

CORN SENSOR DEVELOPMENT FOR BY-PLANT  
MANAGEMENT

By

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CORN SENSOR DEVELOPMENT FOR BY-PLANT  
MANAGEMENT

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## CHAPTER I

### INTRODUCTION

#### **Precision Agriculture**

Technological advances for different industries have benefited agriculture by their incorporation into production systems. The industrial age brought mechanization; the technology age offered engineering and automation (Zhang et al., 2002). Precision agriculture is a practice that has a set of tools that allows an agriculturist to quantify and manage the spatial variability in farm fields (Stombaugh and Shearer, 2000). According to Searcy (1997) precision agriculture is based on the optimization of production inputs in a field where the soil and crop characteristics are known. In the last few years, a great advancement in precision agriculture technology has been developed (Stombaugh and Shearer, 2000). Precision agriculture has a base on the spatial and temporal variability of soil and crop within a field due to the enlargement of fields and the increase in mechanization. Nowadays, the development of revolutionary technologies has become necessary to account for within-field variability (Zhang et al., 2002).

In addition, many investigations have been conducted regarding variability. According to Raun et al. (2005) the time when fertilization could have the greatest impact, could be the growth stage where plant variability is at a maximum. Therefore, identifying the variability among plant-to-plant spacing within the row is crucial for precision farming techniques (Freeman et al., 2007).

Raun et al. (2005) also suggested that the point where by-plant variability was best recognized should theoretically be the same time at which to sense and treat spatial variability. In the experiment they measured daily plant growth and spatial variability in corn over the entire growth cycle. It was found that 6-leaf growth stage (V6) might be the time which treating variability could have the greatest impact, because V6 had the greatest spatial variability.

As well as quantifying variability, research on corn yield prediction has been conducted in the past. Work by Teal et al. (2006) predicted accurately the corn yield potential using normalized difference vegetation index (NDVI) at the V8 growth.

Martin et al. (2010) defined an equation to predict corn grain yield. This prediction was related to the linear distance occupied by each plant, the competition adjustment factor and the days from planting in-season estimated yield (INSEY). The competition factor is dependent of the height of the plant in question, as well as the height of the previous two and the following two plants of the plant in question. INSEY is calculated using NDVI, and the number of growing degree days (GDD).

Further work was conducted by Kelly (2011) to improve in-season corn yield prediction. He analyzed the relationship between corn stalk diameter, plant height, and NDVI with final corn grain yield. The studies were conducted in Lake Carl Blackwell



and Efav near Stillwater, OK, Hassel, OK, and Ciudad Obregon, Mexico. Corn plants were at V8, V10, and V12 growth stages at the time of sensing. Correlations were higher based on both stalk diameter and plant height with values up to 0.67 for V12. Thus, concluding that corn stalk diameter could be a crucial parameter to predict corn grain yield. The best prediction results of by-plant grain yield were given by the multiplication of stalk diameter and plant height from growth stages V8 to V12.

## CHAPTER II

### LITERATURE REVIEW

#### **Stalks and plant population measurement**

A handheld mechanical device to count corn stalks was presented in 1996 (Easton, 1996). The device sensed plants with a small pivoting arm. In addition, the distance was measured with the signals sent by an opto-interrupter that read the teeth of a 60 tooth disc driven by a one meter circumference wheel. Each pulse sent by the microcontroller incremented the distance by approximately 17 mm. The limitation of this device was that it only provided general information for the field, such as standard deviation of plant spacing, and data for individual plants.

Plattner et al. (1996) used an optical sensor to measure stalk diameter and plant spacing statistics with parameters like skips, doubles, and plant spacing. They mounted a photoelectric sensor on a corn combine. It projects a light beam across the row, and the corn stalks break the light beam. The distances were calculated using a ground speed sensor. To eliminate errors due to leaves in the light path, they used spring-loaded leaf retarders. The sensor estimated average plant spacing with an error of  $\pm 3.1\%$  at the early stage, and  $\pm 6.2\%$  of error at harvest stage. Leaves were a major source of interference for this sensor.

Li et al. (2009) developed a proximity sensor using capacitive technology to detect biomass. They simulated, fabricated, and evaluated different capacitive paths in the laboratory. After that, the sensor was evaluated for biomass population quantification in the field to detect corn stalks. The sensor had less than 5% error on plant population for five of the six rows harvested. In addition results showed less than 2% error on the average of the six rows.

Later, research by Lovell et al. (2011) presented a method using the intensity of returns from a scanning light detection and ranging system to identify the location and measure the diameter of tree stems within a forest. The reflectance of the laser light allows detecting trees. The reflectance depends of the range as well as the object's reflectivity. The results showed success in identifying trees, including some that are partially obscured from view. The trunk angular span, and diameter estimations were well correlated with field measurements, but the accuracy for the diameter estimation decreased with range from the scanning position.

Work has also been presented regarding plant population. Shrestha and Steward (2003) developed a machine vision-based corn plant population sensing system to measure corn population. Video was acquired when corn plants were at V3 and V4 stages. Algorithms were developed for the segmentation. The number of plants pixel and the median position were extracted from each segment. This approach gave a correlation to the manual count of 0.90 in low-weed field conditions.

Additionally, Shrestha and Steward (2005) continued with the vision-based approach and developed an algorithm to count corn plants and to estimate plant location with scanned images. Using a chain code they detected the limits of top projected corn

plant canopy objects. The system detected plants with a coefficient of determination ( $R^2$ ) of 0.92.

Luck et al. (2008) processed the voltage output from infra-red sensors to count plants at V7-V9 growth stage. The sensor was on one side of the row, and a plate was parallel to the sensor on the next row to eliminate the possibility of sensing the plants on the next row. Using an algorithm in MatLab they extracted plant populations. The sensor was used on a row crop tractor with constant speed of 3.2 kilometers/hour (km/h) for field testing. Overestimation happened due to leaves or other objects on the rows that were considered as corn plants. The errors ranged from +0.7% to +4.4% per row.

Research has also been conducted related to scale variability. Such research discusses whether or not small-scale is better than large. Solie et al. (1999), conducted two experiments to determine the semi variance range of plant uptake measurements. The results proved that dimensions should be in the meter or sub meter range, because larger intervals will miss short distance changes. These results lead to conduct research on a smaller range, research to create a by-plant management on the field, instead of a broad management using corn population.

Martin et al. (2010) used plant height to predict corn grain yield, however plant height can be difficult to measure for individual plants in production fields. Wind and adjacent plants cause interference. Kelly (2011) predicted corn grain yield using stalk diameter. While measuring stalk diameter comes with its own challenges (leaves and other interfering objects), the sensor used to measure stalk diameter could also measure plant location and spacing. According to the corn grain yield prediction equations, the

distance between plants needs to be measured, therefore the same sensor could be used to measure stalk diameters. This would eliminate the extra sensor that measures height.

### **Research objective**

Previous work has been done sensing different parameters separately, but this research pretends to establish a tool that integrates the advances presented in other industries with precision agriculture. In difference with previous studies this research pretends to develop a sensor capable of measuring two parameters at the same time.

The main objectives for this study were:

1. To develop a sensor capable to locate plants in a field with a photoelectric sensor using an algorithm to detect plants.
2. To electronically measure corn plant diameter of plants correctly located using photoelectric sensor and optical encoder data.

## CHAPTER III

### MATERIALS AND METHODS

#### **Sensor selection**

Initially an ultrasonic sensor was tested to prove the reliability of the measurements to the stalk diameter. Although it had good time response and signal processing, the cone produced by the sound waves, gave a deviation between the results and the actual diameter. And although the error was consistent, that option was dismissed.

