IN-FIELD CORN STALK LOCATION USING RAPID LINE-SCAN TECHNIQUE

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ABSTRACT

Corn plant spacing and population information is important in assessing planter performance and making decisions on field operations. The objective in this study was to investigate the potential of using laser line-scan sensing technique to locate corn plant stalks on-the-go. A mobile test platform equipped with a commercial laser line scanner, an encoder, a DAQ card, a PC and a RGB camera was constructed. Data was collected for two 10m corn rows at their middle growth stages - V8 and V10 - in Lake Carl Blackwell Agronomy Farm of Oklahoma State University, and was processed later in lab with algorithms developed to recognize and locate stalks. A 4% of mean false negative error and a 29% of mean false positive error at growth stage V8, a 6.7% of mean false positive error and a 12.7% mean false positive error at growth stage V10 were achieved. The system setup and data processing algorithms in this study can be integrated into the variable-rate-spray system to help improving real-time, high spatial resolution variable rate application and increasing the nitrogen use efficiency.

Keywords: Corn, plant population, plant spacing, laser line scanner

INTRODUCTION

Information of corn plant spacing variation is important in making decisions on field operations and assessing planter performance. It has been demonstrated that the variation in corn plant spacing affects the yield production. Every inch increase in standard deviation of plant spacing could lead to two bushels decrease yield per acre (Nielsen, 2005). In another aspect, nitrogen use efficiency in world cereal crop production is low (Raun and Johnson, 1999). Most of the time, excessive nitrogen has been applied because of the lack of information to set realistic yield goal based on the in-field variability (Teal et al., 2006). Approaches to automatically obtain plant spacing variations or plant population are useful in solving these problems.

Many researches have been done so far in this field which can be categorized as airborne and ground-based (Dworak et al., 2011). Most of airborne remote sensing approaches use hyperspectral or multispectral analysis (Huang et al., 2010; Thorp et al., 2008; Jacob et al. 2002). The ground-based sensing approaches have been used for obtaining detailed crop and soil information. They can be combined with other in-field operations such as planting, spraying or harvesting. In terms of plant population or spacing measurement, ground-based approaches can be categorized as intrusive or mechanical methods and non-intrusive methods.

Mechanical methods to measure corn plant population usually use the resistant force of stalks on spring loaded arms or gravity pendulum to count the number of stalks (Birrell and Sudduth, 1995; Heege 2004). Some of them have already been commercialized at combine harvesters. Non-intrusive methods are more suitable for sensing corn population at early and middle growth stages. Some of them are based on capacitive sensing: Nichols (2000) invented a moisture detector sensor installed on the combine to count harvested stalks; Li et al. (2009) developed a capacitance-based biomass proximity sensor to count corn stalks during harvesting. Most of the other methods are based on optical sensing techniques.

Several researches have been done using image-based optical sensing. Shrestha & Steward (2003, 2005) developed and improved a machine vision-based corn plant population sensing system. Algorithms were developed to process the video segmented images to count corn plants, estimate plant location and intra-row spacing. They resulted with a 5.4% coefficient of variation for the standard error in population estimate in 2003, and 6.2% RMSE in 2005. Tang & Tian (2008a, 2008b) developed a real-time crop row image reconstruction and plant identification system for automatic emerged corn plant spacing measurement. They achieved a RMSE of 1.7cm.

Range sensing techniques are another category of optical-based sensing methods applied in crop parameter measurement. Wangler et al. (1994) fixed a laser sensor to a mobile sprayer to detect the presence of the foliage and to control a sprayer on selective spraying. Wei and Salyani (2004, 2005) designed and tested a laser system to quantify foliage density of citrus trees. Saeys et al. (2008) estimated the wheat stand density by measuring the variations in the laser penetration depth. Luck et al. (2008) used an infra-red range sensor to count plants in field. They concluded an error of population estimation between 0.7% and 4.4%. They also indicated that the main error source was the leave interference. Few researches were found about the corn stalk location sensing using range sensing techniques.

The objectives of this research were to:

- i) Use the rapid line-scan technique to develop a system to realize noninvasive corn stalk locating;
- ii) Test the system in corn field at their middle growth stages V8 and V10;
- iii) Develop data processing algorithms to determine corn stalk locations and evaluate the system performance by error calculation.

