Weeds detection in UAV imagery using SLIC and the Hough transform

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Abstract— **Traditional weeds controlling tended to be spraying herbicides in all the fields. Such method not only requires huge quantities of herbicides but impact environment and humans health. In this paper, we propose a new method of crop/weeds discrimination using imagery provided by an unmanned aerial vehicle (UAV). This method is based on the vegetation skeleton, the Hough transform and the spatial relationship of superpixels created by the simple linear iterative clustering (SLIC). The combination of the spatial relationship of superpixels and their positions in the detected crop lines allows to detect intraline weeds. Our method shows its robustness in presence of weed patches close to crop lines as well as for the detection of crop lines as for weed detection.**

Keywords— **Weeds detection, UAV, line detection, crop lines detection, Hough transform, SLIC, precision agriculture**

I. Introduction

Currently, losses due to pests, diseases and weeds can reach 40% of global crop yields each year and this percentage is expected to increase significantly in the coming years [1]. Concerning weeds, traditional management relies on crop protection products spraying on the whole field. Such method not only implies huge quantities of herbicides but also represents a damage to environment. Moreover, herbicides residues are threatening human's health [2], [3]. In order to reduce the amount of chemicals while continuing to increase productivity, the concept of precision agriculture is introduced [4], [5]. The principle of precision agriculture is to allocate the right doses of input at the right place and at the right time. Weeds identification and characterization represent one of the major challenges of precision agriculture.

In literature, several approaches have been used to detect weeds with different acquisition systems. Recently, camera mounted on Unmanned Aerial Vehicle (UAV) has been found to be an interesting imagery system, since it enables rapid acquisition of the entire crop area with a very high spatial resolution and at low cost [6], [7]. Despite the huge advances in UAV acquisition systems, the automatic detection of weeds remains a challenging problem. The main approach for weeds detection is to extract vegetation from the image using a segmentation and then to discriminate crop and weeds.

Common segmentation approaches used for vegetation and background (soil and residues) separation use color and multispectral information. Specific indices are calculated from these information to effectively segment vegetation [8].

However, weeds and crop are hard to discriminate by using spectral information because of their strong similarity [9]. Regional approaches and spatial arrangement of pixels are preferred in most cases. In [10], Excess Green Vegetation Index (ExG) [11] and the Ostu thresholding [12] have helped to remove background (soil, residues) before to perform a double Hough transform [13] in order to identify the main crop lines in perspective images. Then, to discriminate crop and weeds in the segmented image, the authors applied a region-based segmentation method developing a blob coloring analysis is computed. Thus any region with at least one pixel belonging to the detected lines is considered to be crop, otherwise it is weeds. Unfortunately, it appears that some weeds patches, close to a crop region, are grouped and assigned as crop.

According to images with no perspective effects, the scene represents a set of parallel crop rows with a constant spacing. So in [14], authors consider in the Hough space all local maxima will be aligned on the global maximum and will have the same angle. A multi-scale analysis is used in [15] to reconstruct crop lines. The large scale highlights structures of crop lines and the small scale brings out objects that lie within crop lines. They have found that the process is strongly affected by the presence of weed plants very close or within the crop rows. Vegetation and no vegetation are segmented using the Normalized Difference Vegetation Index (NDVI) [16].

In [17], the authors rely on morphological variation and neural network analysis to separate weeds from maize crop while some authors seek to characterize weeds using geometric and contour attributes [18]. In [19], deep learning [20] is used to classify three weed species.

Regardless of the huge efforts engaged on weeds detection, an algortithm able to detect efficiently interline and intraline weeds is needed. It is found that those based on alignment and crop line frequency are less effective if the infestation rate is relatively high or if there are patches of weeds which cross two crop lines. Methods that use contours and geometry attributes are difficult to generalize because of heterogeneity and random weeds disposition.

In this paper, we propose a new method of crop and weeds discrimination. This method uses the Hough transform and superpixels formed by the simple linear iterative clustering (SLIC) [21]. The originality of this method is the use of the vegetation skeleton, the Hough transform and spatial relationship of the superpixels created by SLIC for automatic crop line and interline and intraline weeds detection.

This paper is organized as follows. In Section 2, we present the proposed method. Experimental results are given in the third section. Finally, Section 4 contains conclusion and perspectives.