After considering several sensing options, photoelectric technology showed much promise for the intended purpose. These sensors can give excellent response time as well as background suppression, if needed. But the most important condition was that the light used by this sensor does not have signal offset, like the cone on the ultrasonic sensor. Therefore, the electronic measurements in the first year of this study were taken using a SICK (Minneapolis, MN) photoelectric sensor, model number W9-3 (Figure 1). This sensor has a maximum distance sensing range of 2000 mm. It provided a switching output of 0 and 12 V. The switching output was programmed with background suppression at 50 cm to avoid sensing items beyond the row of corn plants. The sensor was placed at 10 cm above the ground to measure at the same height that the manual measurements were taken.



Figure 1. SICK W9-3 Photoelectric sensor

The digital output of the optical sensor used in 2011 did not perform well. Leaves next to a plant resulted in overestimated diameter measurements and the digital output made it impossible to differentiate one from the other. Therefore, for the 2012 study the system was converted to an analog sensor. A SICK DT-10 photoelectric analog sensor was used (Figure 2). This sensor has a programmable range from 5 to 500 mm, and provides a 4-20 milliamps (mA) output for the programmed range. Using the teach button, the sensor was programmed to ignore anything beyond 25 cm from it. A 500 ohms ( $\Omega$ ) resistor was connected between the ground cable, and output signal cable from the sensor to convert the output signal to voltage. After the resistor was connected, the voltage range of the output signal was 0 – 10 volts.



Figure 2. Analog Photoelectric sensor used on the second study

An optical encoder was placed on one of the wheels to calculate the distance and speed of the sensor from the beginning of the row. Rotary encoders convert an angular position into an analog or digital signal. The Dynapar (Gurnee, IL) E14 miniature is an incremental shafted encoder. It provides 200 pulses per revolution (PPR). Each pulse is 5 V in magnitude, the same as its excitation voltage.



Figure 3. Optical encoder used to calculate speed mounted on the front wheel



## **System test and calibration**

The test and calibration of the system was conducted in the Bioystems and Agricultural Engineering Laboratory using Polyvinyl chloride (PVC) pipes. Five pipes of 2.54, 3.81, and 5.08 cm were used. The pipes were placed randomly in a row simulating a corn plants. The cart was then pushed alongside the row of pipes. Data were collected and analyzed to evaluate the system under optimal conditions.

To evaluate the performance of the optical encoder, the cart was pushed through a defined distance. Using MatLab, the number of pulses was counted to calculate the distance. Results provided enough information to prove the functionality of the sensors.

## **Experiment design**

Two locations were selected for the research. During summer 2011 data were collected at Lake Carl Blackwell Research Field, on Stillwater, OK using the resources available at the Biosystems and Agricultural Engineering laboratory, as well as crop fields operated by the Department of Plants and Soils Sciences. Twelve rows of corn plants with 50 plants each were selected for the experiment. They were sensed at V8, V10 and VT growth stages. Additionally data were collected in the spring of 2012 in Ciudad Obregon, Mexico using the resources available at the International Maize and Wheat Improvement Center (CIMMYT). Twelve rows with 50 corn plants each were selected for the experiment. At the time of sensing, four rows were V8 stage, four V12, and four were VT.

## **Manual measurements**

Each plant was measured individually by hand. The dimensions collected were major diameter (D1), minor diameter (D2), cross-section distance (CS), and distance between plants (DB) from center to center (Figure 4). Stalk measurements D1, D2, and CS were measured using a digital caliper in millimeters (mm) with precision of 0.01, at 10 cm above the ground in Oklahoma. For the study conducted in Obregon the height for the stalk measurements was 20 cm from the bottom of the furrow because corn was planted on raised beds.

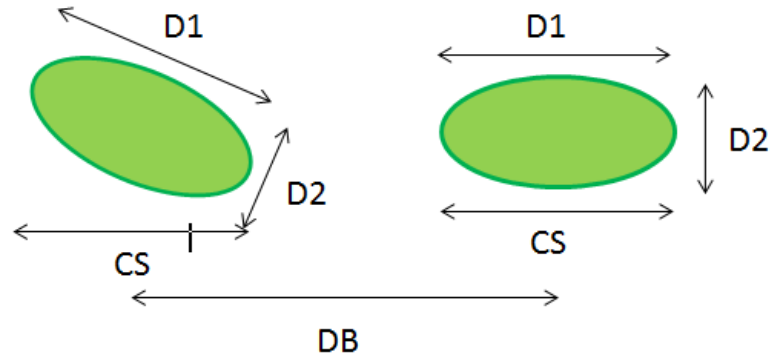


Figure 4. Dimensions measured by hand on each corn plant

DB was measured in centimeters (cm) by placing a measuring tape on the ground next to the row. The beginning of the tape was placed at the edge of the first wooden stake, and the end was placed at the edge of the next wooden stake as it is represented on Figure 5.

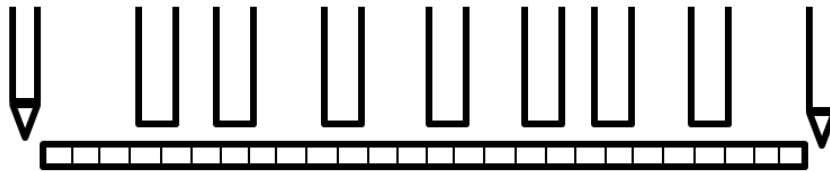


Figure 5. Representation of the tape measurement lying next to the row between the two wooden stakes

For the corn grain yield prediction algorithm only CS and DB are needed, therefore only those were measured by the sensor. D1 and D2 were measured to continue the research on the relationship between stalk diameters and yield.

## Data acquisition

For the 2011 study the main goal of the data acquisition was to collect the elapsed time during a signal of the photoelectric sensor. Additionally, the encoder data was used to calculate speed.

The device used to collect data was an Arduino UNO (Chiasso, Switzerland) microcontroller. This microcontroller uses software based on C++. The board is based on ATmega328. It has 14 digital input/output pins, 6 analog inputs, a 16 MHz crystal oscillator, a USB connection, a power jack, an ICSP header, and a reset button. A shield (accessory) of this microcontroller was also bought to store the data on a SD card. The shield provided portability because data was automatically saved on the SD card. Data were saved in a new comma delimited text file every pass. The Arduino UNO and the shield (Figure 5) were powered with a single 9 V battery.

The equipment was mounted on a four-wheel cart built at the Biosystems and Agricultural Engineering laboratory. The sensor was placed on one side of the cart between the wheels to reach the desired height.



Figure 5. Arduino UNO board, and Arduino Data Logging Shield, used to log data from the sensors into an SD card.

The Arduino code, counted the elapsed time in microseconds ( $\mu\text{s}$ ) between a rising and a falling edge from the sensor signal, and vice versa, as shown on Figure 6. The data were saved as a comma delimited text file on the SD card. Speed was calculated using the encoder signal. The stalk cross-section distance (CS), and the distance between plants (DB) was calculated using Microsoft Excel with time and speed values for each parameter.

