A Computer Vision Approach for Automatic Measurement of the Inter-plant Spacing

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Abstract. Global food demand is increasing every year and it is needed to respond to this demand. In addition, some crops such as corn, which is the most produced grain in the world, is used as food, feed, bio-energy and other industrial purposes. Thus, it is needed the development of new technologies that make possible to produce more from less land. In particular, the corn crop is sensitive to its spatial arrangement and any variation in plant distribution pattern can lead to reduction in corn production. Nowadays, the uniformity of the plant spacing is checked manually by agronomists in order to predict possible production losses. In this context, this work proposes an automatic approach for measuring the spacing between corn plants in the early stages of growth. The proposed approach is based on computer vision techniques in order to evaluate the automatic inter-plant spacing measurement from images in a simple and efficient way, allowing its use on devices with low computational power such as smart phones and tablets. An image dataset was built as an additional contribution of this work containing 2186 corn plants in two conditions: tillage after the application of herbicide (TH) with 1387 corn plants and conventional tillage (CT) with 799 corn plants. The dataset is available at url: http://github.com/Brilhador/cornspacing. The experimental results achieve 90% of precision and 92% of sensitivity in corn plant identification. Regarding the automatic measurement of the inter-plant spacing, the results showed no significant differences from the same measurements taken manually, indicating the effectiveness of the proposed approach in two distinct types of planting.

Keywords: Computer vision · Inter-plant spacing · Pattern recognition · Precision agriculture · Image processing

1 Introduction

The world population is increasing every year and it is needed to improve the global food production in order to be able to feed the world. In this way the precision agriculture techniques can maximize food production, minimize environmental impact and reduce cost.

A. Pardo and J. Kittler (Eds.): CIARP 2015, LNCS 9423, pp. 219–227, 2015.
DOI: 10.1007/978-3-319-25751-8_27

In particular, the corn crop is the most produced grain in the world, being used as food, feed and industrial utilities such as ethanol production [3]. It is a major component of livestock feed. The United States produces 40.2% of the world's harvest and other top producing countries include China (31.0%) and Brazil (9.5%). However, the corn production has its own peculiarities including the sensitivity to its spatial arrangement, which is defined as the geometric area available for planting each of the corn plants, i.e., its distribution pattern [21].

Indeed, the plants compete for natural resources such as water, light and nutrients. The uniformity of inter-plant spacing decreases this competition [16]. Some works address the plant spacing variability (PSV) on corn grain yield, which is defined by the standard deviation of consecutive plant-to-plant spacings within rows [12]. It was reported a reduction of about 2.5 bushels per acre for each centimeter increased in the standard deviation of plant spacing[12]. Similar effects was reported, achieving a reduction of 3.4 bushels per acre for every inch increase in standard deviation [4], which points out the PSV as an important factor in grain production. In general, the PSV is evaluated manually with a tape measure positioned along the row of plants, while the spacings are stored numerically in a notebook or as an audio recorder. Manual methods are exhaustive, time consuming and subject to human error.

The spatial arrangement of plants has been analyzed by many researchers as well as its influence on grain production. In this context there are some works that address this important issue. For instance, in [18] it was adopted three morphological features to distinguish between weeds and corn plants. In [17] it was used the shape and the area of the corn plants to measure the population of plants and the space between them. In [19] it was applied morphological features, color and the center of the planting row to measure the spacing between plants. Recent works [10,11] present approaches based on 3D sensors in order to measure corn plants in later stages. However, these techniques requires a very specific hardware/machine in order to capture and/or analyze the images.

This work address the PSV issue presenting a simple and effective approach for measuring the spacing between plants in two different situations of planting (Sec. 2). More specifically, it was adopted only shape descriptors in order to identify the corn plant and its stem and as a result, to evaluate the automatic inter-plant spacing measurement from images in a simple and efficient way. Besides, the proposed approach can be used on devices with low computational power such as smart phones and tablets.

2 Image Dataset

After an exhaustive search from image dataset of corn crops, it was identified that this matter is still little explored by the scientific community. Thus, an image dataset was built as an additional contribution of this work, which is available at url: http://github.com/brilhador/cornspacing.