II. Proposed Method

As presented in (Fig. 1), the flowchart of our method takes as input an RGB image. This image is segmented to eliminate soil and residues. The skeleton and superpixels are calculated on the segmented image in order to detect crop lines. In the aim to detect the interline weeds, the detected lines are intersected with objects created by an algorithm of blob coloring. To detect intraline weeds, superpixels relationship and crop lines are used.

This method is thus performed in 3 steps. The first one consists in removing soil and residues. Then in the second step, crop lines are detected. Lastly weeds are detected.

A. Background segmentation

Robust pre-processing is required to remove undesirable perturbations such as shadows, soil or stones. In order to discriminate between vegetation and background, we have used color vegetation indices. The ExG is used (Eq. 1) with the Otsu adaptive thresholding since it has demonstrated robustness and simplicity [22].

$$ExG = 2g - r - b \tag{1}$$

where r, g and b are the chromatic coordinates:

$$r = \frac{R^*}{R^* + G^* + B^*}, g = \frac{G^*}{R^* + G^* + B^*},$$
$$b = \frac{B^*}{R^* + G^* + B^*}$$

and R^*, G^* and B^* are the normalized RGB values.

$$R^* = \frac{R}{255}, G^* = \frac{G}{255}, B^* = \frac{B}{255}$$

B. Crop line detection

In fact, a crop line can be defined as a composition of several parallel lines that are very close. After vegetation separation, we applied an morphological operation based on skeleton. This enables overall good representation of structure of the field, namely orientations, periodicity and line number. The skeleton also tends to consider the patches of weeds attached to the crop lines as simple branches with a direction different from that of the crop lines, which could help to reduce the rate of over-detection.

The Hough transform is used to adjust the skeleton in order to create the crop line. This feature extraction technique is one of the most widely used methods for line detection. It is often integrated in tools for guiding agricultural machines because of its robustness and ability to adjust discontinuous lines due to missing crop plants in the crop line. The Hough transform $H(\theta, \rho)$ is computed on the skeleton with a θ resolution equal to $0.1°$ and ρ resolution equal to 1. θ has to be in the range $]-90°; 90°]$. Angles of the skeleton are performed and thanks to a histogram, the angle with the greatest contribution is chosen as the main orientation θ of crop lines. However the Hough transform has been normalized $H_{norm}(\theta, \rho)$ in order to give the same weight to all the crop lines, especially the short ones close to the borders of the image [10]. $H_{norm}(\theta, \rho)$ is defined as the ratio between the accumulator of the vegetation image and the accumulator of a white image of the same size $H_{ones}(\theta, \rho)$. Thus only pics in $H(\theta, \rho)$ that have provided a $H_{norm}(\theta, \rho)$ superior to 0.1 have been retained $H_p(\theta, \rho)$.

In addition to the use of the Hough transform, a superpixel segmentation is used to automatically identify crop lines without knowing beforehand the interline distance. There are several algorithms to extract superpixels; in this work, SLIC is chosen since it is simple and efficient in terms of results quality and computation time. It is an adaptation of k-means for superpixels generation with a control on size and compactness of superpixels. SLIC is performed on the segmented image; the advantage of this procedure is to create homogeneous superpixels which depend on the crop lines structure but not on the vegetation color variations.

Algorithm 1 presents the different steps of the proposed method. This method needs two inputs, vegetation skeleton and superpixels created by SLIC. To reduce the risk of missing crop lines, small superpixels have to be created, which would avoid to obtain superpixels belonging to two different lines in the case of high interline weed infestation rate. In addition, it allows to segment the large patch of intraline weeds in different small superpixels in order to get one of them out of the crop line.

C. Weeds detection

After the line detection, we propose two methods of weeds detection, interline and intraline weeds (weeds very close to the crop lines) detection.

1) Interline weeds detection: All the vegetation which grows up in the interline crop is considered as weeds.

To detect weeds that lie in interline, a blob coloring algorithm is used [23]. This approach considers any region with at least one pixel belonging to the detected lines as crop, weeds otherwise.

2) Intraline weeds: Intraline weeds are regions of vegetation that are in contact with the crop lines and, when compared to their neighbors, stand out much more in the interline.