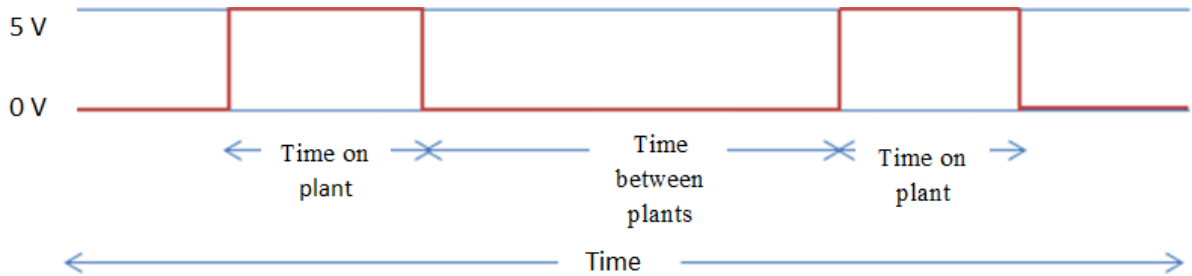


Figure 6. Description of data collected by Arduino from the photoelectric sensor

For the study conducted in 2012 the data were recorded using a USB – 1208 Measurement Computing (Norton, MA) Data Acquisition system (DAQ). The device features up to 8 analog inputs of 13-bit resolution, 16 digital I/O lines, two 32-bit counters, one 32-bit PWM timer output, USB-bus powered, and 1 mega samples/second (MS/s). One analog channel was used to measure the voltage of the photoelectric sensor, and another channel to measure the signal from the rotary encoder. The analog channels were configured as single ended using InstaCal, software provided by Measurement Computing. Using InstaCal the channels were configured to a 0 to 10 V range. Both signals were recorded at 10 kHz. The main reasons for the change in the system between

2011 and 2012 were the resolution and the sampling rate. Although the system lost the stand alone capability, the USB-1208 provided more reliable features in order to reach our objectives.



Figure 7. Data Acquisition system used for the second study

### **Mounting vehicle**

The sensors were mounted on a small golf cart. The cart is a Sun Mountain (Missoula, MT) Micro Cart. The light weight, and folding feature, made this cart a suitable option to mount the devices on.

The cart supported a 12 V battery, a laptop, an enclosure box with the DAQ, the rotary encoder, and the photoelectric sensor. The photoelectric sensor was mounted on one of the side tubes of the cart as shown on Figure 8. The rotary encoder was attached to a mounting plate attached to one of the center tubes of the cart. In addition, as shown on Figure 9, the encoder shaft was attached to a Slim-Tread Drive Roller of 4.1275 cm

diameter. The roller made contact with the inside area of the left front wheel, causing the encoder to move as the wheel moves. Figure 10 shows a picture of the cart with all the devices on it.



**Figure 8. Photoelectric sensor mounted on one side of the cart**



**Figure 9. Roller of the encoder making contact with front wheel**



Figure 10. Picture of the cart with all devices on it

### **Data collection**

Wooden stakes were placed before the first plant measured, and after the last plant to indicate the beginning and end of the 50 plants. The cart was then pushed inside the row right before the first wooden stake, making sure the photoelectric sensor light did not indicate that was sensing something. The cart was then pushed through the row trying to maintain a constant speed until the next stake was reached.

To begin data collection using the USB-1208, the MatLab code was run and the message “ADC ready... Starting” needed to appear on the computer’s screen before the cart was pushed through the row. To stop data collection the command “stop(allmcc)” was typed.



## Data processing and analysis

### Data Logging

The data were logged with a program developed in MatLab. The DAQ was connected to the computer by its USB interface. The program configured and read data from two analog channels. The sampling rate was set at 10,000 Hz; and a time limit of 6 minutes. Data were saved on MatLab's Data Acquisition Toolbox files (.daq). A new file was created every pass. The name of the file included the location, date, and time stamp.

### Analysis of optical encoder signal

The purpose of the encoder signal was to measure the location of the cart as it moved along the row. The equivalent distance of each encoder pulse was calculated using the ratio between the roller and the wheel and PPR. The value was 0.82 mm per pulse.

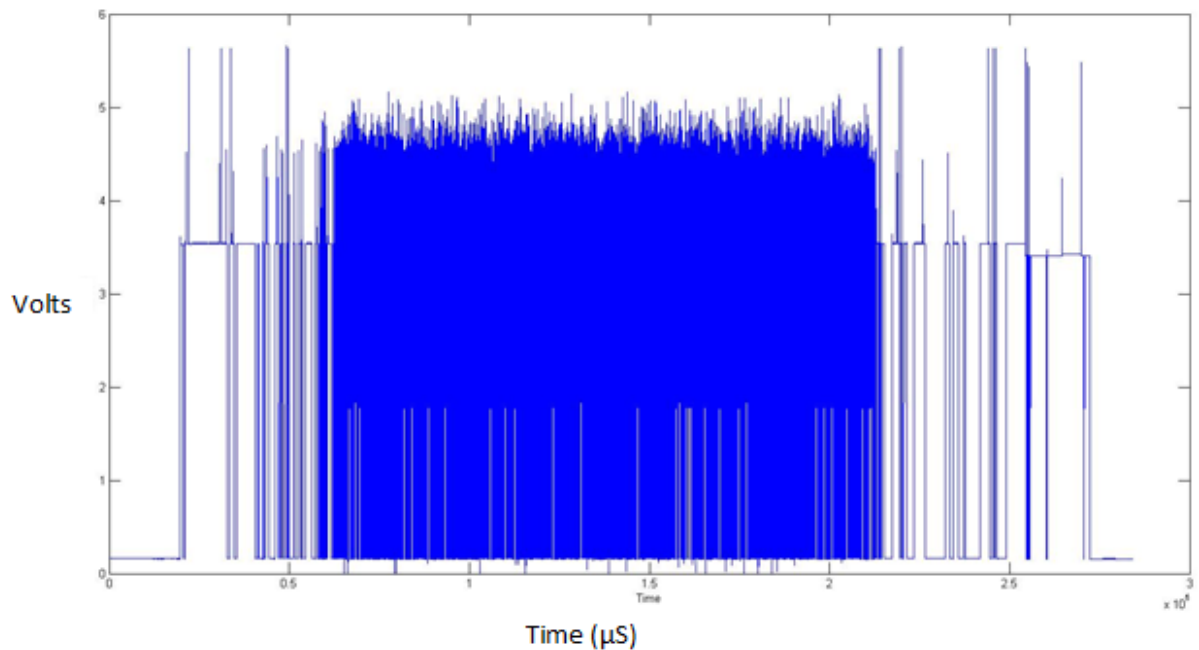


Figure 11. Plot of the encoder signal from the analog channel

The encoder signal was logged using an analog channel resulting in data like that shown on Figure 11; therefore the counts needed to be detected.

Encoder data were analyzed using two approaches to count the number of pulses. The first was using Discrete Fourier Transform (DFT). The DFT was applied to the signal using overlapping windows. Each window had 256 points with steps of 128 points for the overlapping. This value produced an overlapping window from the center. The output from this function is a vector with the frequencies found in the data. A first order low pass filter with filter coefficients equal to 1/100 was applied to the output vector to smooth the signal. The angular frequencies were converted to distance using the ratio between the encoder roller and the inside circumference of the cart wheel, and the outside circumference of the cart wheel. At the end the vector included the speed for every time unit on the data as shown in Figure 12. The vector was used to calculate the average speed of the pass.

Matlab function “findpeaks()” was also used to locate peaks in the data. The function was configured with a threshold of 0.1 V. The function then recognizes as a peak every value greater than its neighbors by at least 0.1 V. The function output was a vector with the time at which each encoder pulse occurred.