The image dataset is composed by corn plants, which were acquired through a mobile device considering panoramic images. The image acquisition process

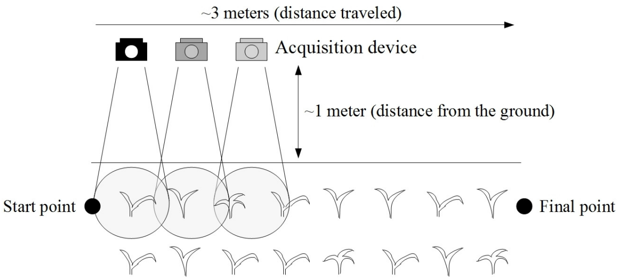


Fig. 1. The image acquisition process.

(Fig. 1) was performed by a person carried a camera at an average height of 1 meter from the ground. The initial starting point for the acquisition was determined randomly and from there it traveled approximately 3 meters capturing the images of corn plants building a panoramic image.

Currently, the image dataset contains 188 panoramic images of corn planting with 24-bit color depth with an average resolution of 3000 x 600 pixels in JPG image format. The image acquisition was performed in a real situation of planting, as a result, the stored images present highly lighting variation and different spacing between corn plants.

The images were acquired in two distinct situations: tillage after the application of herbicide (TH) and conventional tillage (CT). In CT images the soil goes through a mechanical preparation of plowing and harrowing. On the other hand, the TH images there is no mechanical preparation of the soil, in which the ground remains covered with waste from various cultures used in succession or rotation [6]. The elimination of crop residues and weeds are carried out by applying herbicide. These two classes of images are presented in Fig. 4.

The corn plants have phenotypic features related to their growth stages, commonly defined as $V(n)$, where n is the number of leaves fully developed in the plant [15]. This variation of the plant growth modifies the shape of its canopy. The image dataset comprises these phenotypic variations, with images between $V(2)$ and $V(3)$ stages in CT condition and $V(3)$ and $V(4)$ in TH condition. These stages were chosen as they provide better uniformity between plants in the planting row. The $V(1)$ stage presents the initial plant development and some of them remain in a germination process, i.e., buried in the ground.

Another important issue is that the image dataset was built with panoramic images containing corn plants in early stages of development, which turns possible to identify problems in inter-plant spacing at early stages of the plant development, as a result, enables the rapid intervention of the producer avoiding losses in corn crop. Therefore, the proposed image dataset presents real conditions of the plant development in order to provide a suitable benchmark, not only for this work, but for other related works.

2.1 Corn Plants Identification

In order to produce an image dataset that can be used in the validation process, it was necessary to identify plants and their stems in all images.

The superpixel technique was adopted in order to assist this process, in which an image is divided into multiple groups of pixels. More specifically, the simple linear iterative clustering (SLIC) [1] superpixel method was adopted in face of its computational efficiency. The cluster belonging to the plant and to the stem were selected with manual assistance in order to produce a curated identification. Figure 2 shows the corn plant identification using the SLIC method. Figures 2(a) and (c) show the plant area (external rectangle) and the plant stem (internal rectangle). Figures 2(b) and (d) show the plant identification and its parts.

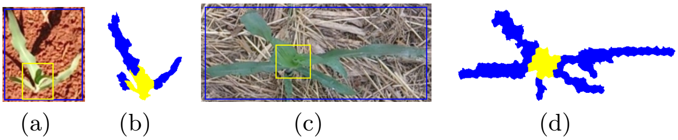


Fig. 2. Figures (a) and (c) show the plant identification, the external rectangle (blue) is the area of the plant. The internal rectangle (yellow) is the stem of the plant. Figures (b) and (d) is the plant identification by superpixel method, all identified pixels belongs to the plant and the yellow pixels is the stem.

As a result, it were identified 2186 corn plants, in which are distributed as following: 1387 in TH condition and 799 in CT condition. The plant and its stem identification were stored in XML (eXtensible Markup Language) files in order to be used in the classification process.

3 Proposed Approach

The main goal of this work is to address the PSV on corn grain yield through an automatic approach to measure the inter-plant spacing in a simple and efficient way. The schematic flowchart of the proposed approach is presented in Figure 3.

After the image acquisition, it was preprocessed by an average filter in order to reduce the reflections on the leaf surface caused by the sunlight. The next step was the image segmentation, in which the goal is to segment the regions of interest (corn plants) from its background (solo and other crop residues).

It is commonly known that vegetation index is a suitable way to improve the image segmentation from its background (soil, rocks and other residues) when the images contain some vegetation. Various vegetation indices were tested in a recent work [9], in which the CIVE (color index of vegetation extraction) shows better results in images with highly lighting variation, achieving more than 90% of accuracy in average. Thus, it was adopted in the proposed approach. The CIVE [8] starts by rescaling the RGB colors individually in the range [0,1].