Based on the assumption that crops are located around detected lines, every superpixel along the crop lines is system-

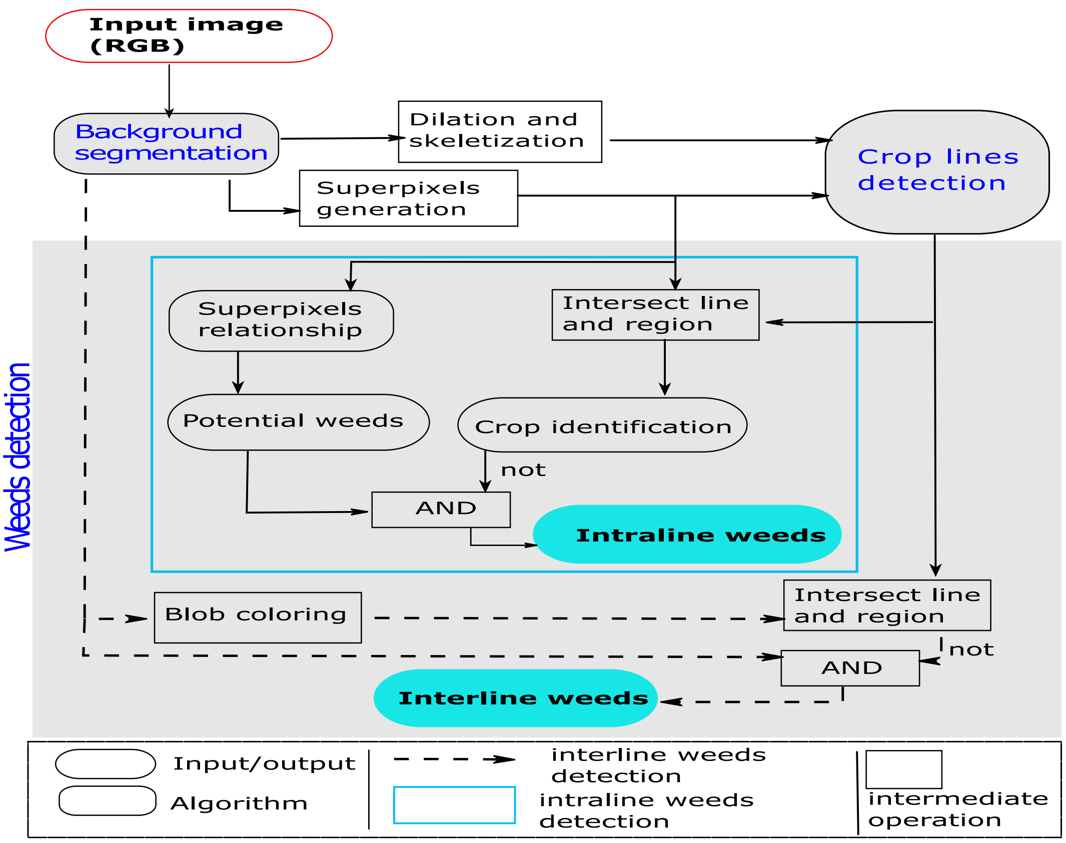

Fig. 1: Flowchart of the proposed method.

Algorithm 1: Crop lines detection.

input : skeleton, superpixels
output: crop lines

Computation of the skeleton angle
Computation of the main orientation θ of the crop lines
Hough transform of the skeleton $H(\theta, \rho)$
$H_{norm}(\theta, \rho)$=$H(\theta, \rho)$/Hones(θ, ρ)
$H_p(\theta, \rho)$= $H_{norm}(\theta, \rho)$> 0.1
while *maximum of* $H_p(\theta, \rho) > 0.1$ **do**
  Computation of the maximum of $H_p(\theta, \rho)$ and the corresponding angle θ_m
  Recovery of the superpixels (sup) which form this maximum
  Hough transform ($H_{sup}(\theta, \rho)$) only on the pixels of the skeleton present in the superpixels (sup)
  $H_p(\theta, \rho)$=$H_p(\theta, \rho)$ $-H_{sup}(\theta, \rho)$
  if $\theta_m > \theta - 20°$ *and* $\theta_m < \theta + 20°$ **then**
    The detected line is a crop line

atically considered as crop. Superpixels that do not touch lines can be crop or weeds. In order to reduce the misclassification rate, we studied the relationship of each superpixel and its neighbors: as presented in Algorithm 2, we obtain potential weed pixels. Under this assumption, pixels belonging to potential weeds and which are not identified as crop are considered as weeds.

