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CROP ROWS TRACKING BY DETECTING INDIVIDUAL PLANTS USING COMPUTER VISION TO GUIDE FARMING VEHICLES

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ABSTRACT One of the uses of computer vision in precision agriculture is the assisted and automatic guidance of farming vehicles. Some experimental and commercial applications use satellite positioning (GPS), even beams of infrared light to detect the crop limit. The objective of this work was to develop a new computer vision system for detecting plant rows in crops without using Hough transform. This system could be applied to guide a farming tractor between rows while cleaning weeds with mechanical implements or spraying crops. A digital NIR (near infrared) camera with CMOS sensor and high resolution was used to acquire images in a continuous way. The camera was mounted on the front part of a tractor, looking forward with different inclination angles to obtain different perspectives. The system for acquiring and processing images was developed and automated with LabVIEW on a laptop. The tractor was driven through two different crops, sunflowers and peas. The individual plants in digital images were segmented from background soil using intensity information from NIR. Then a geometrical model was adjusted to the positions of the plants to detect seed rows. After correlating the rows found in different images of the same sequence, it was possible to predict the route of the vehicle in advance. Several tests were made with different perspective angles and it was shown that small angles (the camera faced to soil) produced higher detection rates of individual plants than large angles. However the accuracy of the predicted vehicle route was higher for large perspective angles.

Keywords: Computer vision, row tracking, vehicle guidance.

INTRODUCTION Computer vision is used in precision agriculture in several ways. Most of them are related to remote sensing from different platforms, such as satellite, aircrafts, observation balloons and terrestrial platforms. Image analysis is employed to make non-invasive measurements of crop and soil and then, to generate maps which help to take decisions in crop management. However, computer vision can also be used to

automate, simplify or improve some farming tasks, for example the guidance of tractors, harvesters and other farming vehicles.

Guidance of vehicles is usually performed by satellite-based systems, mainly GPS (Global Positioning System). These systems offer a very good precision using additional technologies such as RTK (Real Time Kinematic), but sometimes it is necessary to guide vehicles detecting local objects, such as crop plants themselves. Detecting the distribution of plants by image analysis makes possible to improve the satellite-based guidance or even to create an autonomous guidance system.

The most common method to carry out row tracking is the Hough transform, which allows finding potential straight lines in a binary image. It appears in many works along last years: Marchant and Brivot, (1995); Marchant, (1996); Southall, et al., (1998); Astrand and Baerveldt, (2002); Leemans and Destain, (2006); Leemans and Destain, (2007). The objective of this work was to develop a new algorithm for row tracking without using Hough transform, to save some difficulties encountered with that method. These difficulties are found, for example, for in-row crops in the earliest growing stages, where plants do not form a real line, but individual spots. A similar problem occurs for larger plants when there are gaps in lines. Moreover, the new algorithm correlates information from consecutive frames to ensure the correct detection of crop rows.

IMAGE BANK Crops used for the new algorithm development were sunflowers and peas, both sowed in lines with a gap of 60-80 cm between rows. An automatic acquisition system was mounted on the shovel of a tractor, with two digital cameras mounted in parallel and controlled by a laptop. The first camera was a NIR CMOS camera with a 1280×1024 pixels resolution, while the second one was a color (Bayer pattern) CMOS camera with the same resolution. Only the NIR images were used in this work, while the color images were acquired for a future use.

Images were acquired during different growing stages of peas and sunflowers (Figure 1), using different heights from cameras to ground, from 1 to 2.5 m, (Figure 2) and with different framing angles, from perpendicular to 45° to soil (Figure 3). The sampling rate was 1 or 2 images per second, with the tractor moving at 0.5 or 1.0 m/s, depending on the height of the cameras. These values guarantee the overlap of two or more consecutive images.

