REAL-TIME IMAGE PROCESSING FOR CROP/WEED DISCRIMINATION IN WIDE-ROW CROPS

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Abstract. Accurate information about a crop is needed to apply a precision treatment to it as well as to perform other agricultural tasks. To achieve site-specific management of weeds, the first and most important step is the location and density estimation of weeds. In this context, the development of computer vision methods for real-time weed detection can be highly useful in the construction of fully automatic devices for weed control. This paper presents a visual method that discriminates between crop rows and weeds in wide-row crops, working in real time with the images acquired from a conventional camera on board a tractor and under uncontrolled lighting and movement conditions.

Keywords: Crop/weed discrimination, real-time image processing, Precision Agriculture

1 Introduction

Farming practices have traditionally focused on a uniform management of the field, ignoring the spatial and temporal variability that appears in crops. This has basically two types of effects: a) air and soil pollution, with the consequent pollution of groundwater and b) an increase in production costs.

Furthermore, agricultural production must double in the next 25 years, providing increasingly less soil and water, and leading us to a situation where technology will be crucial to minimize production costs while performing safe management of the environment (Srinivasan, 2006), (Stafford, 2000).

In recent years, the development of technologies such as Global Positioning Systems (GPS), crop sensors, humidity or soil fertility sensors, multispectral sensors, remote sensing, Geographic Information Systems (GIS) and Decision Support Systems (DSS) has led to the emergence of the concept of Precision Agriculture (PA), which proposes farming management adapted to crop variability.

Particularly important within the PA are the techniques aimed at selective treatment of weeds (site-specific management) that address the application of herbicide only in infested crop areas (Senay et al., 1998), even varying the amount of treatment applied according to the density and/or type of weeds, in contrast to traditional weed control.
methods. To achieve site-specific management of weeds, the first and most important step is the location and density estimation of weeds. A detection based on visually significant features could be a reasonable approach, but it is difficult for several reasons, including the changing lighting conditions, the humidity range that affects the soil’s texture, vegetation growth and the similarities between weeds and crops that sometimes exist. In short, visual discrimination is a complex task and therefore an open field of research. In this context, this paper proposes a real-time computer vision approach to discriminating between crop rows and weeds in wide-row crops. The proposed method works under uncontrolled lighting conditions and successfully manages the movements of the camera on board the tractor.

2 Materials and methods

2.1 Description of the system

The camera used to test the method was a digital single-lens reflex camera, Canon EOS 7D, placed directly on the roof of a tractor, at a height of 2.15 m above ground, with a 18° pitch angle (Figure 1(a)). The camera was connected to an onboard computer (a Panasonic Toughbook CF-19 laptop with an Intel Core i5 Processor and 2 GB DDR3 RAM) via a USB connector. The test images (Figure 1(b)) were acquired in a maize field in La Poveda (Arganda) on different days at an approximate speed of 6 km/h. All the acquired images have a resolution of 1056×704 pixels. The camera supplies approximately 1.5 frames per second.

![Fig. 1. (a) System used (b) Image taken by the camera](image)

2.2 Real-time image processing

(Burgos-Artizzu et. al, 2010) present several methods for the off-line analysis of overhead images for the extraction of agricultural elements. The images were taken using a tripod, and the image analysis was focused only on the space between two crop rows (both inclusive). The best discriminator of crop rows was selected from the methods proposed in that paper and then adapted to work in real-time and addressing the perspective that appears in the new images. The most relevant aspects of the new approach are described below.

2.2.1 Image segmentation

In this case, an analysis of the space covered by four crop rows is required. To ensure that all four rows appear in the analyzed image, the frame is split into three strips of
the same height. The bottom strip is discarded because there are not four rows in some cases. Similarly, the top strip is removed because it is difficult to distinguish the information contained between rows due to the perspective in the image that reduces the number of pixels (resolution) appearing between the crop rows. Our approach therefore only works with the central strip of the frame.

The objective of this segmentation stage is to isolate the vegetation cover against the background. The aim is therefore to convert the input RGB image into a black and white image, in which the white pixels are the vegetation cover (weeds and crop), while the black pixels are the rest (soil, stones, debris, straws, etc.). Segmentation makes use of the fact that the pixels representing vegetation have stronger green components than any other color. The RGB image can be transformed into a greyscale image by means of a linear combination of the red, green and blue planes, as shown in Eq. (1):

$$
\forall i \in \text{rows}_\text{image} \land \forall j \in \text{columns}_\text{image}:
\text{Grey}(i,j) = r * R(i,j) + g * G(i,j) + b * B(i,j)
$$

(1)

where $R(i,j), G(i,j), B(i,j)$ values are the non-normalized red, green, and blue intensities (0–255) at pixel (i, j) and $r, g, b$ are the set of real coefficients that determine how the monochrome image is constructed. These values are crucial in the segmentation of vegetation against non-vegetation, and their selection is largely discussed in (Woebbecke et al., 1995) and (Ribeiro, A., et. al, 2005). In this study, they were set using the coefficients proposed in (Burgos-Artizzu et. al, 2011), $r = -0.884$, $g = 1.262$, and $b = -0.311$.

