Plant Identification in Mosaicked Crop Row Images for Automatic Emerged Corn Plant Spacing Measurement

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Keywords
Corn plant spacing measurement, Image processing, Machine vision, Robust line fitting, Planters

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L. Tang, L. F. Tian

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Variation in plant spacing can lead to substantial yield variation. Several researchers have investigated the relationship between corn plant spacing and yield. Vanderlip et al. (1988) found that corn plant spacing variability could account for 5% to 23% of grain yield variability. More recently, Nielsen (2005) reported that the uneven corn plant spacing within crop rows could decrease yield up to 106 kg ha$^{-1}$ (2 bu acre$^{-1}$) for every 2.54 cm (1 in.) increase of standard deviation of intra-row plant spacing. Nielsen (1995) also found that the spatial variability in corn plant spacing was largely determined by the planter performance. Thus, plant spacing uniformity has been an important performance goal for planter manufacturers in response to much recent attention by producers. Prior to the release of new planters, planter engineers must conduct extensive field evaluations, in which a large amount of plant spacing data is collected. However, acquiring manual measurements of interplant spacing is labor intensive and time consuming as well as prone to human errors. Within this context, an automated sensing system for collecting interplant spacing data is desirable.

Taking a machine vision approach, measuring corn plant intra-row spacing requires that individual corn plants and their stem centers be identified automatically within individual crop row images or video frames. The use of machine vision systems for corn plant identification has been investigated, with color and morphological features most widely used. Jia et al. (1991) investigated the feasibility of using machine vision for corn plant center identification. In their approach, both top and side views of corn plants were used to locate the plant centers, and two algorithms were developed to detect main veins and leaves. Their system used high-resolution images, and no in-field tests were conducted. Shrestha et al. (2004a) used three morphological features to differentiate weeds from corn plants. These features were projected plant canopy area, plant length in the image row direction, and perpendicular distance of estimated plant centers from the mean crop row position. They achieved an 8.7% error (RMSE) in plant stand counts. Shrestha and Steward (2005) further used shape and size analysis of corn plant canopies for plant population and interplant spacing sensing. Area and roundness features from top-projected plant canopies were used to classify weeds and corn plants. Their algorithm estimated corn plant population with an overall RMSE of 6.2%. The mean interplant spacing estimation error was 0.6 mm with 63.5 mm standard deviation. Spacing error was reported to be partially due to the analysis method, in which each detected plant was matched with the nearest manually measured plant location.

Feature-based corn plant identification can be unreliable since a diversity of weeds and other background objects (e.g., residue) can appear in the scene, and some weeds possess similar color and shape features as those of corn plants. The linear planting geometry of corn plant rows, however, can offer useful structural information for corn plant identification, if these rows can be accurately and automatically detected. Numerous researchers have investigated crop row detection using machine vision for various automated farming operations.

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One approach has been to use the Hough transform (HT; Hough, 1962) for crop row detection in vision-based agricultural autonomous guidance systems (Reid and Searcy, 1986; Marchant and Brivot, 1995; Marchant, 1996). HT is capable of detecting lines or sets of collinear points. Its voting mechanism in parameter space has a certain degree of robustness (Davies, 1997). However, there are two major limitations of HT. First, the search in parameter space is computationally intensive. Also, spurious peaks in parameter space can be introduced by non-target shapes (Trucco and Verri, 1998). For the purpose of detecting top-viewed corn rows in mosaicked images, HT was not preferred for two reasons. First, the corn plant stem center points are not perfectly collinear. Second, the scarcity of plant stem center points makes HT unsuitable, even for the modified HTs such as the accumulator approaches used by Sogaard and Olsen (1999). As a refinement to HT, Dudani and Luk (1978) proposed a least-squares fitting stage. Nevertheless, fitting a line using ordinary least-squares can have erroneous results due to its sensitivity to outlying points that are not associated with the crop row.