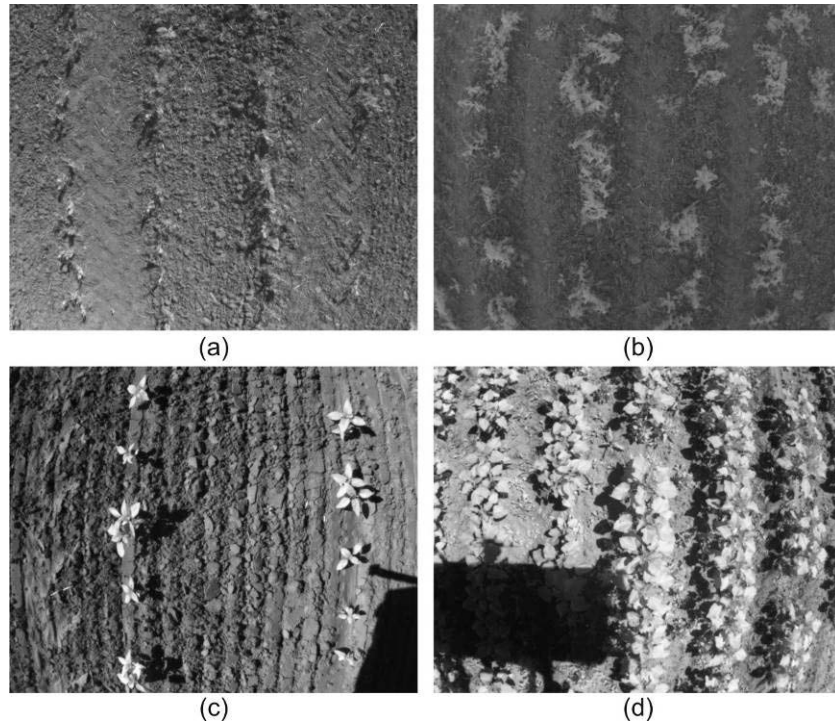


Figure 1. Different plant sizes for peas (a)(b) and sunflowers (c)(d).

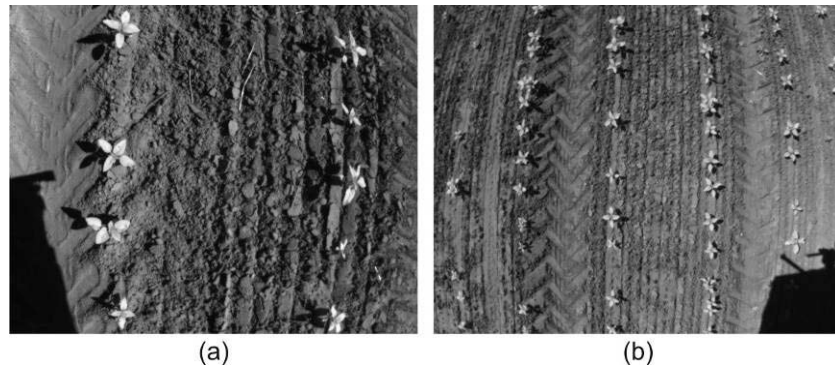


Figure 2. Sunflower images with camera at (a) 1 m and (b) 2 m from soil.

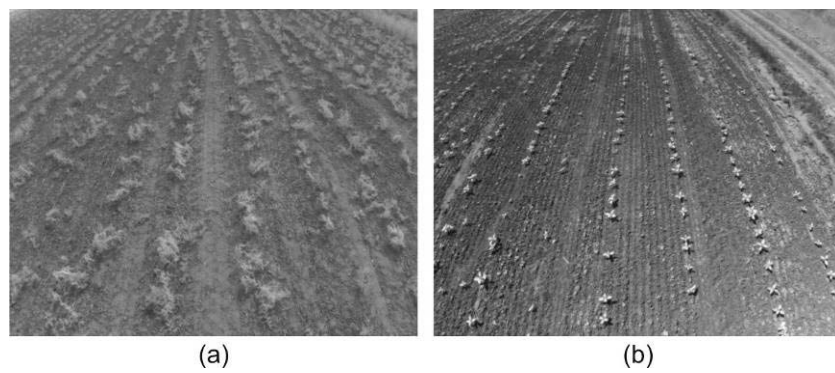


Figure 3. Peas (a) and sunflower (b) images with camera at 45°.