The next step is to use a threshold to convert the monochrome grey level image into a binary image in which the white pixels represent vegetation and the black pixels non-vegetation. The threshold must be set according to the lighting conditions. For this reason, there is no fixed threshold in the approach set out here. It is calculated for each analyzed image as the mean value of the gray intensities that are presented in the current image. A sample that illustrates the segmentation stage is shown in Figure 2.

![Image](image.png)

**Fig. 2.** (a) Original image (b) Segmented image (vegetation cover)
2.2.2  Crop detection

The goal of this stage, which processes the binary images obtained in the previous stage, is to discriminate the white pixels belonging to the crop row from those belonging to weeds.

The method first performs a morphological opening operation (erosion followed by dilation) of the binary image to eliminate isolated white pixels and highlight areas with a high density of white pixels. One of the aims of this operation is to eliminate as far as possible the small groups of black pixels that appear inside the crops. The structural element used for the dilation and erosion is a 3 x 3 size square.

The borders of the resulting image are then extracted using the Sobel operator, so that all the pixels in the transitions (white to black and vice versa) are marked.

The image is divided into five horizontal strips to deal with its perspective. Each strip is processed independently using the following methods.

The centers of the crop rows are considered to be the columns of the strip with the biggest number of white pixels. To find these, a vector is built with as many components as the strip has columns, where each component stores the number of white pixels (vegetation) of the associated column. After it has been built, four search windows are established - one for each center of the four crop rows that are most centrally located in the strip. To find the most centered rows, the method begins in the center of the strip, creating two windows to the left and right, in which the centers of the central crop rows are searched for. After these have been found, and based on their position and the distance between rows (0.75cm) in a maize crop, another two windows to find the centers of the crop rows at the edges of the strip are produced.

The perspective of the original images is also taken into account when defining these windows, so that the distance and size of the windows vary according to the closeness to the camera of the strip analyzed (Thales’ intercept theorem). Because the camera only works at 1.5 fps, there may be abrupt displacements from one frame to the next, making it inappropriate to search for the center of a row in the current frame around the central position found in the previous frame for the same row.

After the centers of the rows have been found, the algorithm begins to find the edges delimiting crop rows, searching to the right and to the left from each of the centers found. In order to ascertain if a crop edge has been reached, the method uses three kinds of label for pixels: white, black and border. When a pixel explored is white, it is marked as belonging to the crop row and the algorithm continues with the next pixel. When a border pixel is found, this may mean that the exploration has reached either a crop edge or a group of black pixels inside the crop. The distance to the next white or border pixel can be used as discriminate feature to distinguish between these two cases. In the former case, the distance to the next crop row or weed between crop rows is greater than that which occurs in the latter, inside the crop row. In fact, two distance thresholds are established, $\theta_1 \leq \theta_2$, in such a way that if the computed distance is above threshold $\theta_2$, the exploration has reached a crop edge, whereas if the distance is below $\theta_1$, a group of black pixels inside the crop has been reached. If the distance is between $\theta_1$ and $\theta_2$, the method uses the vector previously generated to find the centers of the four row and proceeds as follows. The percentage of white pixels in each column is calculated for the range of components of the vector between the current position of the pixel and the position of the edge. If this percentage is higher
than a threshold called \textit{min\_proportion}, the algorithm considers that it has reached a group of black pixels inside the crop, since the column to which this group of black pixels belongs has a large number of white pixels due to it being part of a crop row. If it is lower than this percentage, the algorithm considers that it has reached the edge of the crop row, since the number of black pixels in the columns that separate them from the next crop row or weed is large.

This is all formally set out in Table 1, where \( p \) is the pixel currently being explored, \( n \) is the next (not black) pixel in the processing order at a distance \( d \), and \( \theta_1 \), \( \theta_2 \) and \textit{min\_proportion} are the three attributes of the method.

Due to this perspective, the width of the crop rows varies according to their closeness to the camera. This is taken into account in the method. The parameter \( \theta_1 \) varies between 5 and 10, starting at 5 when the farthest strip from the camera is analyzed, and reaching 10 when dealing with the closest strip. Likewise, the parameter \( \theta_2 \) varies between 10 and 30.

To summarize the proposed method, the crop in the binary image is detected and marked. The other white pixels in the binary image that are not marked as crop are labeled as weeds.

The method explained above has been implemented in C++, using OpenCV libraries. The processing time is less than 0.1 seconds, which is more than enough to achieve real-time processing, since the acquisition frequency is around 1.5 fps, which means that we have around 0.66 s to process each frame acquired.

