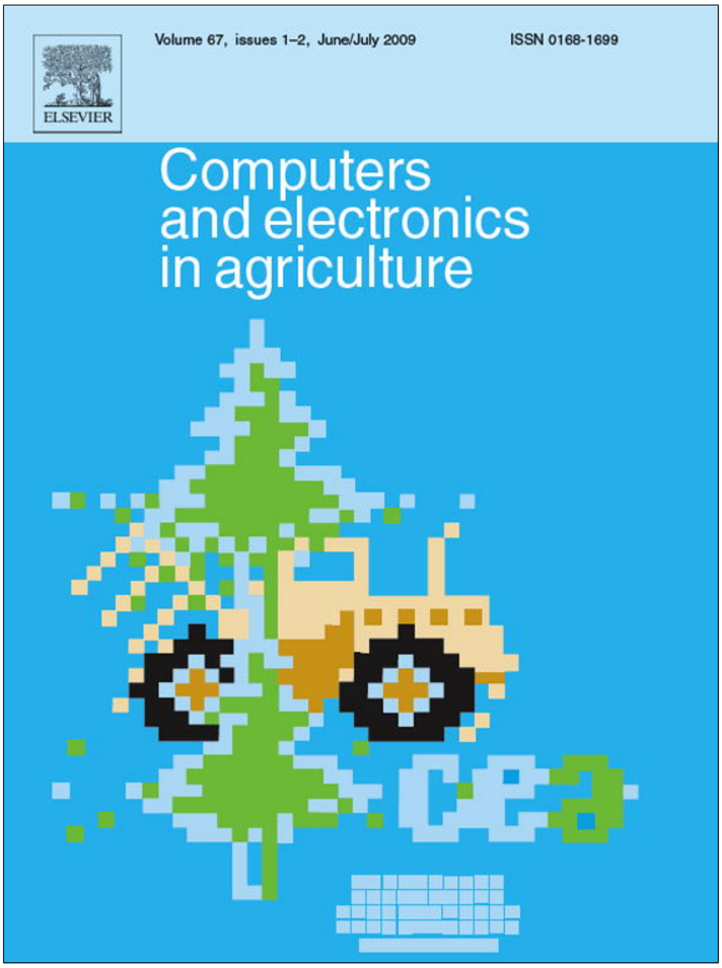
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Original paper

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

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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

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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 $\lambda S = 5$.

The mean weed density in these areas is λ, the same as the entire field, given by $\lambda = N(S)/S$. Assuming that this density is significantly smaller than the maximum number of plants that may grow in an area, the probability of emergence of a number of k weed plants in this area can be expressed by a Poisson distribution with parameter equal to λS, which represents the mean number of occurrences in a small area. Indeed, in the low coverage limit, the emergence of a new weed plant (*i.e.* an event) in a small area is a stochastic process with no memory. The present simulation process generated an image composed of a mixture of small areas containing few weed plants, distributed according to Poisson statistics. Consequently, the probability $P(X=k)$ of finding a small area of the image that contains exactly k weed plants is given by Eq. (1).

2.1.2. Poisson law

$$P_k(\lambda S) = P(X = k) = \frac{(\lambda S)^k}{k!} e^{-\lambda S} \tag{1}$$

where $P(X=k)$ is the probability of an area having k number of occurrences (=weeds).

In this simulation, λS was deduced from the initial weed density parameter. The number of weed seeds in small areas was randomly determined by applying a discrete random number generator (Ripley, 1983) and developed by Goreaud (Pélissier and Goreaud, 2001) for agronomic applications. The weed plant positions were then stochastically chosen in a uniform distribution restricted to each S.

2.1.3. Neyman–Scott process

In crop fields, the weed spatial distribution is usually heterogeneous and more particularly patchy in cereal fields (Brown and Steckler, 1995). To model this type of distribution, an aggregative stochastic process was used: a Neyman–Scott process (Neyman and Scott, 1958). We assumed that growth of weed aggregates were restricted in a pre-defined region. This region was chosen as an ellipsoid rather than a circular region to account for the influence of farming practices; implements tend to make weed aggregates in patches elongated along the crop row.

