From pre-defined length and width of the field and the type of crop plant (*i.e.* wheat with 18 cm row spacing), the number of crop rows in the image is computed. Then lines associated with crop rows were transformed into sets of individual crop patterns, each one associated with each crop type. The individual crop pattern was randomly oriented at four angles (0°, 30°, 60° and 90°), along the centreline of the crop row. To simulate as well as possible a real field and to account for seedling growth problems as occur in real fields, the crop pattern is suppressed with a given probability (*e.g.* 1/3) when the crop rows were discretised.

The situation was more complex for weed plants. Many spatial models have been developed to explain growth and behaviour of plant populations (Williamson, 1996; Hastings, 1997); some used a deterministic approach for growth and spread of plant species using ordinary or partial diffusion equations (*e.g.* differential equations; Williamson, 1996). For instance, an SIS model (Kermack and McKendrick, 1927) is based on the total amount of 'susceptible' (S) and 'infected' (I) land or the Fisher equation (Fisher, 1973) and it represents a nonlinear reaction-diffusion model.

In this study, the simulation of a snapshot of the field is done without knowledge of any edophic (influence of soil type) or demographic factors (seed or vegetation reproduction) (Rew and Cousens, 2001). For this purpose, the investigation is restricted by developing very simple spatial stochastic models of spread of invasive weed species, although reality is much more complex. Indeed, the dynamics of weed population is clearly influenced by farming practices and soil parameters (Mortensen et al., 1998). Assuming no plant–environment interaction (Hastings, 1997), the emergence of new weed plants at new sites in the field can be modelled as a simple two-dimensional stochastic process (Goreaud, 2000). Therefore, in the simulated image the weed plants can be represented by a punctual process. Assuming that weed spatial distribution is a random process with no memory between successive events, and that there is little emergence of weeds compared to crop plants, it can be fully modelled by a Poisson punctual process. Three different stochastic processes were implemented: a Poisson process, a Neyman–Scott aggregative process and a mixture of both depending on the distribution of weed plants.

2.1.1. Poisson process

In the global field, simulated by a two-dimensional surface (D), the weed density (λ: plants/m^2) is defined as the ratio between the number of weed plants (N) and D. D is subdivided into a set of small areas (S) assuming that all the events in one area were independent of those in another area. The size of each S was defined by the number of weed plants required to reach the desired weed density. We assumed that each S will contain a draw of a Poisson law with $\lambda S = 5$.