Another approach has been to use linear regression to identify row guidance information (Billingsley and Schoenfisch, 1997). In this approach, a cost function analogous to the moment of inertia of the segmented object data points about the best-fit line was minimized. The resulting moment of inertia about the fitted line also gave a measure of the quality of fit to guard against errors from outlying points from noise and weeds. In their research, robustness was added by performing row detection for each of three crop row windows in succession. Only one surviving row was used for their guidance system. Slaughter et al. (1997) investigated the use of statistical estimates of mean, median, and mode of the spatial distribution of the seedlings to detect crop row location for a vision-based cultivator. The median was found to produce the most robust results. Up until now, no research using robust statistics for crop row detection has been found, in spite of work in other fields.

Before conducting corn plants identification and plant center location estimation, images that cover the entire length of experimental corn plant rows must be available. Algorithms for mosaicking video frames have been developed to generate corn crop row-long images (Shrestha and Steward, 2003; Shrestha et al., 2004b; Tang and Tian, 2008). The algorithms described in this article were applied to reconstructed crop row images generated with the algorithm developed by Tang and Tian (2008).

Thus, the overall goal of this research was to develop an image processing algorithm for identifying individual corn plants and estimating plant center locations in mosaicked crop row images and subsequently automatically measuring the distance between early growth stage corn plants or interplant spacing. Specific objectives were to (1) determine the corn plant identification performance when utilizing multiple features (color, shape, and crop row geometry) extracted from mosaicked crop row images, and (2) determine the interplant spacing estimation accuracy through field experiments.

### METHODS

The algorithm developed to automatically measure the interplant spacing of corn plants in mosaicked crop row images had three major steps. First, corn plants were differentiated from background (weeds, residue, and soil). Second, the stem center locations of individual corn plants were identified. Third, interplant spacing was calculated based on the detected plant center locations.

Within these steps were a series of imaging processing procedures. Specifically, a mosaicked crop row image was first divided into processing units. Color-based segmentation was then employed to separate plant and plant center areas from the background. After that, shape features of segmented plant objects were extracted and used for a preliminary filtering of corn plants. Following filtering, the remaining segmented plant center areas within the segmented corn plant vegetation regions were used with their skeletons to define the candidate plant center locations. Then a stem centerline was fit through the plant center locations using the $M$-estimate technique. The stem centerline was used to finalize the plant center location estimates as well as recover missing plant center locations. The algorithm also detected and repaired broken corn plant regions at the borders of processing units. Once the corn plant center locations were defined, the algorithm finally calculated interplant spacing. Optional manual on-screen review and correction functions were provided (table 1).

To identify individual corn plants and their centers for interplant spacing estimates from mosaicked crop row images,

<table>
<thead>
<tr>
<th>Steps</th>
<th>Image Processing Procedures</th>
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| 1. Corn plant and plant center area detection | a. Search for the segment by searching mosaicking breakpoints.  
   b. Search for the subsegment for processing at each step.  
   c. Segment the plants and possible stem center areas from background.  
   d. Extract plant features for crop and weed differentiation.  
   e. Filter the plant stem center areas to eliminate noise.  
   f. Label the plants and stem center areas and extract shape features for preliminary corn plant classification. |
| 2. Plant center location estimation | a. Perform the skeletonization on the plants.  
   b. Determine the corn plant stem center location using the maximum saturation point within the stem center cluster, or using the maximum saturation point along the skeleton.  
   c. Split the interconnected plants.  
   d. Define the plant row stem-centerline and the stem-centerline zone using robust line fitting and use them to exclude unfiltered weeds (outliers) and recover small corn plants.  
   e. Detect and repair broken corn plants at the segment and subsegment borders. |
| 3. Plant spacing calculation | a. Calculate the calibrated spacing across sequenced frame fragments, and count the plant population.  
   b. Perform optional manual on-screen error correction. |
several common problems emerge (fig. 1). These problems include split plants at mosaicking breakpoint (fig. 1a), interconnected plants (fig. 1b), and weed interference and plant canopy size variation (fig. 1c). The mosaicking breakpoint occurred when the mosaicked image had to be broken to prevent the crop row from vanishing from the mosaicked image because of camera mounting orientation (Tang and Tian, 2008). At every mosaicking breakpoint, the mosaicked crop row image was shifted either up or down by 40 pixels during the scene reconstruction process.