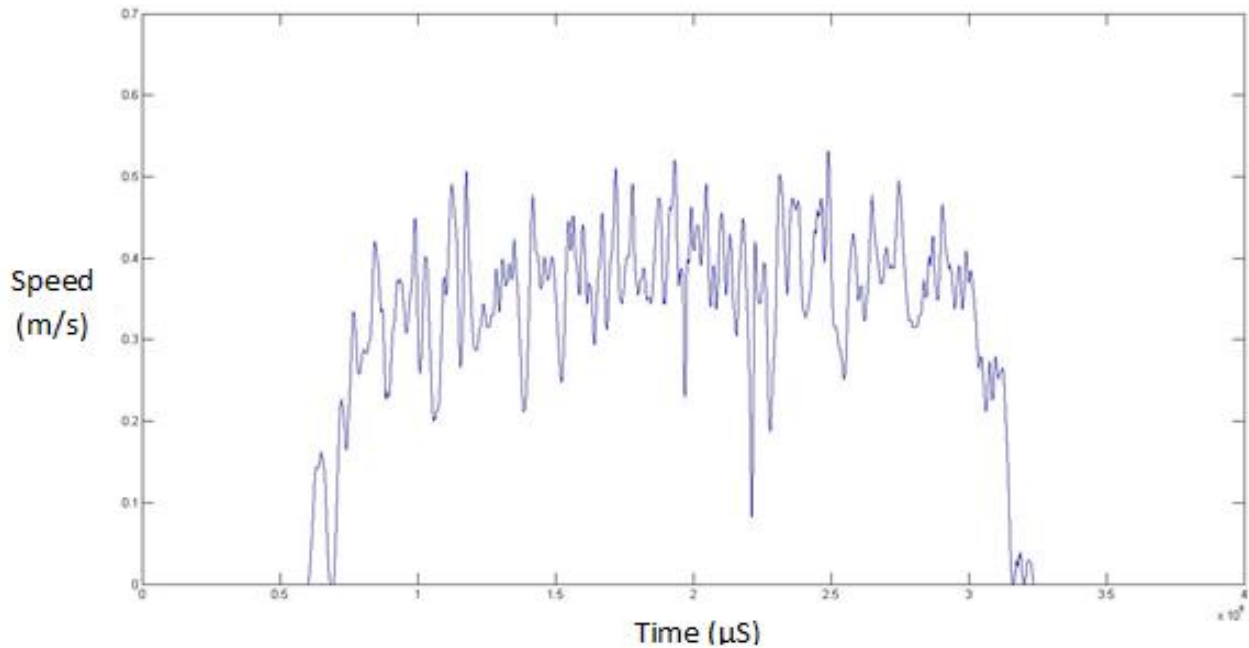


Figure 12. Plot of the speed of the cart over time

### Analysis of photoelectric sensor signal

The data collected from the photoelectric sensor was an array of voltages. It had an element for every  $1/10000$  s. Figure 13 shows a plot of the raw data from the photoelectric sensor. On Figure 13, the line at 4.7 V defines the background suppression. The voltage represents the distance from the sensor. A lower voltage means the object is closer, thus voltage drops when the sensor detects a plant or other object. The photoelectric data were to find the time elapsed between plants and during the sensing of a plant. Therefore, with the known speed at that specific time the distance (DB) and diameter (CS) were calculated.

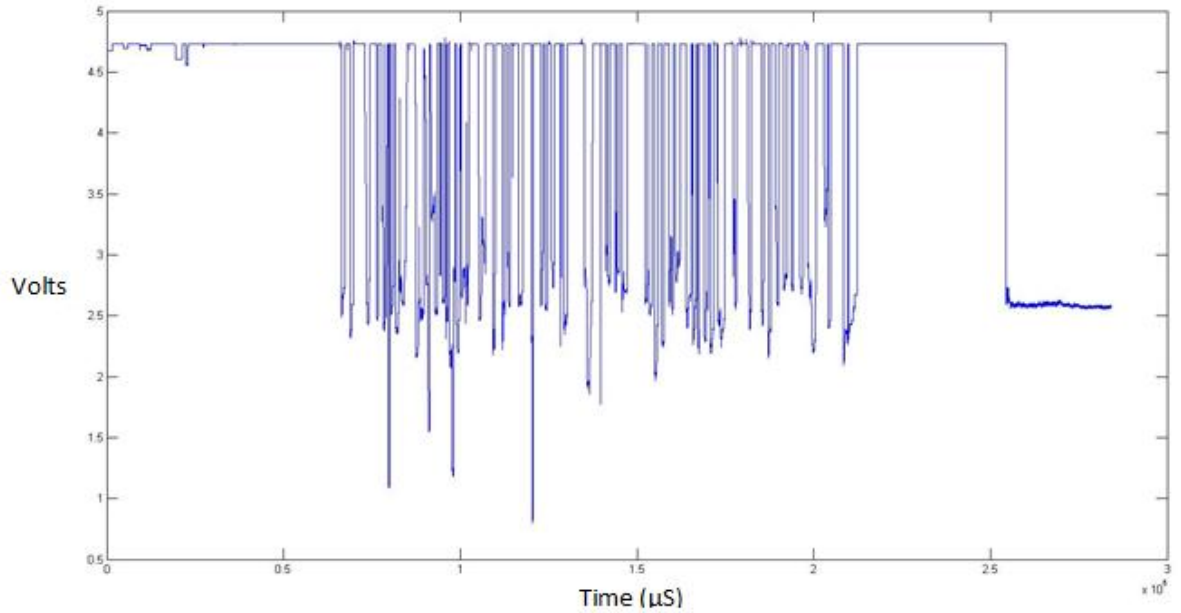


Figure 13. Plot of the raw data from the photoelectric sensor

The algorithm used information previously known from the field, specifically plant spacing and expected minimum diameter. The targeted planting distance used at CIMMYT was 12.5 cm, and the average minimum stalk diameter was defined as 20 mm. Those values were defined in the program and converted to time in each pass using the average speed calculated with DFT. By doing this, each pass had the average time required to push the cart through 12.5 cm and 20 mm.

The time lapse between the rising and falling edges of the photoelectric signal was calculated for every object detected by the sensor. The location and cross section of every object detected was evaluated.

The program evaluated if the time between edges of the object sensed met the criterion of average minimum stalk diameter in time. If it did not meet the criterion, the

voltage value of the signals between the edges was changed to 4.7 V, which is the value when nothing was sensed. If it met the criterion, the position of the object was evaluated.

Position was evaluated using the targeted plant spacing. Every object detected must be 12.5 cm away from the previous object detected. First, the data were evaluated using  $\pm 20\%$  tolerance of the targeted location. Therefore the object needed to be from 10 to 15 cm away from the previous object detected. Data were also evaluated using  $\pm 40\%$  tolerance of the targeted location. Therefore the object needed to be from 7.5 to 17.5 cm away from the previous object detected. If the position criterion was not met for the object, the signal voltage is changed to 4.7 to indicate that nothing was sensed.

After the object was evaluated, the number encoder pulses between the edges were counted, and multiplied by 0.082 mm to calculate cross section (CS) distance. The distance was calculated for every object detected. The same process was used to calculate the distance between plants. Once a falling edge was detected, the program calculated the distance to the next rising edge. The program then created a vector with the values of CS and DB for every plant detected.

A MathCad® 13 (Mathsoft Engineering & Education, Inc) program was used to calculate the error, as well as count misses, multiples, and good measurements by the sensor. For every sensed plant, the program determined which of the actual plants it was closest to by calculating the minimum distance to actual plants. Once these minimum distances were determined, the matrix of minimum distances was queried for each actual plant to determine which of the sensed plants was closest to it. If more than one sensed

plant was deemed closest to the actual plant, only the closest plant was considered a good measurement. Others were considered multiple.

On the other hand, if no sensed plant was closest to the actual plant, then it was counted as a miss.

Therefore, the term “misses” refers to the number of existing plants that were not detected by the sensor and “multiples” refers to the number of objects detected by the sensor that were not actual plants.