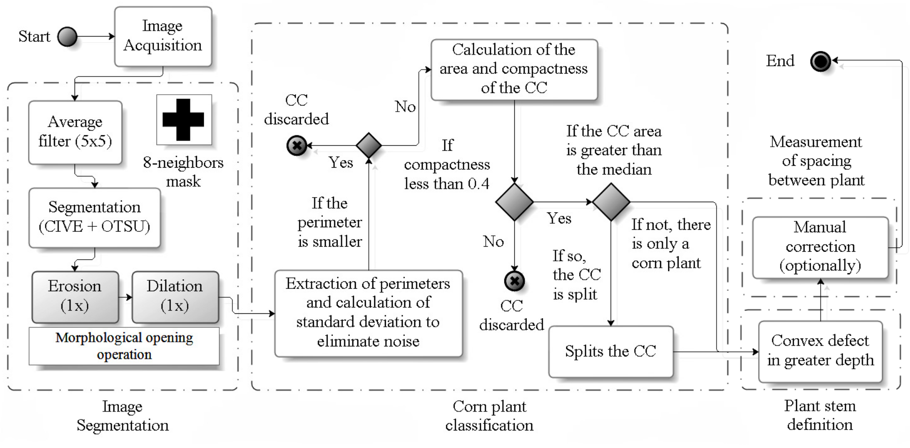


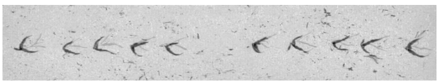
Fig. 3. Flowchart of the proposed approach.

After that, a second rescaling is performed in order to each color band (RGB) gets a relative value, i.e., the fraction of each intensity in relation to the sum of the three bands. This rescaling process is frequently adopted in the agricultural images [7]. As a third step the CIVE index is applied, as a result a grayscale image is produced (Fig. 4 (c) and (d)). In the proposed approach grayscale images were segmented by the Otsu threshold method [13]. However, the acquired images have numerous environmental conditions resulting in noisy segmentation in most of the cases. In order to reduce the noise while preserving the correctly segmented plants it was performed a morphological opening operation[5]. Figures 4 (e) and (f) show the resulting images.

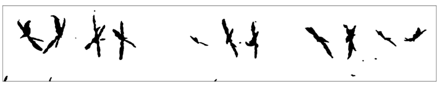
(a) Image example of TH class.

(b) Image example of CT class.

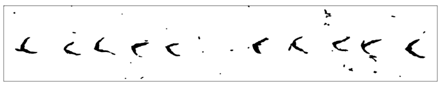
(c) Grayscale image for TH class.



(d) Grayscale image for CT class.



(e) Segmented image for TH class.



(f) Segmented image for CT class.

Fig. 4. (a) and (b) are raw images from proposed dataset. (c) and (d) are grayscale images after performing CIVE. (e) and (f) are binary images after performing threshold.

The correct corn plant classification is crucial for extracting the spacing between plants, because a classification error could lead to a false detection of the planting row. In this way, the first step was to extract some features of each connected component (CC) in the image. It is commonly known that shape features is a relevant information for plants classification [2,5]. Thus, it was adopted the perimeter, defined as the number of pixels belonging to the CC contour. The standard deviation from all perimeters of each image is also taken into account and used as a threshold to eliminate relative small CC, reducing the computational cost of the next steps.

Considering the CC that remain in the image are extracted two features: area and compactness. These CC undergo a new step, in which the regions with less than 0.4 compactness of corn plants are considered and the others are discarded [19]. Then there is a step that attempts to identify the duplicity and triplicity of plants in a segmented area. In this step is extracted the median of the CC areas in the image. If the area of each CC is greater than the median, the CC is divided. This division is recursively applied until that the area of the resulting CC is less than the median.

The plant stem definition is essential for the extraction of the inter-plant spacing with higher accuracy. It was adopted the convex hull, which is commonly adopted for object recognition [14,22]. More specifically, the stem of the corn plant is extracted by identifying the more deeply convex defect, as a result it is found the pixel belonging to the contour with greater distance from the convex hull. Thus, this pixel is used to identify its opposite pixel and then to estimate the average between them as the stem coordinates.

The spatial coordinates of the plant stem are stored and optionally is allowed to the user perform manual corrections to add or remove new plants and move stem coordinates that are outside of its location, ensuring the measurement of distances closer to reality. After this, the inter-plant spacing is measured.