CROP ROWS TRACKING ALGORITHM The novel algorithm for rows detection was developed using *LabVIEW 8.6* and the *Vision Development Module* from *National Instruments*. Figure 4 shows the steps followed by the algorithm to detect crop rows.

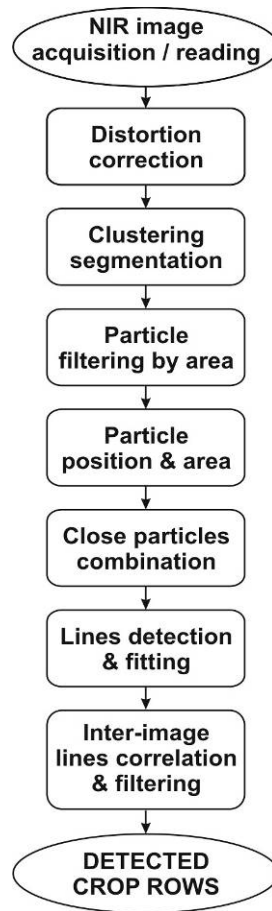


Figure 4. General diagram followed by the algorithm.

Distortion correction This step is necessary since camera optics usually produce certain distortion in images, either barrel or pincushion distortion. In this case NIR camera lenses produce barrel distortion, so it must be corrected by means of a dot pattern. After correction, crop rows appear as straight lines instead of curves (Figure 5).

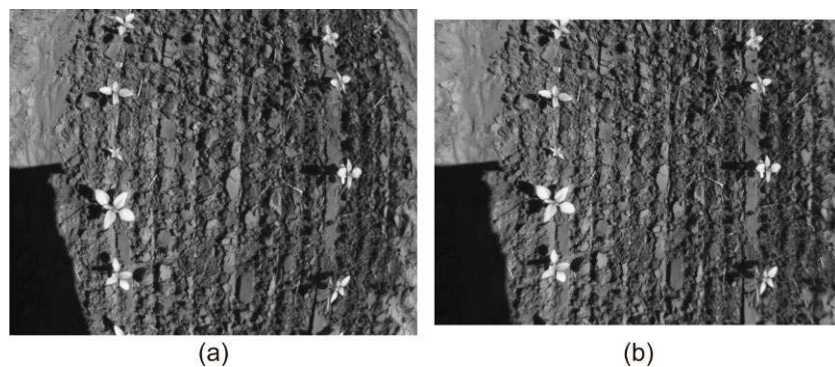


Figure 5. Image with barrel distortion (a) and after correction (b).

Clustering segmentation This step consists of a simple pixel grouping using two classes, vegetation and soil, according to gray level of NIR images. Owing to the high reflectance of green plants in the NIR spectrum in relation to background, clustering works well enough using two seeds and only one iteration. The result here is a binary image (Figure 6).

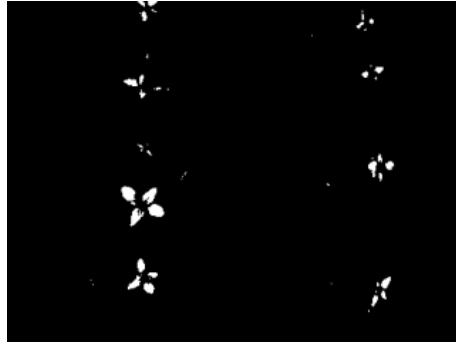


Figure 6. Binary image generated by clustering

Particle filtering by area Each binary particle (regions made of connected pixels) whose area is small enough is considered as noise and erased. Particle size threshold is a parameter which depends on plant size and distance between camera and soil.

Particle position and area For particles passing the filter, the center of mass and area are computed and put in a list.