**PROCESSING UNIT SELECTION**

The corn plant identification and interplant spacing estimation algorithm was applied to mosaicked images of corn plan rows. There were three options for processing the mosaicked image. The first option was to process the whole mosaicked image. Second, the mosaicked image could be processed segment-by-segment, where an image segment was defined by splitting the image at every mosaicking breakpoint. Third, image segments defined by the mosaicking breakpoints could be further divided into subsegments that have a fixed maximum length; processing of the mosaicked image would then occur on subsegment basis.

Two important factors were taken into account to decide which option would be selected. First, image processing usually requires much memory to store intermediate results. More intermediate memory will be needed for longer processing units. Second, a fairly straight crop row segment should appear in every processing unit. Over short distances, the crop row is always approximately straight, and crop row structure can be used for differentiating crop plants from weeds. Based on these two factors, the third option, processing the mosaicked image on a subsegment basis, was adopted. The only drawback of this approach was that a plant object could be split at the subsegment border, which produces a “processing breakpoint.” To solve this problem, since the image was processed from the left-most column to the right in a subsegment image, the algorithm checked for pixels segmented into a crop plant class at the right-most column and adjusted the processing breakpoint so that plant objects were not split. When implemented, the subsegment length was 1280 pixels, which was the maximum horizontal resolution of the computer screen. This subsegment length selection allowed on-screen viewing of the plant identification process and provided about ten plants for crop row detection in each subsegment.

**CORN PLANT IDENTIFICATION USING SHAPE FEATURES**

To identify corn plants, the first step was to differentiate vegetative pixels from the background. Pixels were classified as belonging to vegetative and background classes using a color segmentation algorithm utilizing an EGRBI (excess green, red-blue, intensity) color transformation, K-means clustering for classifier development, and Bayes classification (Steward and Tian, 1998). Once the vegetative pixels were segmented, they were labeled using a four-connected
component labeling method (Rosenfeld and Kak, 1982; Klette and Zamperoni, 1996). Two shape features were used to differentiate corn plants from weeds: the area ($A$) and the compactness ($C$). Area is the number of vegetation pixels contained within a vegetative object. Compactness is a dimensionless quantity defined as:

$$C = \frac{4\pi \cdot A}{P^2}$$  \hspace{1cm} (1)

where $P$ is the perimeter of the object. Compactness has a maximum value of one for a circular region. As a region perimeter increases due to rough edges or elongated shapes, its value decreases. Corn plants have elongated leaves, thus their compactness values were much lower than one.

Vegetative objects were further classified using lower thresholds on these two object features. The thresholds of these corn plant features were either set manually or extracted from training samples. During the field evaluation experiments, the corn plants were at a V3 growth stage. The area threshold was set at 300 pixels, while the compactness threshold was set at 0.4. Applying these two thresholds to all vegetative objects resulted in a set of candidate corn plants.

**CORN PLANT STEM CENTER DETECTION**

After a set of corn plant candidates was generated from the shape feature-based filtering process, the next step was to identify the stem center locations within these candidate corn plants. Similar to vegetation detection, corn plant pixels were classified using the same color segmentation algorithm (Steward and Tian, 1998) into corn plant center and exterior leaf classes. The plant stem center pixels generated by this color segmentation process provided a group of candidate plant center areas or objects (fig. 2).