The term “good measurements” refers to the number of plants located correctly in the row. The number of good measurements was calculated by subtracting the number of misses and the number of multiples to 50 as defined on Equation 1

$$GM = 50 - (NMISS + NMULT) \quad (1)$$

*Where:*

*GM = Number of good measurements*

*NMISS = Number of misses*

*NMULT = Number of multiples*

“ABS Error” refers to the absolute error calculated only for the good measurements. For every plant located right, the difference between the sensed

$$ABS\ Error = |SM - MM| \quad (2)$$

*Where:*

*ABS Error = Absolut error of the measurement (cm)*

*SM = Sensed measurement (cm)*

*MM = Manual measurement (cm)*

The difference between manual and sensed cross section was calculated for each of the good measurements. The next step was to detect the number of plants that were measured with 10, 20, and 30 mm of absolute difference.

## CHAPTER IV

### RESULTS AND DISCUSSION

#### **Fist study**

Data for the first study were processed using Microsoft Excel® 2010. Every comma delimited file consisted of a sensing time for every object detected, and the time between two objects detected (Figure 6). In addition, one column indicated the elapsed time of the current pass for each object. All times were expressed in microseconds ( $\mu\text{S}$ ). Speed was calculated by multiplying the time values by the pulses received from the optical encoder. Each pulse was equivalent to 0.1 mm.

Results for the study conducted in 2011 showed that the sensor performed better at earlier growth stages. The absolute error was as low as 2.9 cm for V8 and as high as 6.7 cm when the corn plant was in tassel stage (Table 1). The average error was less than 5 cm.

For the first study, the results showed that the growth stage affected the performance of the system with an increase of the absolute error and the decrease in the number of good measurements for late growth stages. For V8 the number of plants located right was as high as 82% but, for VT the number of plants detected was as low as 40%. One reason for this might have been the increase of plant residue on the ground. Rows with plants in late growth stages might have dried leaves hanging from the plant or on the ground. The sensor possibly detected those leaves as plants resulting in



measurement errors. This was evident as the number of multiples increased with growth stage (Table 1). For example, rows 1-3 went from an average of a little over 1 multiple at V8 to an average of over 8 when the plant was tasseled.

Another observation was how the number of misses always exceeded the number of multiples even though the number of misses did not increase as considerably as multiples for some of the rows.

For the most part the results were similar between different passes in the same row indicate consistency for the system. Some differences were found but not enough to be consider as a problem.

Table 1. Results from the study conducted in summer 2011

SUMMER 2011

		Pass 1				Pass 2				Pass 3			
	Row	Good	Multiple	Miss	ABS Error (mm)	Good	Multiple	Miss	ABS Error (mm)	Good	Multiple	Miss	ABS Error (mm)
V8	Row 1	38	1	11	4.1	38	0	12	3.6	41	0	9	2.9
	Row 2	36	1	13	3.3	29	3	18	3.8	29	4	17	5.0
	Row 3	38	1	11	3.7	39	1	10	4.0	31	2	17	3.8
	Row 4	32	1	17	3.6	30	2	18	3.5	35	1	14	3.6
	Row 5	26	9	15	6.6	30	6	14	5.5	25	7	18	4.4
	Row 6	29	5	16	6.9	22	11	17	7.9	27	10	13	7.1
V10	Row 1	20	11	19	9.3	25	7	18	6.4	24	4	22	4.8
VT	Row 1	34	7	9	5.4	36	6	8	4.0	35	6	9	4.4
	Row 2	31	6	13	6.1	24	9	17	6.9	30	8	12	5.9
	Row 3	28	11	11	5.3	20	14	16	8.3	24	10	16	6.7

## Second study

The data were processed using MatLab to detect corn plants and remove other objects. The threshold for minimum plant diameter was defined as 20 mm. Data less than that were removed. In addition, plant spacing was defined as 12.5 cm. Figure 14 shows a fragment of the photoelectric sensor data, and the filtered data are shown in Figure 15.

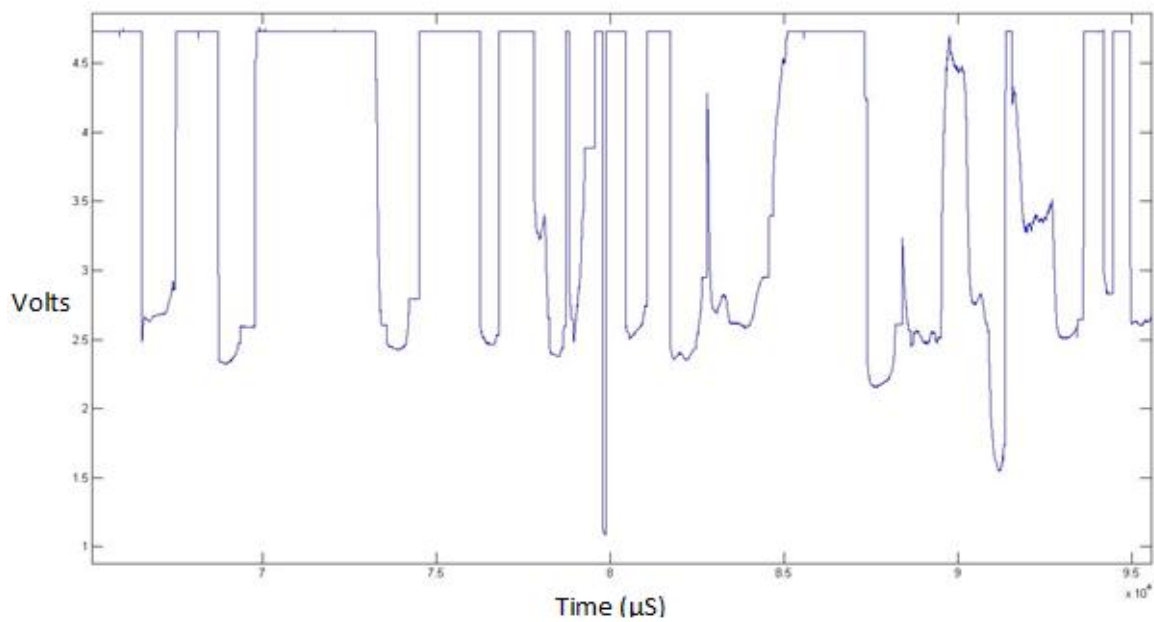


Figure 14. Fragment of the photoelectric sensor raw data for a V8 row

The same MathCad® 13 (Mathsoft Engineering & Education, Inc) program was used to calculate the error, misses, multiples, and good measurements by the sensor. The same method of detection was used for the 2012 study.

The results for the study conducted in 2012 showed that the performance of the system was better for the V12 stage than for V8 (Tables 2 and 3). This was likely caused by the planting methods. Table 4 provides information about the mean plant spacing and

standard deviation for the two growth stages. Note that two different locations were used to obtain plants at two growth stages.