Close particles combination Particles which are closer together than a given distance are combined in a new particle, supposing that they represent leaves of the same plant. The given distance is related to the typical distance between plants. The new particle area is equal to the sum of areas of combined particles and the new center of mass is computed as usual (Figure 7). After particle combination, the list of positions and areas is updated, having N elements.

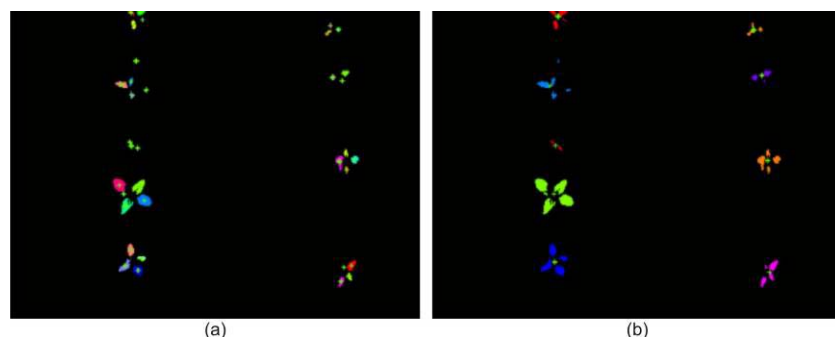


Figure 7. Combination in (b) of nearby particles in (a).

Lines detection and fitting This is the most complex step and represents the core of the algorithm. It takes the list of N positions p_i (center of mass) from the previous step and fit lines to them with high probability of representing crop rows.

Sub step 1 It is calculated the Euclidean distance between each position p_i and each line formed by positions p_j and p_k , with $j \neq k$. Without repetitions it produces a matrix of M by N distances, with $M = (N^2 - N) / 2$.

Sub step 2 Each distance is compared to the typical diameter of plants and set to TRUE if it is lower and FALSE in other case. It generates M binary patterns of N elements, corresponding to positions which are near to each line.

Sub step 3 Repeated patterns are grouped and the number of repetitions is saved for each different pattern.

Sub step 4 TRUE positions in patterns with a high number of repetitions are considered as potential points of the same crop row.

Sub step 5 For each set of potential row points, a line is fitted using a bisquare method.

Inter-image lines correlation and filtering The final step of the algorithm compares detected lines within two or more consecutive images, knowing that a certain region of soil appear in all of them and they represent the same crop rows. Analyzing the persistence of detected lines in consecutive images, the rest which do not appear in a continuous way can be removed as detection noise (Figure 8). After some frames, it is possible to automatically detect the number, position and orientation of real crop rows (Figure 8).

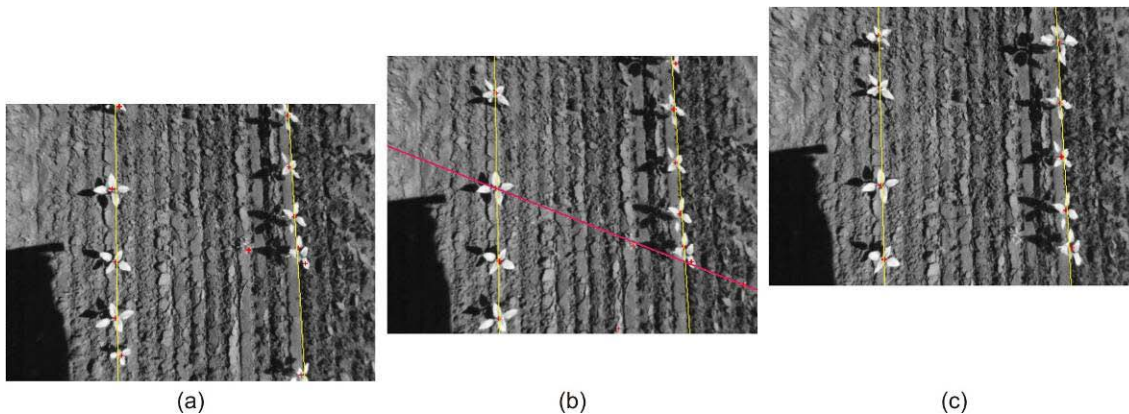


Figure 8. Three consecutive frames. Non-vertical detected line in (b) is removed since it does not is detected in (a) and (c).