Plant center pixel segmentation often resulted in non-plant center pixels being incorrectly segmented as plant center pixels. A morphological erosion filter was used to remove these noise pixels that had two or less 4-connected pixels. Every plant and plant stem center object was labeled independently using a connected component labeling method (Rosenfeld and Kak, 1982; Klette and Zamperoni, 1996). In addition, every plant stem center object was also tagged with its host plant index to indicate which corn plant object was associated with it. Meanwhile, the area and centroid of every plant stem center object were computed and embedded into its identity information. Following that, for every pair of plant stem center objects with same host plant tag, the distance ($d$) between their centroids was computed and a distance-area-filter was employed based on the following rule:

If $d$ is smaller than $d$-threshold, then eliminate the plant stem center object having the smaller area value.

The $d$-threshold was a user-defined constant that depended on how close the interconnected corn plants usually appeared in sample images and was set at 30 pixels. After ap-

![Figure 2](image.png)

Figure 2. Illustration of segmentation results using $K$-means clustering and the Bayes classifier: (a) original image; (b) image (a) after $K$-means clustering, where the images was clustered into eight color groups; and (c) image (a) after a segmentation using Bayes classifiers for vegetation, plant stem center, and background pixels, where the classifiers were trained by using image (b).
plying this distance-area-filter throughout the entire subsegment, the set of remaining corn plant center objects was indexed again to form an updated set of corn plant center object candidates.

There are several possible approaches to estimate the locations of corn plant centers after obtaining the plant center objects. One approach would be to calculate the corn plant stem center area centroid and use the centroid as the best estimate of plant center location. Many times, however, it was observed that the actual plant stem location was not collocated with the corn plant stem center area centroid. Another approach would be to search for the maximum saturation point within the plant stem center area based on the observation that the color saturation level in the region around the plant stem location was often substantially higher than the rest of canopy area. However, since the color saturation level around the leaf edges or folds of leaves created by wind could also be high, the saturation level alone could not be used as a general stem location detection criterion. Furthermore, in some cases, the plant stem center areas were not detectable through the corn plant center pixel segmentation process. For example, when a plant was small, its plant stem center color cluster might not be well formed in the image due to inadequate camera resolution or non-ideal lighting conditions. A more robust approach thus taken was to find the maximum saturation location along the plant skeleton and use this location as the best estimate of the actual stem center location.

Plant skeletons were created through a skeletonization process, which extracts a network of thin curves that describe the overall shape or “skeleton” of objects in a binary image (Klette and Zamperoni, 1996). A parallel algorithm was implemented using the 8-connectivity of plant pixels (Rosenfeld, 1975). The algorithm iteratively discarded the subsets of the boundary of a set of object pixel in a parallel fashion. One problem with skeletonization is the production of skeleton artifacts. The most common artifact, line fuzz, is the creation of small extra line segments connected to the main skeletal segment (Parker, 1997). Line fuzz is usually caused by small irregularities in the object outline. Convolving the image with a smoothing filter before skeletonization can effectively remove the line fuzz artifact (fig. 3). After skeletonization, the plant skeletons were searched for the maximum color saturation location, which was set to be the stem center location. These locations were marked with sequential plant indices starting from the very first detected stem center location in the mosaicked image. In the case where multiple plant centers were located within a single corn plant object, the algorithm treated such a corn plant object as an object having interconnected plant canopies, and each plant center location within it was given an individual plant index. In this way, the interconnected corn plants were located using the detected corn plant center locations (fig. 4).

CORN PLANT IDENTIFICATION USING GEOMETRIC INFORMATION OF CROP ROWS

The straight line planting geometry of crop rows provided another useful layer of information that assisted with corn plant identification. To use this information, a corn plant row stem-centerline zone (SCLZ) was defined as a narrow strip formed around a stem centerline (SCL) that “best” represented the corn plant row linear geometry retained in a mosaicked image subsegment. The SCLZ was used to further exclude weed objects remaining after feature-based filtering and recover smaller unidentified corn plants located within the SCLZ. The length of the SCLZ was the length of the processing unit, and the SCLZ width was defined to enclose the plant row and also include those corn plants that diverged slightly from the SCL.