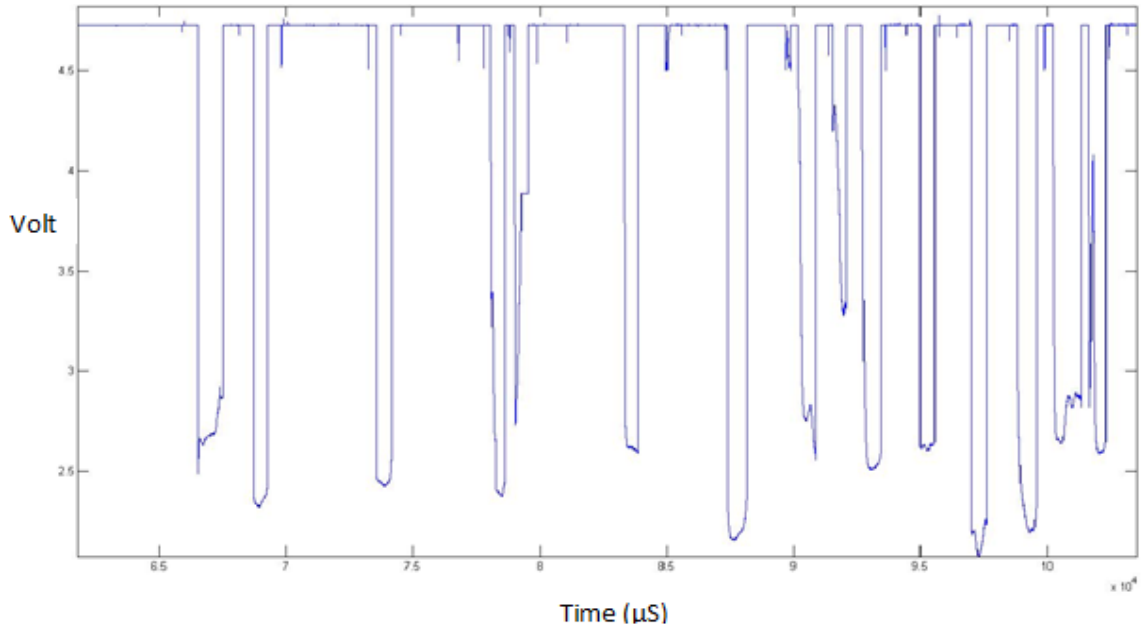


Figure 15. Fragment of the filtered photoelectric sensor data

Table 2 shows the results using  $\pm 20\%$  tolerance for plant location, and results in Table 3 provide information using  $\pm 40\%$ . Results using  $\pm 40\%$  tolerance were improved when plants were at V8, but worse for plants at V12. Thus increasing the tolerance for expected plant location did not consistently improve sensor accuracy and is not expected to be a solution for poor field performance.

Table 2. Results from the study conducted in spring 2012 using  $\pm 20\%$  tolerance

SPRING 2012

		Pass1				Pass2				Pass3			
		Good	Multiple	Miss	ABS Error (mm)	Good	Multiple	Miss	ABS Error (mm)	Good	Multiple	Miss	ABS Error (mm)
V8	Row 1	9	4	37	14.1	8	4	38	14.7	8	5	37	9.5
	Row 2	12	7	31	6.6	13	8	29	7.5	10	6	34	9.7
	Row 3	15	5	30	10.6	17	5	28	9.5	19	8	23	7.7
	Row 4	12	4	34	7.4	15	5	30	6.2	19	5	26	6.3
V12	Row 1	33	12	5	4.3	31	11	8	4.4	31	9	10	4.8
	Row 2	27	11	12	5.5	30	9	11	6.4	37	6	7	4.3
	Row 3	28	10	12	6.1	30	9	11	5.8	32	5	13	5.5
	Row 4	16	17	17	10.1	18	15	17	7.3	16	16	18	9.1

Table 3. Results from the study conducted in spring 2012 using  $\pm 40\%$  tolerance

		PASS 1				PASS 2				PASS 3			
		Good	Misses	Multiple	ABS Error (mm)	Good	Misses	Multiple	ABS Error (mm)	Good	Misses	Multiple	ABS Error (mm)
V8	Row 1	29	14	7	3.3	37	8	5	3.6	26	17	7	3
	Row 2	25	13	12	5.1	29	11	10	4.9	23	18	9	4.2
	Row 3	20	17	13	7.1	27	13	10	4.9	24	17	9	6
	Row 4	23	19	8	7.6	16	27	7	8.3	23	19	8	7.6
V12	Row 1	27	13	10	5.1	23	14	13	4.2	31	10	9	5.3
	Row 2	26	13	11	5.6	32	10	8	6.6	34	9	7	4.2
	Row 3	30	11	9	6.1	27	13	10	6.1	30	14	6	5
	Row 4	11	21	18	12	19	17	14	7.7	18	16	16	7.9

**Table 4. Standard deviation of plant spacing for study conducted in spring 2012**

	V8		V12	
	Standard deviation	Mean	Standard deviation	Mean
Row 1	5.0	12.0	15.8	24.0
Row 2	4.6	13.4	13.8	22.0
Row 3	12.1	18.6	13.2	21.6
Row 4	17.6	21.8	13.8	22.2

Unfortunately plants at CIMMYT were not planted using precision planting methods, thus increasing the standard deviation of plant spacing. As previously stated, the detection of plants in the raw data was aided using the mean spacing targeted by CIMMYT. Therefore, the program was not able to detect plants out of the range, causing a poor performance of the algorithm for the plots without precision planting techniques. Table 4 shows the values of mean and standard deviation of plant spacing at CIMMYT. Mean plant spacing for V12 plants was constantly out of the range having an average value of 22.45 cm, almost 10 cm greater than the target spacing (Figure 16). Some of the planting problems could be solved by changing planting techniques. It would be highly recommended to do so before trying to solve problems less relevant. Technology that could improve nutrient management like presented in this research should be utilized after such problems have been removed from the fields.



Figure 16. V8 Row planted without precision planting techniques

In addition to the errors caused by deficient planting techniques, another possible problem for this study's result could have been the same as 2011. This problem is that of leaves and plant residue that may have been in the sensor's path thus creating errors.

As in the 2011 study, the number of multiples also increased with the growth stage. The average number of plants located correctly on Table 2 was 13.08 for V8, and goes up to 27.42 for V12.



In contrast the absolute error is considerably smaller for plants in V12 than those in V8 growth stage. The only exception was row number 4, which showed an absolute error greater than 10 cm.

Tables 5 and 6 contain the slope, intercept, and the coefficient of determination ( $R^2$ ) for each of the passes for sensed diameter as a function of measured diameter. Results showed that the system is still in need for improvements. The slope shows that the system overestimated stalk diameter for most of the passes, going up to five times the actual dimensions for one of the passes. In addition, there was not much correlation between the measurements with the greatest  $R^2$  being 0.3154.

Table 5. V8 Stalk diameter results

STAGE	ROWS	PASS	INTERCEPT	SLOPE	R-SQUARE
V8	ROW 1	PASS 1	59.221	0.5701	0.0117
		PASS 2	118.45	-1.8958	0.2401
		PASS 3	35	0.9423	0.0178
	ROW 2	PASS 1	36.798	0.5775	0.0161
		PASS 2	69.649	-0.1396	0.0002
		PASS 3	123.23	-1.6978	0.0271
	ROW 3	PASS 1	14.692	1.2209	0.0282
		PASS 2	12.916	1.2901	0.0622
		PASS 3	54.142	-0.2468	0.0035
	ROW 4	PASS 1	159.18	-3.2954	0.1155
		PASS 2	118.21	5.8631	0.3154
		PASS 3	53.852	0.12	0.0005

Table 6. V12 Stalk diameter results

STAGE	ROWS	PASS	INTERCEPT	SLOPE	R-SQUARE
V12	ROW 1	PASS 1	64.197	0.0041	7.00E-07
		PASS 2	7.5597	1.8429	0.0758
		PASS 3	84.426	-0.786	0.0203
	ROW 2	PASS 1	63.923	-0.4476	0.005
		PASS 2	34.383	0.7138	0.0091
		PASS 3	39.11	0.4633	0.0103
	ROW 3	PASS 1	17.07	1.6885	0.0159
		PASS 2	58.617	-0.0962	9.00E-05
		PASS 3	59.933	-0.1377	9.00E-05
	ROW 4	PASS 1	21.337	1.242	0.0204
		PASS 2	62.144	0.1425	0.0003
		PASS 3	99.471	-1.5428	0.0393

Figures 17 and 18 show graphs with the greatest correlation for V12 and V8 respectively. The graphs show each manual measurement with the corresponding sensed measurement. Results show that even though plants were correctly located, the diameter was not accurately measured. One reason could be leaves or plant residue next to the plant.