To simulate aggregated weed seedlings in a small area, the number of aggregates is determined and then the number of weed plants per aggregate. The number of aggregates (*i.e.* germs) was defined by the ratio of the global number of weed plants to the average number of weed plants per aggregate, a predefined parameter of the simulation. Then the germ positions were randomly chosen using a uniform distribution restricted to the image size.

Afterwards the number of weed seeds per aggregate was determined by applying the Poisson discrete random number generator. Finally, the weed seed positions were randomly chosen using a uniform distribution assuming that they are included in an ellipsoid area.

2.1.4. Mixture

In this simulation, it is also possible to simulate images with the two types of weed spatial distributions, as usually observed in real fields. For the best visualisation and recognition of weeds from every spatial distribution, two different seed patterns were modelled (Fig. 1).

2.2. Construction of virtual photographs

The pinhole camera model is used (Faugeras, 1993), where a linear transform maps a point $\mathbf{M}$ (X, Y, Z) of the real world (3D space) into a point $\mathbf{m}$ (u, v) of the camera space (in pixels). This model uses intrinsic (camera model) and extrinsic (camera location and orientation) parameters.

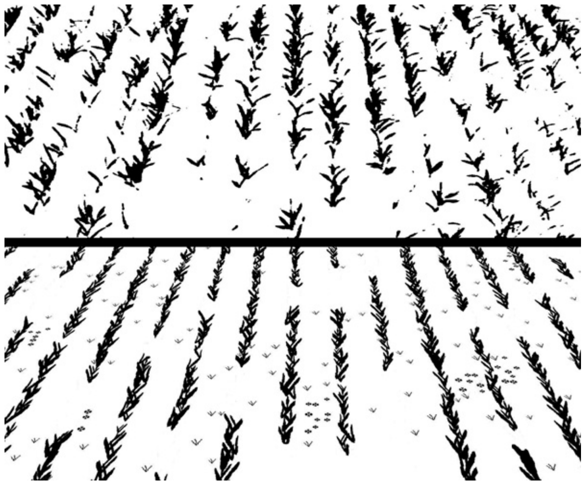

Fig. 1. Visual comparison between a picture of a wheat field (upper picture) and its simulation (lower picture).

The five intrinsic parameters of a camera are: the focal length (f), the coordinates (u_0, v_0) of the principal point, the two scale factors (α and β) and the skew coefficient (γ) defines the angle between the two image axes.

The six extrinsic parameters of the optical system are three rotations, R_X, R_Y and R_Z (along the X, Y and Z axes, termed roll, pitch and yaw angle, respectively), and three translations, T_x, T_y and T_z.

Applying this camera modelling to the virtual crop field with weed plants, a new virtual image is processed (*i.e.* a virtual photograph). As an example, a visual comparison between a real and a virtual picture is presented in Fig. 1.

In the present study, the simulated images (Fig. 2) were obtained according to the experimental conditions of the vision-based real time patch-sprayer (a U1000 SONY camera, CCD dimension: 7 mm × 5.28 mm) developed in our laboratory (Bossu et al., 2006b). The five intrinsic parameters of the SONY camera were deduced from the calibration toolbox (Bouguet, 2005). Table 1 summarizes the initial parameters used for the simulation.

2.3. Weed infestation rate (WIR)

In the image of a virtual field, initial vegetation densities (*i.e.* crop and weed) can be perfectly controlled. The knowledge of the