Algorithm 2: Potential weeds detection.

input : θ
output: potential weeds

for *All superpixels (Sup)* **do**
  $MajAx$ = compute major axis of Sup
  Sup_N = compute of neighbors of Sup
  for *All neighbors of Sup* (Sup_N) **do**
    $mergeSup$ = merge Sup and Sup_N
    $mergeMajAx$= major axis of $mergeSup$
    $mergeOrientation$= orientation of $mergeSup$
    if $mergeMajAx > MajAx$ ***And*** $(|\theta| - 40° < |mergeOrientation| < |\theta| + 40°)$ **then**
      we are in the crop lines
    else
      Sup and Sup_N are potential weeds

The presence of weeds alongside the crop lines generally presents a branch of the skeleton with a different orientation from that of the crops, often close to or greater than 45°. To identify the bad ones very close to the lines of cultures we studied the orientation of the superpixels, considering that the orientation formed by the fusion of a superpixel located in the line of cultures and those belonging to the weeds will present a difference greater than d. By testing different values of d ranging from $10°$ to $90°$, the value of $d = 40°$ showed the best result. In order to focus solely on fusions involving aligned superpixels, we have also compared the major axis of the superpixels before fusion and those after fusion. An increase in the major axis means that the superpixels are aligned.

III. Experimental Results

The images utilized in this work were acquired under different illumination conditions and different plant growth states in 2016 with a RGB Canon Ixus camera of 12MPx mounted on an eBee UAV of SenseFly®. The flight altitude is about 100m above ground level. Experiments were conducted in two fields of corn and beet. Table 1 presents the data used in these experiments. Here we evaluated the two phases of the proposed method which are the line detection and the crop/weeds separation. Samples were randomly selected and were splitted from the orthophotos by using the Qgis® software. Each sample represents an area of about $0.01\ ha$ and a size of 400*400 pixels (Fig. 2). Both fields are infested with thistle. The method has been implemented in Matlab R2016b.

(a) (b)

Fig. 2: Examples of RGB image. a) Images extracted from corn field, b) Images extracted from beet field.

Table 1: Description of the samples used.

	Samples	Resolution	Size (pixels)
Corn images	50	2.5 cm	400*400
Beet images	49	2.5 cm	400*400

The aim here is to evaluate the two main phases: the crop line detection and the weeds detection. The results obtained for the line detection algorithm are compared with those obtained by manual assessment (ground truth). For each field, the rates of good detection (GD), misdetection (MD) and over-detection (OD) of crop lines are computed. We calculate the Weed Infestation Rate (WIR) (Eq. 2) and the accuracy defined in (Eq. 3) to validate the weeds detection algortihm. Fig. 3 and Fig. 4 present examples of line detection and weeds detection. The corn images have a WIR ranging from 0 to 15% and the beet field has a relatively low infestation rate, less than 1%. Infestation rate is classified into three categories: low ($WIR <$ 3%), moderate ($3\% < WIR <$5%) and high ($WIR > 5\%$). WIR includes interline WIR ($WIRinterline$) and intraline WIR ($WIRintraline$). Among the 50 images retrieved from the cornfield, 28 are weakly infested, 12 have a moderate infestation rate and 10 are heavily infested. Qualitatively, a low infestation rate corresponds to the presence of few weeds in the image. A moderate infestation rate shows in the image small patches of weeds at different places of the interline; weeds in intraline are also not very visible in the interlines. We assess a high rate of infestation if we note the presence of a high weeds density between crop lines; sometimes these weeds even join certain crop lines together. With this rate of infestation, intraline weeds can be clearly visible in the interline.

$$WIR(\%) = \frac{Weedpixels * 100}{(Weedpixels + Crop\ pixels)} \tag{2}$$

$$Accuracy(\%) = \frac{TPweeds * 100}{GTweeds} \tag{3}$$

where the $TPweeds$ is the number of true weeds detected and $GTweeds$ is the number of weeds to detect.

However SLIC needs the number of superpixels and the compactness value to create superpixels. After having tested several superpixels and compactness values for images of 400 * 400 pixels size, we retained 2500 superpixels with a compactness of 20 for a regular shape. The compactness of SLIC implemented in Matlab has values in the range $[1-20]$: a low value of compactness involves superpixels that best fits boundaries and a great value of compactness allows to form superpixels close to a square shape.

Table 2: Results of the line detection.