MATERIALS AND METHODS

System Setup and Principle

The key part of this system was a laser line scanner (SICK LMS291, SICK, Germany) which profiles its surrounding based on distance measurement in a

continuous line scanning with 100° field of view and 0.5° resolution. The sensor output was read and converted from polar coordinates to Cartesian coordinates in a control program developed in LabVIEW and then saved as MS Excel files. Mounted close to ground on a trolley, the laser scanner was viewing almost horizontally at the bottom section of corn stalks – about two inches above plant roots – while the trolley was pushed along the alley between corn rows (Fig. 1). That two-inch correlated with the earlier work done by plant scientists (Kelly, 2010). Due to the inconvenience of mounting and driving the sensor such close to the ground, the sensor was actually mounted higher and had a 20° angle down to keep its actual view on plant stalks was about two inches above plant roots. Multiple neighbor stalk sections within a row were usually showed up in one scan. The number of shown-up stalk sections depended on the distance between the sensor and plants, as well as how far neighbor plants apart. A shaft encoder was mounted at one rear wheel to get where each scan was taken regarding to the start point. The same control program mentioned earlier also interfaced a DAQ card (USB 6008, National Instruments, TX) connecting to this shaft encoder, and saved its readings corresponding to the sensor scan data.



Fig. 1. System setup: (a) actual trolley with sensor; (b) illustration of top view of the system setup.

Field test was conducted from June to July, 2011 in the Lake Carl Blackwell Farm in Stillwater, OK. Two 10m rows, in total 100 corn plants, were picked out in the field and sensed at two growth stages – V8 and V10. Same trolley setup used in the lab test was adopted here. A normal RGB camera was mounted next to the laser scanner on the trolley beam to take the video tapping during each trial which was used later as part of the ground truth. Three replications were performed for each row at each sensing growth stage. The horizontal distance between the sensor and the corn row was about 35cm (14 inches) and the sensing plane on the stalks was kept in between 5cm (2 inches) to 10cm (4 inches) above the plant roots. Manual measurements of stalk diameters were taken for all 100 plants at each sensing growth stage as the major ground truth data.

Data Processing Algorithms

All Excel files collected from the field were processed later in lab using MATLAB[®], though our ultimate goal in the future is to realize on-line processing. In this study, individual scan was first converted from the file and encoder readings were corrected according to the manual measured distance. Then each scan was processed to eliminate noise followed by a two-stage clustering procedure to automatically recognize stalk sections. Locations of each recognized stalk were obtained in each scan. Finally, all scans in a trial were matched with each other to generate a whole non-overlap data set for all plants recognized by the algorithm and the location and stalk diameter of each recognized plant was calculated.

Pre-processing

Individual scan and its corresponding encoder reading were extracted from Excel files. The time-consuming work in this procedure was to correct encoder distance readings between the 1st and the 50th plants in each trial based on the manually measured ground truth so that both of them could have same start and end locations. As described in the system setup, the quality of encoder readings depended on the rotation of the wheel the encoder roller attached. If in some moment that particular wheel did not rotate while the other wheels were still rotating forward, or the trolley was moving backward to overcome obstacles, encoder readings messed up then. This error was natural and hard to be avoided under the field experiment setup in this research. One way to partially correct it was to stretch or compact encoder readings and the ground truth would have an equal total length in between the 1st and the 50th plants as what it was in the ground truth.

Filtering

After pre-processing, data was prepared in the form of individual scan and was ready for advanced processing (Fig. 2 (a)). Each scan was in a local Cartesian

coordinate and the origin was where the sensor was at the moment this scan was done (Fig. 2 (b)). The distance between the origin and the stalk sections was kept within 30 cm to 50cm due to the relative constant distance between the sensor and corn row during the experiment. We eliminated data out of this range which represents ground data points far from the sensor or leaves too close to the sensor. By doing this, less data was input to the next processing procedure.

Clustering

The objective of the clustering procedure was to automatically recognize and locate corn stalk sections within a scan. The algorithm had two clustering stages: the primary clustering and the secondary clustering.

In the primary clustering, data points were clustered based on the distance between each two of them. It started from a random data point, found its neighbors within a certain range and assigned them to a same group; each neighbor data point would find its neighbors which had not been visited yet and include them into its group. If a data point only had one neighbor and that neighbor had already been visited, it was at the edge of the cluster and the expansion of that path ended there. The expansion of one cluster stopped when all its members had no more unvisited neighbors, and the algorithm moved to next potential cluster then. Once all data points were visited and assigned to groups, the algorithm checked the size of each cluster. Only those clusters had enough members were kept while others were treated as noise and eliminated.