Fitting SCL by Least-Squares as a Maximum Likelihood Estimator

Least-squares fitting techniques are based on the assumption that the probability distributions of all data points converge to a normal distribution. However, real data often do not follow a normal distribution and contain outlying points or “tail points.” Although the probability of occurrence for outliers in the assumed Gaussian model is small, the least-squares estimator does not differentiate between outliers and the data points that are within the modeled distribution. The least-squares curve fit will then be distorted by the outliers (Press et al., 1992). Outliers (e.g., objects 58, 62, and 66 in fig. 5) can then easily turn a least-squares fit on otherwise ad-
Figure 4. Examples of corn plant stem center detection and interconnected plant splitting. Images on the left side are marked with skeleton lines together with plant and stem center area clusters; correspondingly, images on the right side show the original images overlaid with plant stem center labels.

Figure 5. Least-squares fitting for corn plant SCLZ detection where the SCL was skewed due to outliers (noisy points were intentionally and randomly introduced by lowering the corn plant feature thresholds).

equate data into nonsense. The problem of typical least-squares line fitting methods is that the fitted line can be skewed due to outliers (fig. 5).

To overcome this problem, a more robust line fitting algorithm is needed. A line fitting technique based on robust statistics, or $M$-estimates, provides a remedy for the outlier problem (Meer et al., 1991). Robust statistical techniques were developed to address situations where the Gaussian model is a poor choice for the data or where outliers are present.

**Robust Crop Row Centerline Fitting Using $M$-Estimates**

To overcome the problem of least-squares fitting outlier sensitivity, one approach is to use a distribution that has larger tails than the corresponding Gaussian, i.e., to use a distribution in which outliers are more likely to occur. In the literature (Press et al., 1992; Forsyth and Ponce, 2002), a generalized probability equation of a data set that embraces any suitable noise distribution function can be written as:

$$P = \prod_{i=1}^{N} \{ \exp[-\rho(r_i)] \Delta y \}$$  \hspace{1cm} (2)

where $N$ is the total number of data points in the data set, and $\rho(r_i)$ is the negative logarithm of the probability density.

$M$-estimates follow from maximum-likelihood arguments and are usually the most relevant class for model-fitting (Press et al., 1992). $M$-estimates estimate a total of $M$ model parameters ($a_1, \ldots, a_M$) through minimizing the sum of $\rho(r_i)$ over $a_1, \ldots, a_M$. To incorporate the influence of each data point, an influence function $\varphi(r_i)$ is defined, where:

$$r_i = \frac{y_i - y(x_i; a_1, \ldots, a_M)}{\sigma_i}$$  \hspace{1cm} (3)

where $\sigma_i$ is the standard deviation of data point $(x_i, y_i)$; $a_1, \ldots, a_M$ are the parameters of model $y(x_i; a_1, \ldots, a_M)$; and $\rho(r_i)$ is the negative logarithm of the probability density.
By introducing this influence function \( \psi(r_j) \), the M-estimator determines the model parameters, \( a_1, \ldots, a_M \), by satisfying the equation:

\[
0 = \sum_{j=1}^{N} \left[ \psi(r_j) \frac{\partial \psi}{\partial a_k} \right] k = 1, \ldots, M
\]  

(5)

There is a wide range of residual distributions devised to suit different data sets. A good example of a noise distribution is the double exponential distribution, which has the probability density function:

\[
P_{\text{dex}} \propto \exp[-|r_j|]
\]  

(6)

Although the tails of \( p_{\text{dex}} \) are exponentially decreasing, they are much larger than any corresponding Gaussian distribution. When double exponential noise distribution is adopted, then \( \rho(r_j) = r_j \) and \( \psi(r_j) = \text{sgn}(r_j) \). Correspondingly, a derived merit function minimizes \( \Sigma_{j=1}^{n} \text{sgn}(r_j) \) and, in essence, is a median optimization. The optimization process will eventually move the median to the origin.