		Corn images	Beet images
Low	GD%	99	99
	MD%	0.5	0.3
	OD%	0.2	0
Moderate	GD%	99	-
	MD%	0.9	-
	OD%	0	-
High	GD%	100	-
	MD%	0.5	-
	OD%	0.01	-

Table 2 illustrates the algorithm performance for different weeds infestation rates. The use of the Hough transform on the skeleton rather than on the segmented image enables us to obtain a good overall detection rate close to 100% and a low rate of over-detection even for images with high infestation rates. We notice that a misdetection is usually encountered on lines that are on the edges of the images because they do not appear sufficiently to be detected.

The interline weeds detection is hardly linked to the effectiveness of the crop line detection (Fig. 4e). The better the line detection is, the better the detection of weeds is. Thanks to the efficiency of the line detection method, the detection of the

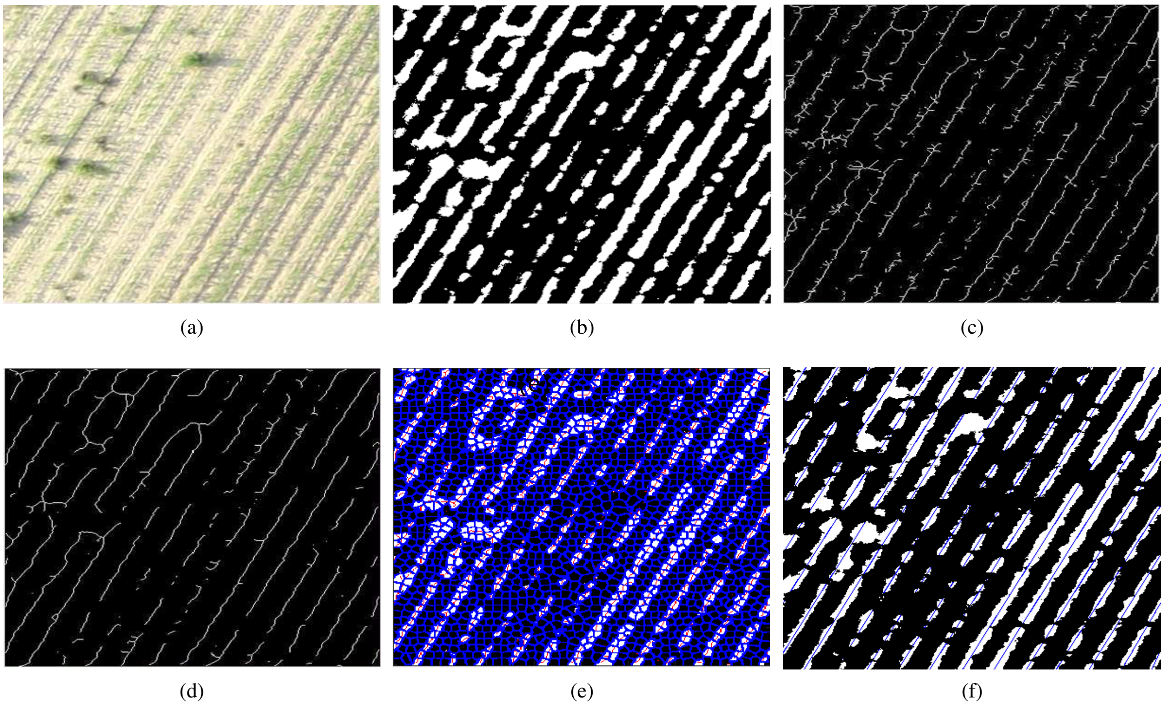

Fig. 3: Example of line detection: a) RGB image, b) Background segmentation, c) Skeleton, d) Skeleton after dilation, e) Superpixels performed in blue and skeleton in red. f) Detected lines in green.