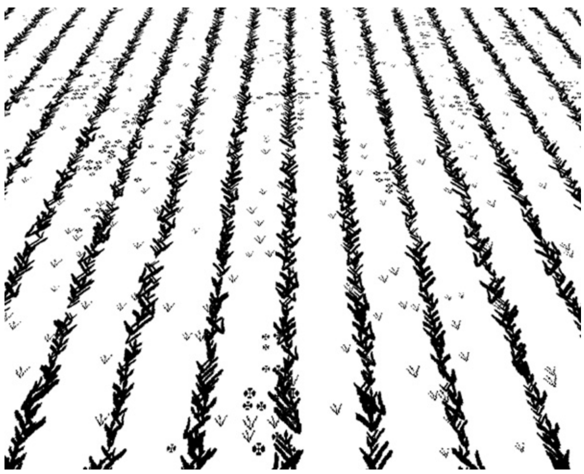

Fig. 2. Picture of a virtual field through an optical system. The simulation parameters are summarized in Table 1 for a wheat field with a mixture of two weed spatial distributions. The initial inter-row WIR ($\mathrm{iWIR_{inter}}$) is 15.28%.

inter-row and intra-row weed pixels allows deduction of different WIR:

total plant pixels = Crop pixels + Weed pixels

Weed pixels = inter-row Weed pixels + intra-row Weed pixels

$$\text{initial WIR}_{\text{global}}(\text{iWIR}_{\text{g}}\%) = \frac{\text{weed pixels} \times 100}{\text{total plant pixels}} \quad (2)$$

$$\text{initial WIR}_{\text{intra-row}}(\text{iWIR}_{\text{intra}}\%) = \frac{\text{intra-row weed pixels} \times 100}{(\text{crop} + \text{intra-row weed})\text{pixels}} \quad (3)$$

$$\text{initial WIR}_{\text{inter-row}}(\text{iWIR}_{\text{inter}}\%) = \frac{\text{inter-row weed pixels} \times 100}{(\text{crop} + \text{inter-row weed})\text{pixels}} \quad (4)$$

2.4. Picture database characteristics

A database of simulated images was created with the camera parameters of Table 1. In the present study, the efficiency of the image processing algorithms was tested with only one camera configuration, as used for the real-time precision sprayer developed in our laboratory. A total of 2520 images were simulated and analysed. Three different configurations of images were used, depending on the three different weed spatial distributions: Poisson, Neyman–Scott and a mixture of both. For each case, simulated images were performed with $\text{iWIR}_{\text{inter}}$ of 0–40% with a 2% step. For each $\text{iWIR}_{\text{inter}}$ value, 20 images were simulated to have a statistical set large enough to be representative of the situation. For all images two methods of Crop/Weed discrimination were tested and compared.

3. Methods

3.1. Crop row detection

The algorithm developed for processing perspective images is based on a Hough Transform (Hough, 1962), filtered according to knowledge of the vanishing point. The polar (ρ, θ) line parameterisation suggested by Duda and Hart (1972) was introduced. The parameter ρ is the perpendicular distance from the image origin to the line, and ρ is the angle between the normal and the horizontal-axis.

The procedure to detect crop rows was as follows:

- *Hough Transform*: Following the Hough Transform, the vegetation image (binarisation of the initial image) was mapped in a two-dimensional array $H(\rho, \theta)$ where all points corresponding to each crop row were grouped into a cluster. Thus, the problem of line detection in an image was replaced by an easier local peak detection in Hough space and the detected peaks correspond to all the straight lines (*i.e.* crop rows) in the original scene.
- *Detection of the local maxima*: To eliminate insignificant data in Hough space, a threshold was applied to keep cells containing the highest values corresponding to the most likely plant row structure of the initial image.

  The crop rows were usually more than one pixel wide so that in Hough space the associated peaks were not concentrated in one cell but were grouped into clusters from a classical region-based segmentation method based on a blob-colouring analysis (Ballard and Brown, 1982). The aim of this method was to group connected pixels of an image into components depending on a common image property such as pixel intensity values. Once all regions were determined, each pixel was labelled with a colour (colour labelling) according to the component it was assigned to.
- *Extraction of lines associated with crop row*: From this method all peaks associated with crop rows could not be detected but the vanishing point can be determined (*i.e.* the cross-point of the main lines) Then, using the coordinates of the vanishing point in the initial image allows the detection of all crop rows in the initial image. In fact, in Hough space parameterised with polar coordinates, the vanishing point is associated with a sinusoid curve and only peaks associated with crop rows belong to this curve. A new normalised accumulator was created by a linear combination between the accumulator associated with the vanishing point and the one associated with the initial image, to highlight the peaks associated with crop rows. Afterwards, the local peak detection was performed by an automatic intensity threshold done after a region-based segmentation. For each intensity threshold value, in the range of 1–30% of the highest intensity in the accumulator with steps of 0.1%, the number of detected regions is counted and the best result (corresponding to the higher number of detected regions) gave the correct number of crop rows from the initial image. This information provides lines for each crop row that will be used for the Crop/Weed discrimination.