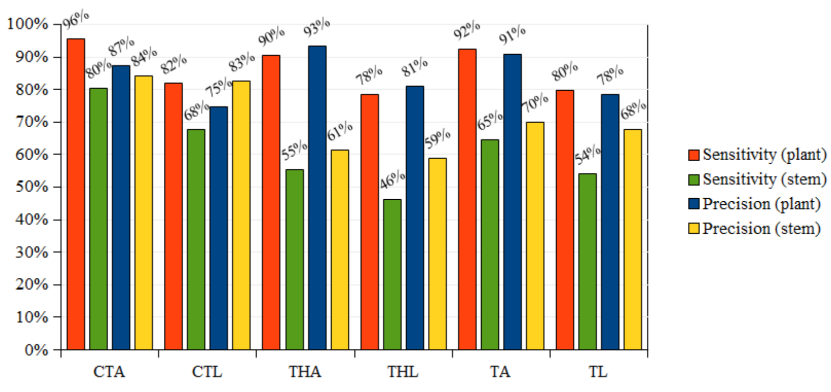


Fig. 5. Classification results.

4 Results and Discussions

This section presents the experimental results in order to evaluate the proposed approach regarding the inter-plant spacing. The experiments were performed addressing two important issues: (1) The automatic corn plants identification; (2) The automatic measurement of the inter-plant spacing.

The automatic corn plants identification was performed considering its area and stem individually (Sec. 2.1) for TH and CT images (Sec. 2). Thus, it were produced six classes: the area for TH images (THA);the stem for TH images (THL);the area for CT images (CTA);the stem for CT images (CTL);the area for CT and TH images (TA); and the stem for CT and TH images (TL).

Figure 5 presents the results by considering the precision and sensitivity measures [20]. It is possible to observe that TA achieve 92% of sensitivity and 91% of precision for plant classification. For TL were obtained 80% e 78%, respectively. The sensitivity was 96% for CTA and 90% for THA with a precision of 87% e 93% respectively. These results were coherent and expected because the area of the plant is larger than its stem. Moreover, the precision for the stem identification was higher in the images in CT condition, achieving 84% (CTA) and 83% (CTL). On the other hand, the results for TH condition were lower than the previous, obtaining 61% (THA) and 59% (THL), which affects partially the inter-plant spacing measurement, since the corn plants were identified with more than 87% of precision and sensitivity in average. This result was due to the stage of maturity of the plants between classes. The CT condition presents corn plants with stages between $V(2)$ and $V(3)$, in which the leaves has a deeper convex defect, while in TH condition contains corn plants with $V(3)$ and $V(4)$, in which this defect can be covered by another branch of the leaf.

The experiments for automatic measurement of the inter-plant spacing were performed comparing the measurements from a manual tape and the measurements inferred by the proposed approach. The obtained differences in average were 1.4 cm for images in CT condition and 1.33 cm for images in TH condition with standard deviations of 0.96 cm and 0.99 cm respectively, presenting very close results. In summary, the results indicate the suitability of the proposed approach for the automatic corn plant identification and the automatic measurement of its inter-plant spacing. Furthermore, the proposed approach present a faster and reliable method than manual analysis for PSV measurement.

5 Conclusions

This work presented an objective approach for the automatic measurement of the inter-plant spacing. An image dataset was built as an additional contribution of this work containing 2186 corn plants in two conditions: tillage after the application of herbicide (TH) with 1387 corn plants and conventional tillage (CT) with 799 corn plants. In addition, both cases present phenotypic variations caused by different stages of plant development.

The experimental results achieve 87% of precision and 96% of sensitivity for CT and 93% of precision and 90% of sensitivity for TH, when considering the automatic corn plants identification. The stem identification achieve 84% of precision when considering the area of the plant and 83% when considering only its stem for CT images. On the other hand, the results for TH images were lower than the previous, obtaining 61% of precision considering the area and 59% considering only the stem, which affects partially the inter-plant spacing measurement, since the corn plants were identified with more than 87% of accuracy and sensitivity in average. Regarding automatic measurement of the inter-plant spacing, the presented results are very close to the manual measurements. In summary, the results indicate the suitability of the proposed approach as an auxiliary tool in preventing grain losses due to variations in spacing between plants caused by the poor performance of planters or low seed quality.

Future work includes to test other strategies for image segmentation and to explore more image features as shape and texture in order to improve the proposed approach, in particular regarding the precision of the stem identification.

Acknowledgements. This work was supported by CNPq, Fund. Araucária, UTFPR and Belagrícola.

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