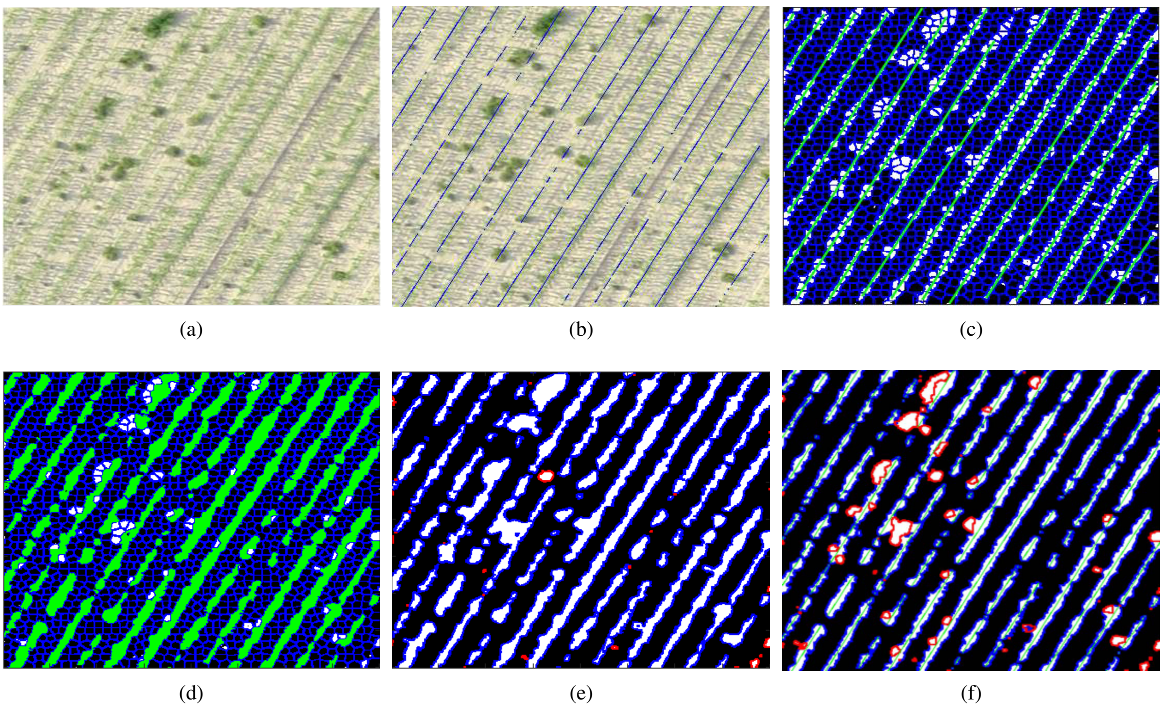

Fig. 4: Weeds detection: a) Original RGB image, b) line detection (blue), c) superpixels (blue) and detected lines (green), d) Detected crop (green), superpixels which not touch the detected lines (white), e) Interline weeds (red), f) Detected weeds (red).

interline weeds has proved to be effective (100%) with a slight over-detection rate (Table 3): this is due to the line detection error encountered on the edges of certain images. The intraline weeds detection algorithm is evaluated only on corn images because beet images do not contain intraline weeds.

Table 4 illustrates the results of the weeds detection (interline and intraline). The weeds detection method demonstrates its effectiveness for the different infestation rates with an

Table 3: Results of the interline weeds detection.

	Corn images	Beet images
Real WIRinterline %	2.08	0.07
WIRinterline result %	2.14	0.15
Accuracy %	100	100

Table 4: Results of the interline and intraline weeds detection in 50 samples of corn images with a low, moderate or high infestation rate.

	Low	Moderate	High
Manual WIR %	1.38	3.64	7.58
Detected WIR %	3.11	5.43	8.81
Accuracy %	94.87	90.97	90.82

accuracy superior to 90% and an over-detection inferior to 2%. The over-detection is caused by certain superpixels of crops which are not in contact with the crop line and which have the same characteristics as the potential weeds. The misdetection is mainly due to patches of intraline weeds which do not appear sufficiently in interline. However, for efficient spraying, farmers prefer to treat weed-free areas rather than missing weeds that could compete with crops [24].

IV. Conclusion

In this paper, we proposed a complete weeds detection method. Without knowing the characteristics of the field, this new method has proven to be effective for the detection of crop lines and also interline and intraline weeds in fields with a relatively high infestation rate, even in the presence of weed patches close to crop lines. The use of the Hough transform on the vegetation skeleton has permitted to obtain better results in a shorter time than if it has been used in the segmented image; this procedure has also allowed us to reduce the risk of line over-detection. The combination of the spatial relationship of superpixels which have been created by SLIC and their positions in the crop lines have helped to detect intraline weeds. Therefore the proposed method is highly linked to the background segmentation; as future work, we plan to use multispectral imagery where the NDVI might improve the background segmentation.

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