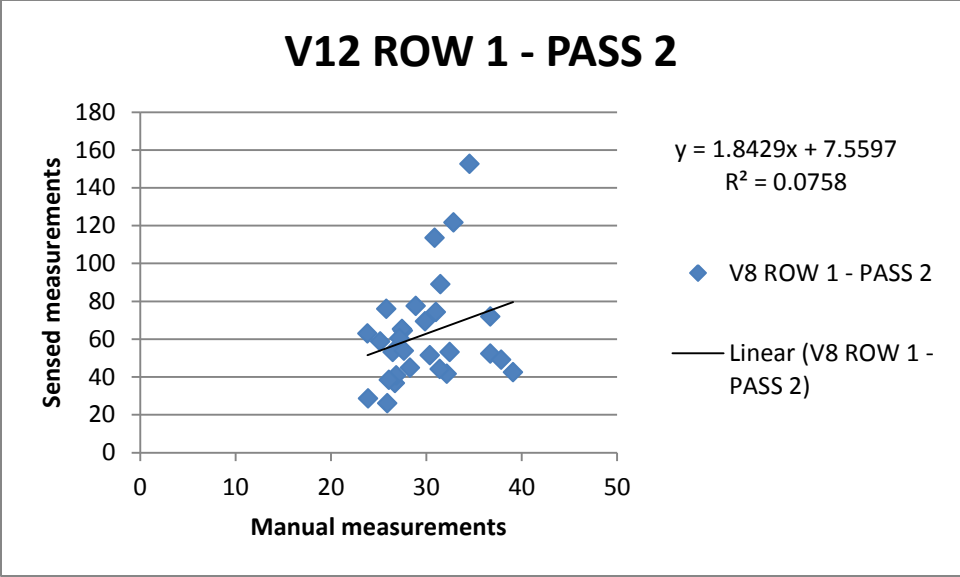


Figure 17. Graph of the pass with the best correlation for plants on V12

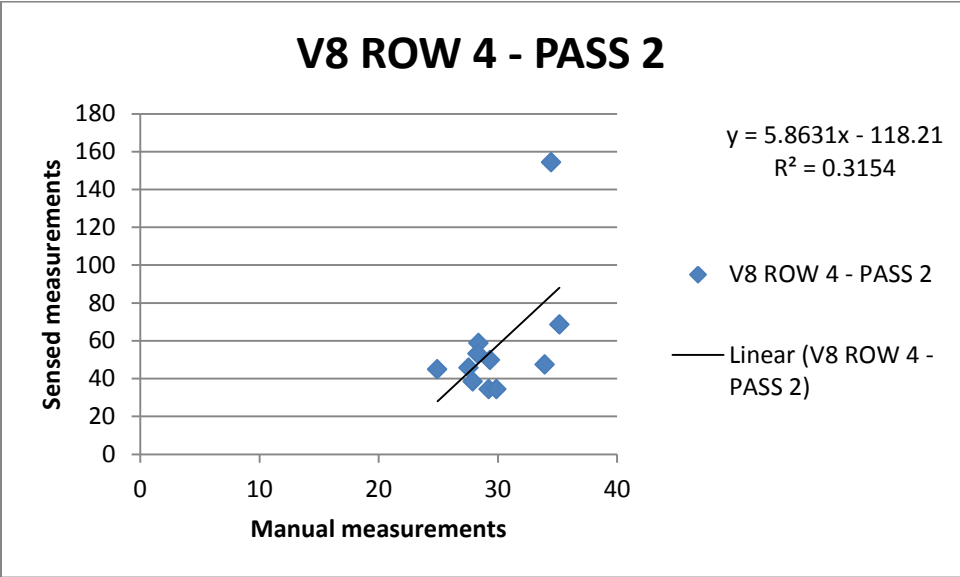


Figure 18. Graph of the pass with the best correlation for plants on V8

## CHAPTER V

### CONCLUSION

Different problems were detected during data analysis. Some were problems in the system and others correspond to field practices.

Practice problems were present in the second study at Obregon. The V8 plots in Obregon were not planted using precision planting techniques causing difficulties for the algorithm to detect plants. Results for plant location were as high as 78% for one of the rows in V8 in Oklahoma, but decreased to 16% the next year in Obregon. In addition, 33 plants were located right for V12 in Obregon in comparison with only 8 for V8. This system is meant to provide an improvement of by-plant management after greater problems were solved in the field. But when a plot presents problems like weeds, or poor plant spacing the use of this system will not provide the extra aid for plant management.

In addition problems were encountered when counting multiples and misses. Plants in late growth stages usually have dried leaves hanging from the stalk, or on the ground. The sensor did not function correctly when this condition was present. The same problem was present in diameter measurements. Correlation between manual and sensed measurement did not showed the expected results. Correlations were constantly low, being 0.34154 the greatest. Diameter was constantly overestimated even when the plant was located right, meaning that objects were present to the plant and the system was not able to differentiate them.

Solving problems that make plant detection difficult would highly improve the system's performance. Good measurements varied between each stage, but this study provided information to say that the optimal stage to sense is V8.

## CHAPTER VI

### FUTURE WORK

The system did not provide the expected optimal performance. There is much to be done before the system can provide the tools for a better nutrient management.

Photoelectric technology proved to be a reliable approach for this study, but further research should be conducted using other technologies that could provide better results.

In addition, as stated before, dried leaves and plant residues were a problem when trying to detect plants. Therefore, research should be conducted to develop a solution to this problem that has been present in other studies with similar objectives.

There is much to be done before this system can reach the optimal performance. More research should be conducted regarding the sensor to be used. In addition, an improvement in the algorithm is needed to eliminate objects present in the row that are not plants.

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## APPENDICES

### Appendix A: Matlab Program

```
clc
clear all
fd_id=0;
flag=0;
d1_ind=0;
d1_idx=0;
counts=0;
d1=daqread('2012_3_4_17_14_50_Obregon.daq');
l=length(d1);

i=0;
j=0;
k=0;
sen_sig=0;
plant_id=0;
edge_id=1;
plant_idx=0;
edge_idx=1;
plant_id2=0;
edge_id2=1;
plant_idx2=0;
edge_idx2=1;
plant_id3=0;
edge_id3=1;
plant_idx3=0;
edge_idx3=1;
last_val=0;
same_val=0;
same_ini=0;
flag_same=0;
bandera=0;
avg_temp=0;
avg_bet=0;

% %Indexing all the data times(1 every 10,000 of second)
% %d1_ind stores the index numbers from 1 to the number of datapoints
```

```

d1_l=length(d1);
d1_ind=1:1:d1_l;

%Attach the index to each datapoint
%e.g. 1 8.92 4.25
%     2 8.91 4.25
d1_ind=d1_ind';
d1_idx=horzcat(d1_ind,d1);

%Create vector with optical sensor data
sen_sig=d1_idx(:,2);
sen_sig_bu=sen_sig;

%Get speed values from encoder signal
speed=enc_post(d1);

%Calculates speed mean value
speed_pro=mean(speed);

%Distance bet plants (In theory) [cm]
dbp=(12.5/100);
t_dbp=dbp/speed_pro;
%p_dbp is the number of pulses of the average distance between plants,
using the
%average speed of the pass
p_dbp=t_dbp/(1/10000);

%Stalk diameter (Average) [mm]
sd=(20/1000);
t_sd=sd/speed_pro;
%p_sd is the number of pulses of the average stalk diameter, using the
%average speed of the pass
p_sd=t_sd/(1/10000);

%Detect the edges of plants
%plant_id is a vector that contains the id of every dge
%flag is equal to 1 when an leading edge has been detected, and returns
to
%0 when the end of the plant is detected
i=1;
while i<=length(sen_sig)
    if sen_sig(i)<4.5
        plant_id(edge_id)=i;
        edge_id=edge_id+1;
        flag=1;
        j=i;
        while flag==1&&j<=length(sen_sig)

