Crop/weed discrimination in simulated images

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ABSTRACT

In the context of site-specific weed management by vision systems, an efficient image processing for a crop/weed discrimination is required in order to quantify the Weed Infestation Rate (WIR) in an image. This paper presents a modeling of crop field in presence of different Weed Infestation Rates and a set of simulated agronomic images is used to test and validate the effectiveness of a crop/weed discrimination algorithm. For instance, an algorithm has been implemented to firstly detect the crop rows in the field by the use of a Hough Transform and secondly to detect plant areas by a region based-segmentation on binary images. This image processing has been tested on virtual cereal fields of a large field of view with perspective effects. The vegetation in the virtual field is modeled by a sowing pattern for crop plants and the weed spatial distribution is modeled by either a Poisson process or a Neyman-Scott cluster process. For each simulated image, a comparison between the initial and the detected weed infestation rate allows us to assess the accuracy of the algorithm. This comparison demonstrates an accuracy of better than 80% is possible, despite that intra-row weeds can not be detected from this spatial method.

Keywords: Hough transform, simulated images, spatial statistic, vanishing point, crop row detection, weed infestation rate, precision agriculture.

1. INTRODUCTION

For weed management, a wide range of weed control techniques are nowadays available (mechanical, chemical, non chemical, biological). In industrial countries, chemical weed controls are the most widely used management tools but they are particularly problematic, i.e. they may contribute to environment pollution (soil, water and air contamination) and to produce resistant biotype of weed. So, a particular attention can be done on herbicide savings. Therefore, in the past few years, researchers have tried to reduce the herbicide applications by developing different automatic weed control systems in order to spray specifically the weed infested areas of the field and so developing different optical sensors (i.e. photodiodes). These systems are able to discriminate plant to soil based on their reflectance [1,2,3]. Although these systems can easily discriminate soil to vegetation, they can not discriminate between crop and weed. More recently, Åstrand and Baerveld [4,5] attempt to realize a robot, with two vision systems, which followed a crop row, a mechanical tool remove the weeds in the intra row of the crop by a mechanical tool. However in literature, no information can be found concerning 1) weed detection and 2)the accuracy of the image processing developed for a crop/weed discrimination. In this context, an efficient image processing for a crop/weed discrimination is required in order to quantify weed infestation rate from image. The aim of this study is to test and validate the efficiency of a crop/weed discrimination algorithm based on the accuracy of its weed infestation rate detected. The first originality of this work is to test the algorithm from simulated agronomic images where the initial parameters are perfectly well-known (crop pixels, inter- and intra-row weed pixels). The image processing proceeds with two steps: a crop row detection and a crop/weed segmentation. Hough Transform was applied to detect the main lines in images and the second originality of this study is to develop a crop row detection method based on the vanishing point of agronomic images. Then a database of simulated agronomic images was used to test the method to detect an automatic weed infestation rate. These images are obtained from a virtual field modeled by a sowing pattern for crop plants and the weed spatial distribution is modeled by either a Poisson process or a Neyman-Scott cluster process. For each image, a comparison between the weed infestation rate detected and the initial one, chosen for the realization of simulated images, allows us to conclude about

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the accuracy of the weed infestation rate detected. This comparison demonstrates an accuracy of better than 80% is possible.

2. METHODOLOGY

The tested algorithm can be depicted into two steps: a crop row detection based on Hough transform and a crop/weed discrimination based on a blob coloring which allows us to extract a Weed Infestation Rate (WIR).

2.1 Binarization and pre-processing stage

At first, all agronomic grey level images were converted into a Vegetation image which is a binary image (1:vegetation (Crop or weed) and 0: soil, rock) in order to separate plants from soil or residues. The threshold is equal to 0.1.