Therefore, for each centroid of each region in Hough space, the corresponding line was overlaid on the original image as in Fig. 3a.

3.2. Crop/Weed discrimination

The discrimination between crop and weeds is the last step of this algorithm for an automatic inter-row WIR estimation, and was performed by a region-based segmentation method.

Two classification methods were investigated for this Crop/Weed discrimination: a standard method implying a region-based segmentation analysis based on blob-colouring and an optimized method, including a crop-row boundary detection to improve the pixel classification between Crop and Weed classes.

- *Standard method*: As the detected lines corresponded to crop rows, we used this information to classify vegetation pixels. From the initial binary image (vegetation image), a region-based segmentation is performed using a blob analysis for region labelling (Fig. 3). Each region intercepted by a line is labelled as Crop and the remaining regions are considered as Weed. From this classification an automatic inter-row WIR ($\text{dWIR}_{\text{inter}}$) is estimated and compared with the initial one ($\text{iWIR}_{\text{inter}}$) deduced from the photograph of the virtual field (Fig. 2).

  This method could not separate a region composed of both crop and weed, leading to overestimation of crop detection.
- *Optimized method*: (Fig. 3) Under these conditions, to improve the algorithm, the boundaries of each region previously labelled as Crop are determined. This was done by estimation of the *X*-gradient followed by a linear regression (least mean square) to approximate each border with a simple straight line. Then all vegetation pixels, labelled as Crop (or Weed), outside (or inside) the region bounded by these lines were re-assigned as Weed (or Crop) class (Fig. 3b). By this method, the classification results are significantly improved by avoiding some misclassifications. An automatic inter-row WIR ($\text{dWIR}_{\text{inter}}$) can be easily calculated by this method.

Nevertheless, whatever the value of $\text{dWIR}_{\text{inter}}$, it does not give relevant information about correct pixel classification into Crop and Weed classes between the initial (Fig. 2) and final images (Fig. 3a and b). Thus for each simulated image, a confusion matrix (Kohavi