One thing needs to be pointed out here is that the distance the algorithm used to cluster varied based on the distance a data point away from the origin. This was because the further two consecutive data points are away from the origin, the further they are separated due to the diversity of laser beams.

In the secondary clustering, clustering results from the primary clustering were refined. Clusters were combined if they were radially close to each other while not too far away in their Euclidean distance. By doing this, we partially avoided multiple counts for one stalk section. Fig. 2 (c), (d) and (e) shows the results after the two clustering stages for three scans in a trial. Locations of all clusters in each scan were stored for the following registration processing.

Stalk diameter was estimated by the size of its corresponding cluster. Due to the radial sensing pattern of the laser scanner, the size of each cluster was calculated along the perpendicular direction of the laser beam through the cluster center. However, the stalk diameter estimation was not the main focus in this paper.

Registration/Matching between Scans

The advantage of using laser scanner under the experiment setup in this study was that we could get multiple scans for the same stalk but from different points of view, so that we had a better chance to correctly recognize the stalk and recover more field information. A stalk usually showed up in about thirty scans without considering the leave interference which means, in the best situation, we could have thirty different perspectives of view for one stalk. It is not only helpful

in getting rid of leave interference for stalk location sensing, but also helpful for stalk diameter sensing since the corn stalk is an oval instead of a perfect round shape. This advantage would never be made use of unless successive scans are matched with each other, or registration between scans is achieved. In this algorithm, successive scans were matched based on the difference of their encoder readings. The algorithm used the stalk locations in current scan and the difference of encoder readings in current scan and previous scan to calculate approximate stalk locations previous scan. Then it looked for stalk section cluster around that calculated location within a certain range. If a stalk showed in current scan but did not in some previous scans due to the leave interference, the algorithm would search back up to twenty scans to find corresponding stalk. Once a corresponding stalk was found, the stalk in the current scan was assigned as the same number and its location in current scan was also stored. If no corresponding stalk was found, then this stalk in current scan was a stalk newly coming into the field of view if this was a latest stalk the algorithm observed; otherwise it was a noise cluster most likely corresponding to leaves. Sub figures (c) and (d) in Fig. 2 are two successive scans – scan #128 and #129 in replication 1 of plant ID #1~#50 at V10 growth stage, sub figure (e) is the scan #138 in the same trial. The algorithm recognized there were four stalks in sub figure (d) which corresponded to the same four stalks in sub figure (c). It also recognized three out of the four stalks in sub figure (e) corresponding to the right three stalks in (d) but also a new show-up stalk at the very right. The most left stalk in (d) had moved out of the field of view of (d).

After implementing the registration for all scans, the algorithm output estimated number of stalks as well as locations and stalk diameters for each stalk in all related scans. The interquartile data was averaged and used as the final results of location for each recognized stalk.



(b)



Fig. 2. Examples of data processing result at each step: (a) raw data of scan #128 of one trial; (b) result of scan #128 after filtering; (c) result of scan #128 after clustering; (d) result of scan #129 after clustering; (e) result of scan #138 after clustering.

RESULTS and DISCUSSIONS

The data processing results are shown in table 1 in which (a) shows the result of stalk #1 to #50 and (b) shows the result of stalk #51 to #100. Both sub tables summarize the information of each replication in each growth stage: the soil

moisture, the sensing plane height, the quality of encoder readings, quality of sensor data, false negative error, false positive error and percentage of sensor measured location within 5cm to 10cm of ground truth location. The purpose to investigate the quality of encoder readings and sensor data here with the data processing results was to discuss the source of error in this experiment.



Fig. 3. Sensor measured and ground truth stalk locations of replication 1 of row 1 at V10.

In the column of quality of encoder readings, 'fine' means the trolley did not have significant backward movement during the trip, there were insignificant missing counts and the encoder readings were increased almost linearly; 'ok' means the trolley had some backward movement or there were some missing counts, but did not affect significantly to the encoder readings and the encoder readings were acceptable for being used in sensor data processing; 'not good' means the backward movement or missing counts significantly affected the encoder readings for being used in the sensor data processing. In the last case, the whole data set was ignored which was the case for growth stage V10 for stalk #51 to #100. All sensor data was good except one replication under growth stage V10 for stalk #1 to #50 lost the logging of some scans but the whole data set was still acceptable.