2.2 A Hough transform for a crop row detection

Among the main line detection algorithms, the most "popular" and the more efficient against noisy is the Hough transform [6]. According to the fact that images were acquired with a virtual camera with a θ-angle different of zero, perspective effects would appear and all crop rows would have the particularity to converge on a unique vanishing point. Consequently in the Hough space, the line detection problem is reduced to an easier problem of maxima detection and only maxima associated to crop rows would belong to the sinusoid curve associated to the vanishing point [7].
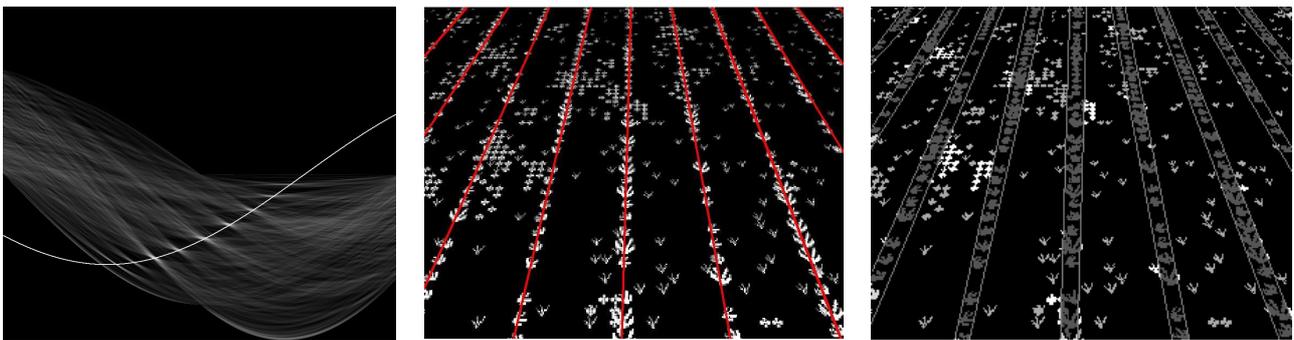

Fig. 1. a) In Hough space detection of the main local maxima (white color) belonging to the sinusoid curve associated to the vanishing point. b) Results of the crop row detection applied on the left image of figure 1. c) Results of crop/Weed discrimination from a blob coloring analysis + edge detection. The detected inter-row weed infestation rate is WIR=16.64%

Sinusoid curve detection. To eliminate insignificant data, a threshold has been applied in order to keep cells containing the highest values corresponding to the most likely plant row structure of the initial image. Moreover to detect only the main peaks associated to crop rows, this threshold has been defined as being 80% of the global maximum intensity, this maxima detection procedure is just an help for the vanishing point detection and so for the detection of the sinusoid curve (Figure 1a).

Maxima detection. This maxima extraction consists in a detection of local maxima along the sinusoid curve. As the shape of the sinusoid curve can be more or less noisy, the following method has been applied. The selection of the maxima is done by computing pixel intensity along the sinusoid curve and applying adaptive thresholds. In the first pass, the gap between a maximum and its following minimum (a maximum is always followed by a minimum) is considered. When the gap is long enough, the concerning maximum is retained, otherwise both maximum and minimum are deleted. In order to collect the maximum amount of maxima, this process is performed another time from the end to the beginning. Resulting maxima are put together, verifying that a line does not appear twice. The mean of gap between each detected line is computed to prevent double detected lines. This mean is also used to verify that no line was forgotten: the gap between two maxima is compared with the mean, if the gap is too big, we look for a maxima in the concerned

position. As it can be observed on Figure 1b, all the lines have been detected. Then, each pixel of the detected lines is set to one and is labeled as crop otherwise it is in black color and it is not labeled. According to this line detection algorithm, weeds located into the intra-row of the crop will be classified as crop.

2.3 A blob coloring for a crop/weed discrimination

To discriminate between crop and weeds, we realize on the Vegetation image a region based-segmentation method developing a blob coloring analysis. We deduced that if a pixel of a straight line belongs to a region then this last one is classified as crop (i.e. 1), otherwise, it is weed (i.e. 0). Then the boundaries of each region labeled as crop are detected in order to fit each border by a simple straight line as observed in Figure 1c. From this classification we are able to estimate an inter-row Weed Infestation Rate (WIR) and to compare it with the initial one deduced from the photography of the virtual field. The WIR is defined as:

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

3. IMAGES DATABASE

A set of simulated agronomic images was performed to test and validate the effectiveness of the crop/weed detection algorithm. Before to model photographs taken from a virtual camera, a model of a crop field with different Weed Infestation Rates is required.