```

```

        %j=j+1;
        if sen_sig(j)>4.5
            flag=0;
            plant_idx(edge_idx)=j;
            edge_idx=edge_idx+1;
        end
        j=j+1;
    end
    i=j;
else
    i=i+1;
end
end
end

if length(plant_id)>length(plant_idx)
    plant_id(end)=[];
end

%Delete (change value to 4.7284) the detected objects that have less
than
%500 datapoints of width
ii=1;
width_dif=0;
while ii<length(plant_id)
    width_dif=plant_idx(ii)-plant_id(ii);
    if width_dif<p_sd
        jj=plant_id(ii);
        while jj<plant_idx(ii)
            sen_sig(jj)=4.7284;
            jj=jj+1;
        end
    end
    ii=ii+1;
end

%Detect the edges of plants again
%plant_id2 is a vector that contains the id of every dge
%flag is equal to 1 when an leading edge has been detected, and returns
to
%0 when the end of the plant is detected
i=1;
j=0;
while i<=length(sen_sig)
    if sen_sig(i)<4.5
        plant_id2(edge_id2)=i;
        edge_id2=edge_id2+1;
        flag=1;
        j=i;
        while flag==1&&j<=length(sen_sig)
            %j=j+1;
            if sen_sig(j)>4.5
                flag=0;
                plant_idx2(edge_idx2)=j;
                edge_idx2=edge_idx2+1;
            end
        end
    end
    i=i+1;
end

```

```

        end
        j=j+1;
    end
    i=j;
else
    i=i+1;
end
end

if length(plant_id2)>length(plant_idx2)
    plant_id2(end)=[];
end

dbp_index=p_dbp;
dbp_in=p_dbp-(p_dbp*0.4);
dbp_out=p_dbp+(p_dbp*0.4);
%Find center and compare location
ii=1;
width_dif=0;
while ii<length(plant_id2)
    location=plant_id2+((plant_idx2(ii)-plant_id2(ii))/2);
    if dbp_index-dbp_in<location<dbp_index+dbp_out

    else
        jj=plant_id2(ii);
        while jj<plant_idx2(ii)
            sen_sig(jj)=4.7284;
            jj=jj+1;
        end

    end
    ii=ii+1;
    dbp_index=dbp_index+p_dbp;
end

%Detect the edges of plants again
%plant_id3 is a vector that contains the id of every dge
%flag is equal to 1 when an leading edge has been detected, and returns
to
%0 when the end of the plant is detected
i=1;
j=0;
while i<=length(sen_sig)
    if sen_sig(i)<4.5
        plant_id3(edge_id3)=i;
        edge_id3=edge_id3+1;
        flag=1;
        j=i;
        while flag==1&&j<=length(sen_sig)
            %j=j+1;
            if sen_sig(j)>4.5
                flag=0;
                plant_idx3(edge_idx3)=j;
            end
        end
    end
    i=i+1;
end

```

```

        edge_idx3=edge_idx3+1;
    end
    j=j+1;
end
i=j;
else
    i=i+1;
end
end
end

if length(plant_id3)>length(plant_idx3)
    plant_id3(end)=[];
end

[values,location]=findp(d1);

pulsesdiam=zeros(length(plant_id3),1);
for index=1:length(plant_id3)
    for index2=2:length(location)
        if location(index2)>plant_id3(index)
            if location(index2)<plant_idx3(index)
                pulsesdiam(index)=pulsesdiam(index)+1;
            end
        end
    end
end

val_zeros=length(plant_id3)-1;
pulsesbet=zeros(val_zeros,1);
for index=1:length(plant_id3)-1
    for index2=2:length(location)
        if location(index2)>plant_idx3(index)
            if location(index2)<plant_id3(index+1)
                pulsesbet(index)=pulsesbet(index)+1;
            end
        end
    end
end

total=0;
for hh=1:length(pulsesdiam)
    total=total+pulsesdiam(hh);
end

for hh=1:length(pulsesbet)
    total=total+pulsesbet(hh);
end

for ll=1:length(pulsesdiam)
    pulsesdiam(ll)=pulsesdiam(ll)*0.81643;
end

for ll=1:length(pulsesbet)
    pulsesbet(ll)=pulsesbet(ll)*0.081643;
end

```

```

function [picos,pos] = findp(data)

clc
encsig=data(:,2);
picos=0;
pos=0;
i=1;
j=1;
k=0;
inc=0;
resolution=15;

while i<length(encsig)
    inc=inc+1;
    res=length(encsig)-i;
    if res>=resolution

        j=j+resolution;
        if j-i>2
            [pic,loc]=findpeaks(data(i:j,2),'THRESHOLD',.1);
        end
        i=i+resolution;

    else

        j=j+res;
        if j-i>2
            [pic,loc]=findpeaks(data(i:j,2),'THRESHOLD',.1);
        end
        i=i+res;

    end

    for ii=1:length(loc)
        loc(ii)=((inc-1)*15)+loc(ii);
    end

    if i<resolution+1
        picos=pic;
        pos=loc;
    else
        picos=[picos;pic];
        pos=[pos;loc];
    end
end
end

```

```

function velfps = enc_post(data)
clc
encsig=data(:,2);
step=128;
Fs=10000;
windowsize=256;
encppr = 200;
gearratio = (7.5*0.0254)/(1.625*0.0254);
circum = ((8.5*0.0254)*pi);
timepad = 1000;

N = length(encsig);
NFFT = 2^nextpow2(windowsize);
f = Fs/2*linspace(0,1,NFFT/2+1);

velProf = [];
pt = [];
for i = 1:step:N
    if i + windowsize < N
        endidx = i+windowsize-1;
        Y = fft(encsig(i:endidx),NFFT)/windowsize;
        Y(1) = [];
        P = 2*(abs(Y(1:NFFT/2+1))).^2;
        [val, idx] = max(P);
        pt = [i, f(idx), val];
        for j = 1:step
            velProf = [velProf; pt];
        end
    else
        for k = i:N
            velProf = [velProf; pt];
        end
        break;
    end
end

maxP = max(velProf(:,3));
for i = 1:length(velProf(:,3))
    if velProf(i,3)/maxP < 0.1
        velProf(i,2) = 0;
    end
end

smoothvel = smooth(velProf(:,2),4*windowsize);

velfps = ((smoothvel./encppr)/gearratio)*circum;

```



VITA

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Institution: Oklahoma State University

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Title of Study: CORN SENSOR DEVELOPMENT FOR BY-PLANT MANAGEMENT

Pages in Study: 50

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Major Field: Biosystems and Agricultural Engineering

Scope and Method of Study:

The goal of this research was to develop a sensor capable of sensing corn stalk diameters, and the distance between corn plants in a row. The measurements were calculated using an optical encoder to obtain location. The sensor and the encoder signal were logged using a data acquisition system. The data were analyzed to determine if the dimensions were accurate compared to the ones measured by hand.

Findings and Conclusions:

Plots in Obregon were not planted using precision planting techniques causing difficulties for the algorithm to detect plants. Results for plant location were as high as 78% for one of the rows in V8 in Oklahoma, but decreased to 16% the next year in Obregon. In addition, 33 plants were located right for V12 in Obregon in comparison with only 8 for V8.

Correlation between manual and sensed stalk diameter measurement did not showed the expected results. Correlations were constantly low, being 0.34154 the greatest. Diameter was constantly overestimated even when the plant was located right, meaning that objects were present to the plant and the system was not able to differentiate them.

ADVISER'S APPROVAL: Randal K. Taylor

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