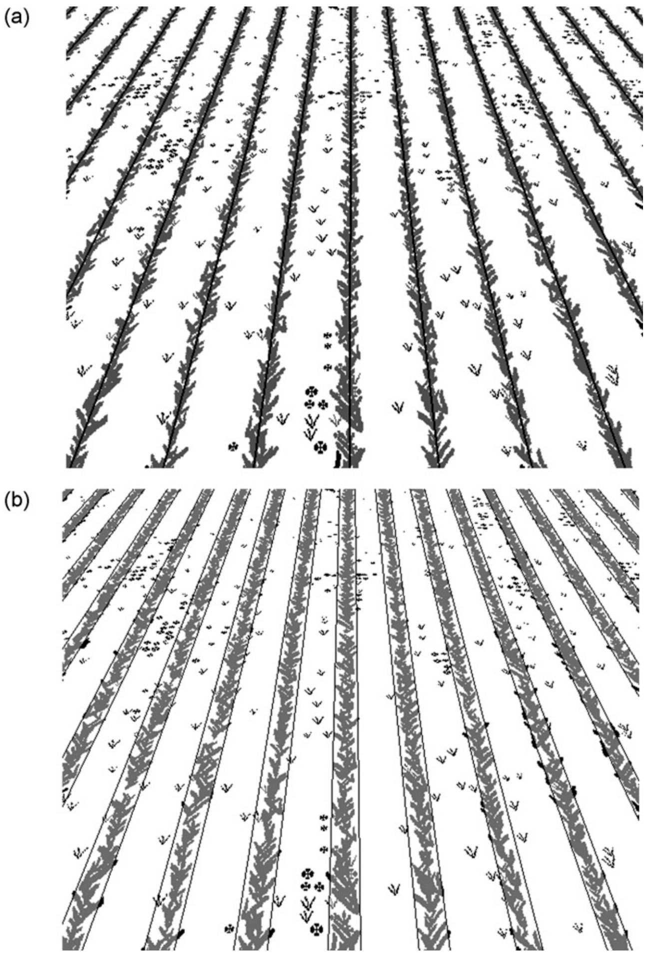

Fig. 3. (a) Results of a Crop/Weed discrimination by the use of a standard method-Hough transform (with detected lines in black) + blob-colouring analysis; $dWIR_{inter}$ = 12.36% and (b) results of Crop/Weed discrimination from an optimized method-Hough transform + blob-colouring analysis + edge detection; $dWIR_{inter}$ = 14.62%.

and Provost, 1998) for a two-class (*i.e.* Crop and Weed classes) classifier was performed for the two algorithms to examine their efficiency.

- *Confusion Matrix*: For a two-class classifier, the confusion matrix can be expressed (Table 2 or Table 3) with four different outcomes: TC, FC, TW and FW are the number of correct/incorrect predictions for the initial Crop/Weed classes.

Consequently, the detected inter-row Weed Infestation Rate $dWIR_{inter}$ is defined as follows:

$$dWIR_{inter} = \frac{TW + FW}{TW + FW + TC + FC} \quad (5)$$

Table 2
Confusion matrix indicating information (in pixel) about the initial and predicted classification done by the standard classification method from Fig. 1. The $iWIR_{inter}$ (Eq. (4)) value is 15.28% whereas the detected one (Eq. (5)) is 12.36%.

	Detected class		Correctly recognized (%)
	Crop	Inter-row Weed	
Initial class			
Crop (8792)	8707 (TC)	85 (FW)	99
Inter-row Weed (1586)	388 (FC)	1198 (TW)	75.53
Overall accuracy (%)			95.44

Table 3
Confusion matrix indicating information (in pixel) about the initial and predicted classification done by the optimized classification method from Fig. 1. The $iWIR_{inter}$ (Eq. (4)) value is 15.28% whereas the detected one (Eq. (5)) is 14.62%.

	Detected class		Correctly recognized (%)
	Crop	Inter-row Weed	
Initial class			
Crop (8792)	8732 (TC)	60 (FW)	99.31
Inter-row Weed (1586)	128 (FC)	1458 (TW)	91.92
Overall accuracy (%)			98.18

Thus it is composed not only of weed correctly detected, but also of crop incorrectly detected and assigned as weed.

For all simulated images of the database, such a comparison was performed when the Crop/Weed classification used either the standard or the optimized method to examine performance of both.

4. Results

- *Detection of the inter-row WIR*: For each simulated image, automatic $dWIR_{inter}$ (Eq. (5)) was measured for both methods (*i.e.* standard and optimized) and compared to the initial true one of the photograph of the virtual field (Fig. 2). The results for the three different weed spatial distributions are presented in Fig. 4a–c. The average values of $dWIR_{inter}$ (Eq. (5)) are plotted against $iWIR_{inter}$ (Eq. (4)).

There were better results for the optimized than for the standard method, and the classification was also very regular. Nevertheless, at high coverage of weed plants, the efficiency of both Crop/Weed discrimination methods decreased slightly.

The identity lines is plotted on each graph and it can be noticed that

- for high $iWIR_{inter}$, $dWIR_{inter}$ values were always less than $iWIR_{inter}$, revealing an underestimation of the detected Weed pixels especially in the standard method,
- for low $iWIR_{inter}$, $dWIR_{inter}$ values were always higher than $iWIR_{inter}$, indicating overestimation of the detected Weed pixels especially in the optimized method.