RESULTS AND DISCUSSION Preliminary qualitative results show that the algorithm is very effective for images taken in the earliest growing stages, with not much weeds and

the camera faced to soil. In these cases, crop rows appear in images as vertical and parallel lines, which make easier filtering possible rows (Figure 9).

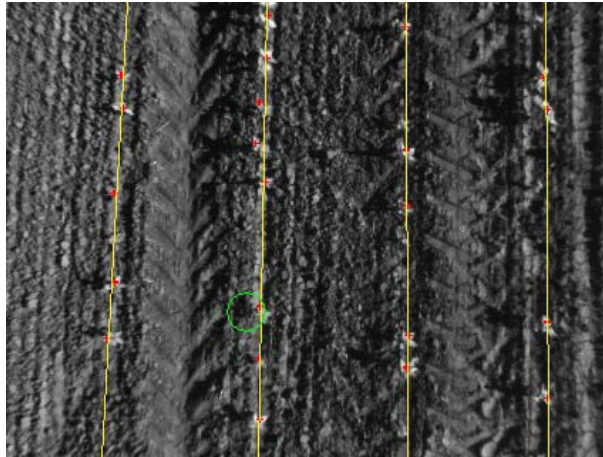


Figure 9. Crop rows detection in a image with camera at 2 m height.

About images with higher rates of weed infestation, it is necessary to make a more precise calibration of the algorithm, mainly with particle size for area filtering, distance for particle combination and number of pater repetitions to extract potential crop rows.

While perpendicular images simplify rows detection, images taken with a sloping angle require a more precise calibration. Crop rows appear in these images as sloping lines with different angles, which depend on angle and transverse movement of the camera. However, perpendicular images have a limited framing area and it makes impossible to predict changes in rows way. Using images in perspective allows knowing in advance rows turns (Figure 10).

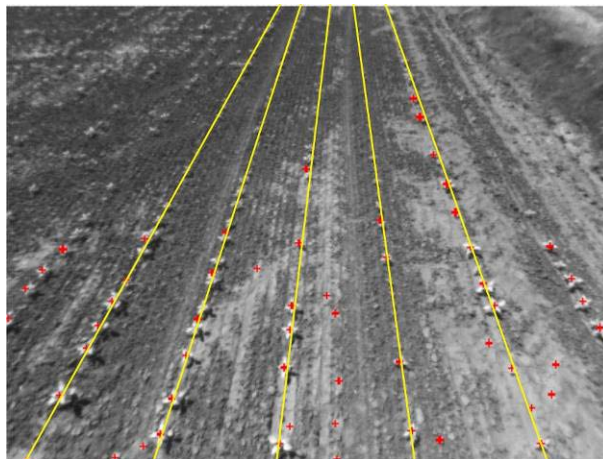


Figure 10. Crop rows detection in an image with perspective.

Finally, it is necessary to point out the importance of line fitting method with regard to processing time. After combining particles and extracting their centers of mass, the list of

points to analyze, N , is quite low. For example, for a perpendicular sunflower image representing two rows, N is between 10 and 20 and the number of distance patterns, M , is between 45 and 190. On the other hand, for a sloping image N can reach a value of 200 and therefore, M could be 19900. In any case, amount of data to be process is low enough to reach high processing speed.

CONCLUSION A novel algorithm was developed in order to detect and track crop rows in pea and sunflower real fields. The algorithm did not use the typical Hough transform since it presented some problems working with images under study. NIR images from a CMOS camera were segmented by clustering and then nearby particles were combined. A geometrical algorithm fitted lines to particles positions, choosing those ones with high pattern repetition. Finally, rows detected in consecutive frames were correlated to improve results and to predict rows turns.

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