<table>
<thead>
<tr>
<th>Type of current pixel</th>
<th>Distance ( d ) (in pixels) until next pixel not black</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( d \leq \theta_1 )</td>
<td>( \theta_2 &lt; d \leq \theta_2 )</td>
</tr>
<tr>
<td>White</td>
<td>Mark all pixels from ( p ) to ( n ) and jump to ( n ) (( p \equiv n ))</td>
<td>Mark all pixels from ( p ) to ( n ) and jump to ( n ) (( p \equiv n ))</td>
</tr>
<tr>
<td>Border</td>
<td>Mark all pixels from ( p ) to ( n ) and jump to ( n ) (( p \equiv n ))</td>
<td>If \textit{White pixels(input(1...N),p...n min_proportion}} THEN Mark all pixels from ( p ) to ( n ) and jump to ( n ) (( p = n )) ELSE Stops</td>
</tr>
<tr>
<td>Black</td>
<td>Jump to ( n ) (( p \leftarrow n ))</td>
<td>Jump to ( n ) (( p \leftarrow n ))</td>
</tr>
</tbody>
</table>

3 Results

Four sequences, a total of 370 frames, were processed using our approach, and the results obtained for each frame were registered. In addition to obtaining the ground-truth set, 46 randomly chosen frames were manually processed using image editing software, labeling each pixel as soil, crop or weed. Figure 3 shows the result of our approach in some selected frames, while Table 2 shows the full performance over the four sequences (370 frames). Sequence 1 is the
fairest of all, with a very little presence of weeds. Sequence 2 shows a greater presence of weeds and sowing errors in the crops. Sequence 3 and Sequence 4 present a great density of weeds, which is higher in the latter. All the sequences included camera movements due to significant terrain irregularities. The results are analyzed in terms of the mean percentage of crop and weed pixels correctly labeled (Hits), false positives (FP) and false negatives (FN). For each frame, we need to know the number of pixels representing crop and weeds, because the relation between the growth state of the crop and the weed density provides a measure of the weed infestation risk (Ribeiro et al., 2005) and could therefore be useful in establishing the treatment dosage. Additionally, false positives for weed are preferable to false negatives, because excess treatment is better than leaving weed patches untreated and uncontrolled.

![Fig. 3. Results of the proposed approach. (a) Sequence 1 – example of a scenario with very few weeds. (b) Sequence 2 – example of a scenario with weeds and sowing errors. (c) Sequence 3 – example of a scenario with a heavy presence of weeds. (d) Sequence 4 – example of a scenario with a large weed density. Color code: green - crop Hits; black - crop FP; yellow - crop FN; red - weed Hits; red; white - weed FP; blue - weed FN.](image-url)
In the results obtained for crops, a similar response can be seen in all sequences, with our approach performing well even with high weed density, sowing errors and camera movements. The FP mainly occurs along the border of the crop rows, meaning that although the FP value appears high in some cases, the error is acceptable. The FN are mainly due to the non-detection of some of the endings of the largest leaves. The maize crop was highly developed when the sequences were acquired.

An analysis of the results of the weed occurrences provides the following conclusions. In all sequences, most FP are due to a mistake in labeling the edges of maize leaves. This leads to a better performance of our approach when the weed density is high (high Hits and lower FP), since infestations are detected reasonably well. Moreover, the greater the contribution of Hits to the total number of pixels of weeds (Hits + FP + FN), the lower the percentage of FP. These percentages of FP make the results worse, although false positives are preferable to false negatives in weed labeling. Most FN occurs because the algorithm detects some weeds as crop. It should be pointed out that even expert users sometimes find crop and weeds difficult to distinguish.

These results make us optimistic about the performance of the method proposed herein, since the results obtained are mainly related to the growth level of the crop used. Indeed, the results will be much better in less developed crops, which is the usual situation at the time of treatment.

| Table 2. Results of the system (|Crop| Weed| |
|---|---|---|---|---|---|---|
| | Hits | FP | FN | Hits | FP | FN |
| Seq.1 | 74.09 | 22.81 | 3.08 | 16.03 | 72.65 | 11.31 |
| Seq.2 | 80.76 | 12.96 | 6.27 | 29.49 | 51.87 | 18.62 |
| Seq.3 | 80.65 | 14.53 | 4.80 | 54.76 | 25.74 | 19.48 |
| Seq.4 | 70.08 | 15.24 | 5.67 | 56.21 | 20.83 | 22.94 |

4 Conclusions and future work

In order to achieve site-specific management of weeds, the first and most important step is the location and density estimation of weeds. In this paper, a real-time approach based on computer vision is proposed for weed detection in wide-row crops.

The method is only applied in a central strip of the image to ensure that there will
always be 4 rows. The method has a first segmentation stage, in which the vegetation cover is well distinguished from the rest (soil, stones, debris, straws, etc.) under uncontrolled lighting conditions. The method then labels the pixels as weeds and crop rows.

Several experiments have been conducted to test this approach. The results obtained are a promising starting point, especially in view of the difficulty presented in this kind of image. To improve the proposed approach, work is required to correctly label the pixels on the border of the very long leaves, and to distinguish the weeds that are very close to the crop row and possibly connected to it.

Furthermore, bearing in mind the current good results of this approach in the identification of the crop rows, the method could be used to include a visual control for guiding autonomous vehicles using crop row tracking.

Acknowledgments

The Spanish Ministry of Economy and Competitiveness and the European Union have provided full and continuing support for this research work through the following projects: PLAN NACIONAL - AGL2011 - 30442 - C02 – 02 (GroW) and NMP-CP-IP 245986-2 RHEA.

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