These results highlighted some pixel classification errors and thus $dWIR_{inter}$ alone was not sufficient to assess the quality of the Crop/Weed discrimination algorithm. A complementary study is required to confirm: (1) correct assignment of each pixel of the image between Crop and Weed pixels, and (2) that the optimized method was better than the standard method.

- *Crop/Weed discrimination*: The aim of this classification study was to confirm that a pixel classified as Weed (or Crop) in the initial image (Fig. 2) was detected as Weed (or Crop) by the image processing algorithms (Fig. 3a and b).

We provide typical examples of classification results from a simulated image of the standard (Fig. 3a) and optimized (Fig. 3b) methods when the weed spatial distribution was a mixture of the Poisson and Neyman–Scott processes. For this image $iWIR_{inter}$ was 15.28%, whereas $dWIR_{inter}$ was 12.36% and 14.62% for the standard and optimized methods, respectively.

Detailed analyses of pixel classification between Crop and Weed classes can be seen for the standard method (Table 2) and the optimized method (Table 3). Each table, usually called a confusion matrix, indicates the correct/incorrect classification results and confirms the optimized method as more efficient; overall accuracy was 98.18% compared to 95.44% for the standard method.

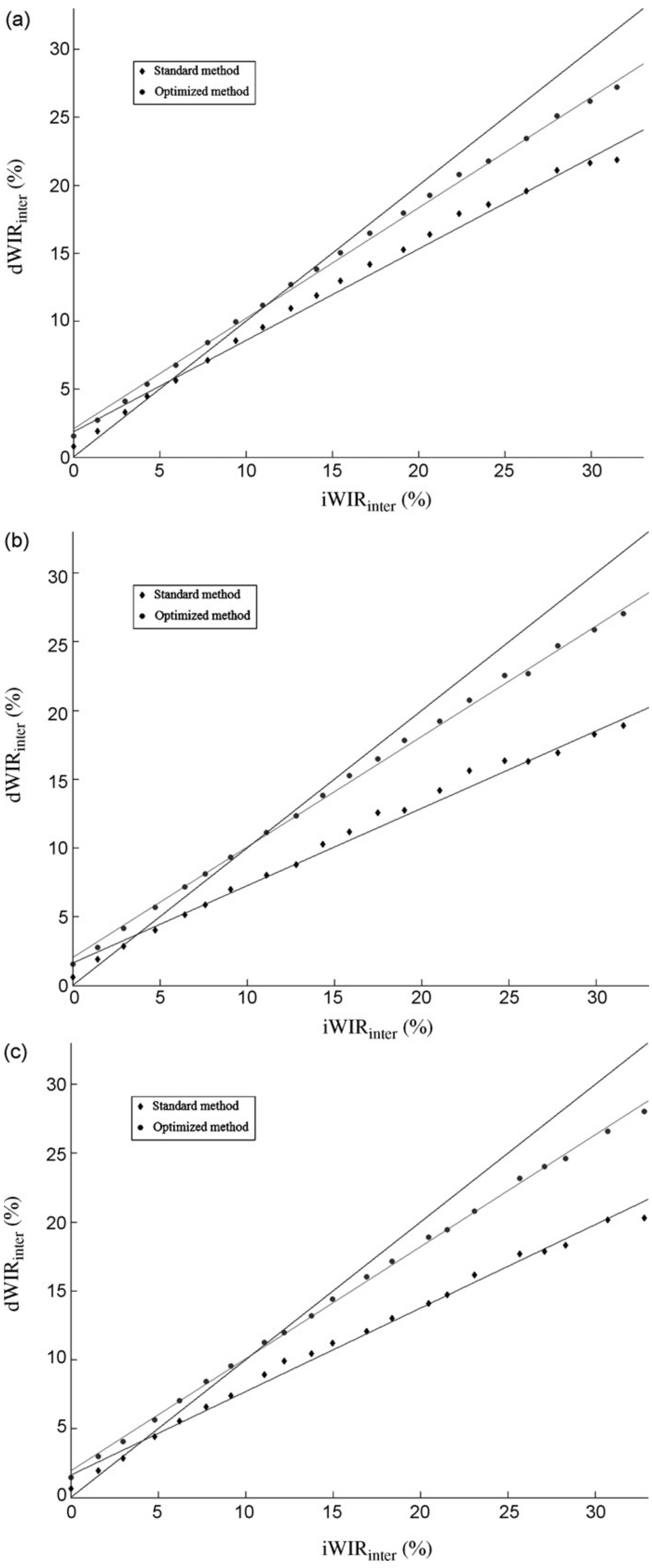

Fig. 4. Plots of $dWIR_{inter}$ (♦: standard method or ●: optimized method) vs. $iWIR_{inter}$ (Eq. (4)) for (a) a Poisson weed distribution, (b) a Neyman–Scott aggregative weed distribution and (c) a mixture of both weed spatial distribution. The identity line is also shown in all the graphs.

5. Discussion and perspectives

- *Crop image simulation*: The model allows simulation of a real crop field with three different weed spatial distributions based on statistical processing and it provides a photograph of this field taken from a virtual camera. This virtual camera can simulate a camera embedded in either agricultural or aerial engines. For this simple model, the individual crop pattern is a predefined size (*i.e.* 11 pixels × 11 pixels) and can take four different orientations on the field surface and can have different positions regarding the crop row. The individual weed density was chosen to be deliberately lower than that of crop, simulating a real crop field where tillage has occurred before sowing. Currently, these patterns cannot be stretched in the three dimensions to account for the growth stage of plants. Consequently, the simulated images issued from this model must be used to simulate plants at an early growth stage (which is rather well adapted for spraying). The use of simulated images is the best way to test, validate and optimize the image processing algorithms owing to perfect knowledge of the number of plants and also the density of the different plants (Crop, intra-row Weed and inter-row Weed) in the field.