The false negative error in the table corresponds to stalks which were not recognized by the algorithm but should be actually there; while the false positive error corresponds to objects mistakenly recognized as stalks by the algorithm but were actually leaves or other type of noise. Figure 3 shows an example of sensor measured stalk locations and ground truth stalk locations as well as the false negative error and false positive error. A 4% of mean false negative error (mean of row 1: 0%, mean of row 2: 8%) and a 29% of mean false positive error (mean of row 1: 24%, mean of row 2: 34%) were achieved for both row sections at V8. A 6.7% of mean false positive error and a 12.7% mean false positive error was achieved for row 1 at V10.

From the table we can see that, at growth stage V8, false positive errors tend to be larger than false negative errors for both row sections (row 1 had a mean false positive error at 24% and a mean false negative error at 0; row 2 had a mean false positive error at 34% and a mean false negative error at 8); at growth stage V10, false positive errors tend to decrease while false negative errors tend to increase (row 1 had a mean false positive error at 6% and a mean false negative error at 6%). This is mainly because of the change of leave interference. At growth stage V10, most of the leaves on the bottom of stalks (2 to 3 inches above the roots) are fully dehydrated and lay on the stalk. Those leaves prevent the sensor to see the stalk clearly so we tend to have more false negative errors. This problem was even severe due to the drought in Oklahoma last summer. Sensing at various heights would help reduce this problem in the future. While at growth stage V8, most of leaves on the bottom of the stalk are still vital and stand out of the stalk, so they would not prevent the sensor to see the stalks, but would cheat the sensor to treat them as stalk objects. Improvement on the stalk recognition and scan registration algorithms is needed to reduce such error in the future.

Table 1. Results of stalk location estimation. (a) results of row 1: stalk #1~#50; (b) results of row 2: stalk #51~#100.

Row 1: Stalk #1 ~ #50										
		Soil moistur e	Sensin g plane height	Quality of encode r reading s	Quality of sensor data	False negativ e error (%)	False positiv e error (%)	Sensor measure d location within 5cm of ground truth (%)		
V8	Rep 1	Dry	5~8cm above the roots	Fine	Good	0	24	98		
	Rep 2			Fine	Good	0	28	96		
	Rep 3			Fine	Good	0	20	96		
	Mea n					0	24	97		
V1 0	Rep 1	Very dry		Fine	Good	4	8	94		
	Rep 2			Fine	Lost part of the data betwee n 200cm	10	24	71		

					and 300cm						
	Rep 3	-		Fine	Good	6	6	96			
	Mea n					6.7	12.7	87			
				(a)							
Row 2: Stalk #51 ~ #100											
		Soil moistur e	Sensin g plane height	Quality of encoder readings	Qualit y of sensor data	False Negativ e Error (%)	False Positiv e Error (%)	Sensor Measure d Locatio n within 5cm of Ground Truth (%)			
V8	Rep 1	Dry	5~8cm above the roots	Ok. Some missing counts happene d between 300cm and 400cm	Good	12	34	77			
	Rep 2			Fine		6	32	89			
	Rep 3			Fine		6	36	89			
	Mea n					8	34	85			
V1 0	Rep 1 Rep 2 Rep 3	Very dry		Not good. Having backwar d moveme nt	Good						
	n n										
(b)											

The absolute error of stalk location measurement was also calculated for each correctly recognized stalk by getting the absolute difference between the sensor

measured location and the ground truth location. The last columns in both sub tables show the percentage of sensor measured locations within 5cm of ground truth locations. A 91% was achieved for both row sections at V8 and an 87% was achieved for row 1 at V10. Combining this result with the false negative errors discussed earlier, we can achieve an 87.4% of on-target spray at V8 and an 81.2% of on-target spray at V10.

CONCLUSIONS

A laser scanner based system sensing at bottom sections of corn stalks as well as corresponding data processing algorithms was developed to locate corn stalks in their middle growth stages in field. This research demonstrated that:

- Using laser scanner to sense corn stalks from different point of view onthe-go is a feasible method for identifying and locating stalks. The result after data processing showed a 4% of mean false negative error and a 29% of mean false positive error at growth stage V8, a 6.7% of mean false positive error and a 12.7% mean false positive error at growth stage V10.
- The stalk identifying and locating results could be improved by having better quality encoder readings by modifying the encoder mounting mechanism, sensing at different height to avoid dead leave interference and improving data processing algorithms.
- More information can be obtained using this method such as stalk diameter estimation.

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