3.1 Virtual field

A black and white simulated field composed of crop and weed populations is modeled. The vegetation pixels are in white color whereas the soil pixels are in black color. Crop plants were sown with a spatial inter-row frequency (i.e. 17cm for wheat). Inside the crop row a continuous crop pattern has been implemented with a random orientation (0,30,60 and 90 degrees). Nevertheless a random hole pattern has been taken into account in order to signify seedling growth problems. For weed plants, they have been positioned in the crop field image from three statistical pre-defined spatial distributions. A statistical rather than a determinist approach has been chosen due to the fact that we just want to model a snapshot of the field without any knowledge of the history of the field (soil parameters, vegetation reproduction and dynamics). Either a Poisson process or a Neyman-Scott cluster process or a mixture of both have been implemented [8].
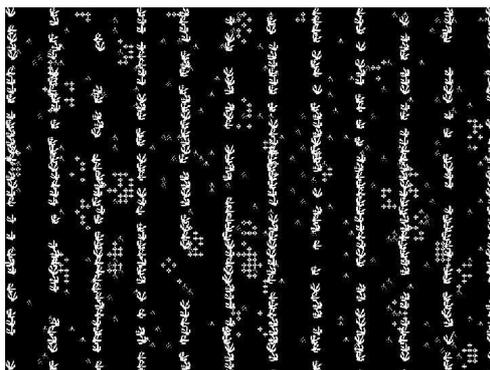

Fig. 2. Virtual crop field where the real size is 2.37m (width) x 3.55m(length). The image size is 240 x 300 pixels. The weed spatial distribution is a mixture of a Poisson process (v pattern) and Neyman Scott process (cross pattern). The initial inter-row WIR =15.28%.

The weed spatial distribution can be fully modeled by a Poisson punctual process [9] according to the fact that it is a random process with no memory between successive events and that occurrence of the emergences of weed plants compare to crop plant in field is very low. Then, in order to form a statistical ensemble we subdivide the global field surface (*D*) of the image into a set of small areas (*S*). If we suppose that all the events occurring in one area are independent to those occurring in another 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 defined as follow:

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

Afterwards the number of weed seeds in small areas are randomly determined applying a discrete random number generator which generates such a statistical variable [10]. Then, the seed positions (x, y) are randomly chosen using a uniform distribution restricted to the image size.

Neyman-Scott process: The Poisson process is complemented by a Neyman-Scott aggregative process to generate a more realist weed spatial distribution where it is usually a patchy distribution in cereal field [11]. We assume that the growth of weed aggregates are restricted in a pre-defined ellipsoid region ($S_{ellipsoid}$) depending of the farmer practices which elongate the weed distribution along the crop row direction.

3.2 Virtual photographs

A virtual camera is located in the field with free 3-axes orientations (roll: theta-angle; pitch:phi-angle). From the classical pinhole camera model, we are able to map the real world coordinates of a point into its pixel coordinates in the camera space according to the knowledge of the intrinsic and extrinsic parameters of the camera (Hccd= 5.28mm and Lccd=7mm; f=16mm; H=1m, θ =70°; φ=0°). Thus, a new virtual image (i.e. a virtual photography) is obtained as it is presented in Figure 3. From these initial camera parameters, a database of simulated images has been done.

Fig.3. Example of a photography, image of a virtual field through an optical system. Initial camera parameters : H=1m, θ =70°; φ=0°. The pixel size of the photography is 240 x 300 pixels. The initial inter-row WIR =15.28%.

4. RESULTS AND DISCUSSION

Three different configurations of images were simulated depending on the three different weed spatial distributions: Poisson, Neyman-Scott and a mixture of both. A total of 2520 images have been constructed and analyzed. For each case, simulated images have been performed with an initial $WIR_{inter-row}$ varying from 0% to 40% with a step of 2%. For each initial $WIR_{inter-row}$ value, 20 images were constructed in order to have a statistical set large enough to be representative of the situation. The 21 average values of the detected $WIR_{inter-row}$ are plotted against the true $WIR_{inter-row}$ values in Figure 4a, 4b and 4c. Applying the crop/weed discrimination algorithm, the correlation coefficient between the detected $WIR_{inter-row}$ and the initial $WIR_{inter-row}$ is up to $r^2=0.99$ for three weed spatial distributions.
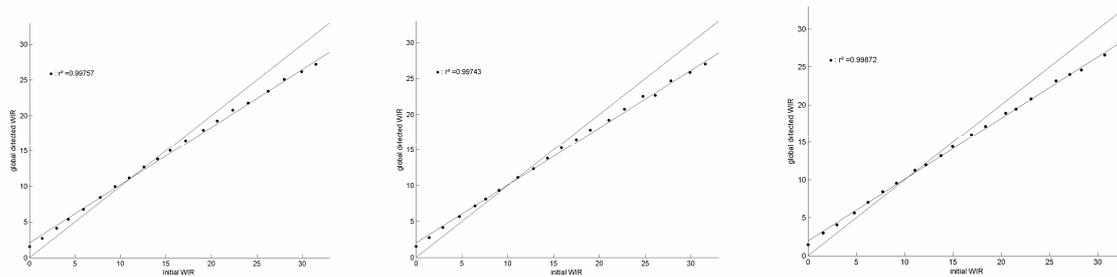