The present version of this model could be a helpful tool to test and optimize the precision of some agricultural implements. Indeed, to reduce use of herbicides, some researchers (Tillet et al., 1998; Åstrand and Baerveldt, 2002; Gripentrop et al., 2006; Gobor et al., 2005) have investigated the development of mechanical weed control techniques to remove single weed plants within the crop row. Usually, such implements require a vision system with a high precision of single plant detection, this information is sent to the controller of the weeding tools to remove weed plants. However, during the trial period of these tools, extensive tests must be done either outdoors in real fields, depending on weather conditions and the stage of plant growth, or indoors by positioning artificial plants in a corridor. Implementing simulated agronomic images in a computer which controls the tool (*i.e.* cycloid hoe, rotary-tine weeder or rotary hoe, etc.), is an easy way to test without spending a lot of time preparing and managing experimental crop fields.

In this model only the spatial approach was explored and the simulated images do not contain spectral information. The spectral approach can be implemented to develop a projection model of incident light (*i.e.* the sun) on the virtual field, to simulate the reflection of plant leaves depending on their location. For instance, some authors report different modelling of radiation propagation and absorption in plant leaves to determine their spectral signatures (Jacquemoud and Baret, 1990; Baranoski, 2006). A better Crop/Weed discrimination algorithm could be investigated, based on a spatial and spectral approach, according to the fact that some plant groups and species could be discriminated by spectral reflectance measurements (Vrindts, 2000; Gée et al., 2004, 2006a).

- *Classification method efficiency*: The image processing algorithm developed for Crop/Weed discrimination were based on Hough Transform to detect crop rows in the field. It is important to note that maxima detection in Hough space is exclusively based on the sinusoid curve associated with the vanishing point. In the case of simulated images where the vanishing point is at infinity (*i.e.* crop rows are parallel), the sinusoid curve could be line-fitted due to the fact that all peaks would have the same θ polar parameter. Therefore, this algorithm could be easily extended to images for the special case of a camera pointing vertically downwards on the field (aerial images).

This algorithm is rather well adapted whatever the weed density. Problems could occur especially for an aggregated weed spatial distribution in the case of a high WIR. Taking into account farmer practices, the weed patches were deliberately oriented in the direction of the crop rows. Consequently, they could be detected as crop rows in the Hough space and assumed to belong to the same sinusoid curve associated with the vanishing point. However, we took care of this situation by implementing a threshold procedure to remove some peaks of low intensity which belonged to the sinusoid curve. Thus, there is no doubt of the efficiency of the maxima detection procedure in Hough space to detect all crop rows in the simulated images whatever the WIR. This first step allowed us to label all line pixels as Crop.

The choice of the blob-colouring method, a region-based segmentation, led to a very simple and low cost segmentation strategy, but revealed some inherent problems. Currently the simulated images were binarised before the blob-colouring analysis. This method grouped connected pixels in regions according to their colour properties, thus, necessarily Weed pixels close to Crop pixels were grouped into one region labelled Crop. Therefore, for patchy weed distribution and when weed aggregates were close to crop rows, the limits of blob colouring are clearly highlighted. Nevertheless, as shown in Fig. 3b, this method is particularly well adapted especially if combined with boundary detection of crop regions.

At low WIR, the results showed that $dWIR_{inter}$ was usually an overestimation of $iWIR_{inter}$ (Fig. 4a–c), and at high WIR an underestimation. This was particularly the case when weed distribution was Poisson (Fig. 4a). The detected rate from the two Crop/Weed classification methods corresponded to the number of pixels assigned as inter-row Weeds. However, due to classification errors, this rate was not only composed of Weed pixels correctly assigned, but also of Crop pixels incorrectly assigned. This composition is explained in the confusion matrices (Tables 2 and 3), and for low weed coverage the standard method was more sensitive to accurate crop detection (correct/incorrect) compared to weeds. In contrast, for high WIR, the weed plants were underestimated due to the blob-colouring method which grouped weed plants, close to crop, in a region labelled as Crop.

Other spatial Crop/Weed discrimination algorithms (based on Gabor Filter and Wavelet Transform) have been evaluated by Bossu et al. (2009) and Jones et al. (2009). The comparison of these algorithms proved excellent result as well as reduced computing time for the Wavelet Transformed for the Crop/Weed discrimination.

Finally, the problem of intra-row weed was not considered in this study. In the case of cereal fields, the detection of intra-row weeds could be attempted by the spectral approach, since plants have different spectral signatures. Consequently, new algorithms will be considered to develop fusion data for Crop/Weed discrimination.

6. Conclusion

In this study, we proposed a complete approach to test and validate a Crop/Weed discrimination from an image processing algorithm. This study has been successfully attempted due to the modelling of agronomic images with perspective effects.

A very simple model of spatial plant distribution has been developed to simulate a two-dimensional crop field with different Weed Infestation Rates. In the case of spatial weed distribution, stochastic processes following Poisson law or Neyman–Scott aggregative distribution are applied. However, this simple model of spatial plant distribution does not take into account determinist parameters such as soil parameters, incident light or farming practices and so needs to be improved. But, it is sufficiently efficient to validate the robustness of any Crop/Weed discrimination algorithm face to a spatial approach at an early plant growth stage. Moreover, the simulated images can be a good approach to compare the accuracy of different algorithms.

We use this modelling to test an algorithm devoted to an inter-row weed plant detection based on a Hough Transform and region-based segmentation. These algorithms were successfully applied to perspective simulated agronomic images. Limiting the Hough space and so optimizing processing time, provides a promising image processing for the development of real-time machine vision for precision agriculture. The assessment of the inter-row Weed Infestation Rate by this method is accurate. Therefore, this image processing method can be a promising technique for Crop/Weed discrimination. Inherent errors (no intra-row weed detection) of the method could probably be reduced by investigating the spectral properties of vegetation by implementing an information concerning the illumination. In these conditions, we will be able to assign a spectral signature for all plants and optimize the spatial algorithm for Crop/Weed discrimination in order to detect the intra-row weed plants by this spectral approach.

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