Fig.4*: Plots of the global WIR inter-row versus the initial inter-row WIR for a) a Poisson weed distribution b) a Neyman-Scott aggregative weed distribution and c) a mixture of both weed spatial distribution. The identity line is also shown in all the graphs.*

It can be noticed that for a high $WIR_{inter-row}$, the detected $WIR_{inter-row}$ values are always lower than the ones of the true $WIR_{inter-row}$ and so these graphs reveal an underestimation of the detected weed pixels. But, for a low WIRinter-row, the detected WIRinter-row values are always higher than the ones of the initial WIRinter-row and so these graphs reveal an overestimation of the detected weed pixels. Then these results highlight some pixel classification errors and the value of the detected WIRinter-row alone is not sufficient to assess the powerfulness of this crop/weed discrimination method. A complementary study is required to confirm the good assignment of each pixel of the image between crop and weed. Consequently, whatever the result of the inter-row weed infestation rate (WIR Inter-row), it does not inform us about the good pixel classification into crop and weed classes between the initial image (Figure 3) and the final image (Figure 1c). That is why for each simulated image, a confusion matrix for a two-class (i.e. Crop and Weed) classifier has been performed in order to examine the efficiency of the crop/weed discrimination algorithm (Table 1). From this matrix we are able to detect: 1)True Crop (TC), which is the number of correct predictions for the initial Crop class, 2)True Weed (TW), which is the number of correct predictions for the initial Weed class, 3) False Crop (FC), which is the number of incorrect predictions for the initial Crop class and 4)False Weed (FW) which is the number of incorrect predictions for the initial Weed class. It results that, whatever the Weed Infestation Rate, about 5% of the global inter-row Weed Infestation Rate detected originates from False Crop (crop pixels misclassified).

Table 1: Confusion matrix indicating information about the initial and predicted classification done by a classification method. The global detected $WIR_{inter-row}$ is defined by (FW+TW)/(TC+FC+TW+FW).

		Detected Class		Correctly recognized (%)
		Crop	Inter-Row Weed	
Initial Class	Crop	TC	FW	$\dfrac{TC}{TC+FW}$
Initial Class	Inter-Row Weed	FC	TW	$\dfrac{TW}{TW+FC}$
Overall accuracy (%)				$\dfrac{TC+TW}{TC+FC+TW+FW}$

Thus, in these intrinsic and extrinsic camera parameters, the efficiency of this algorithm has been clearly established thanks to simulated images where the initial parameters (i.e. number of crop pixels, number of inter-row and intra-row weed pixels, weed spatial distribution) are well-known. However to confirm these results, the algorithm must be tested on other simulated images corresponding to different camera locations in the virtual field. Moreover, in a future work, we could try to test this algorithm on real images and currently we are looking for calibration curve in order to transpose the results issued from simulated images to real images. Moreover we would like to test the efficiency of other crop/weed discrimination algorithms such as a 2D Gabor filtering currently applied in our laboratory for the development of a machine vision system for a real-time precision sprayer[12,13].

5. CONCLUSION

The robustness of this algorithm has been successfully validated working with a huge database of simulated images varying the Weed Infestation Rate. The comparison between the initial and the detected weed infestation rate demonstrates an accuracy of better than 80% is possible on cereal crop images. Inherent errors of the method (i.e. no detection of intra-row weed plants) can probably be reduced by investigating the spectral properties of vegetation and developing a fusion data method.

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