Another good example of a noise distribution is the Cauchy distribution, which is defined as:

\[
P_{\text{cauchy}} \propto \frac{1}{1 + r_j^2}/2
\]  

(7)

Given a Cauchy distribution, we will have \( \rho(r_j) = \log(1 + r_j^2/2) \) and \( \psi(r_j) = \frac{r_j}{1 + r_j^2/2} \). Since its influence function initially increases with deviation and then decreases as deviation becomes larger, the Cauchy distribution is mathematically better-behaved than the double exponential distribution. This behavior will better limit the effects of the true outliers. However, like with most influence functions, it is important to carefully set up the scale factor to obtain an optimal match to the scale of the variation in the data.

In case of the SCL detection for a corn row, a straight line:

\[
y(x;a,b) = a + bx
\]  

(8)

is fit to the plant center locations. The double exponential and Cauchy distributions were used to robustly estimate the parameters \( (a, b) \). The robust M-estimator for double exponential distribution is:

\[
\min_{(a,b)} \sum_{i=1}^{N} \left| y_i - a - bx_i \right| / \sigma
\]  

(9)

For Cauchy distribution, the robust M-estimator is:

\[
\min_{(a,b)} \sum_{i=1}^{N} \log \left( 1 + \frac{(y_i - a - bx_i)^2}{2\sigma^2} \right)
\]  

(10)

To solve the above multidimensional minimization problems, a simplified method was adopted to reduce the two-dimensional optimization problem into two one-dimensional optimization processes. This dimension reduction method was originally presented by Press et al. (1992) for fitting a double exponential distribution modeled straight line. This method was extended to a Cauchy distribution in this research.

For both minimization problems described in equations 9 and 10, the key simplification was to first fix variable \( b \) and then solve \( a \) by finding the median by:

\[
a = \text{median}\{y_i - bx_i\}
\]  

(11)

Then, the corresponding influence functions were used to solve \( b \) as given in equation 5. For the double exponential distribution, \( b \) can be solved by:

\[
0 = \sum_{i=1}^{N} x_i \text{sgn}(y_i - a - bx_i)
\]  

(12)

and for the Cauchy distribution, \( b \) can be solved by:

\[
0 = \sum_{i=1}^{N} x_i \left[ \frac{y_i - a - bx_i}{\sigma^2 + (y_i - a - bx_i)^2/2} \right]
\]  

(13)

When the parameter \( a \) in equation 12 or 13 is replaced with the solution to equation 11, the resulting equation has a single variable \( b \), which can be solved by classic bracketing or bisection methods.

Once the SCL was determined, the width of the SCLZ was determined through using a Gaussian distribution to describe the residuals of the estimated plant center locations to the SCL. The residual standard deviation \( (\sigma) \) was calculated. The bound (outer bound) of the SCL zone was defined by \( \pm 3\sigma \) limits. This outer bound was used to ensure that any plant object would be detected 99.7% of the time if its area and compactness features already passed the shape feature-based test. To recover those smaller misclassified corn plants that failed the shape feature-based test, a tighter bound (inner bound) defined by \( \pm \sigma \) limits was used. If any object had an area value greater than 1/4 of the area threshold and its stem location was inside the inner bound, it would be reclassified as a corn plant. Here, the factor 1/4 was determined empirically through observations. The use of M-estimates for corn plant SCLZ detection with both double exponential and Cauchy distribution data models greatly outperformed the least-squares fitting method with respect to the robustness to the outliers (fig. 6).

SPACING CALCULATION

Broken corn plant objects can occur at mosaicking breakpoints and processing breakpoints. If those broken plants were left unrepair, they could be either misidentified or double counted. To avoid these problems, processing unit borders within the SCLZ were searched for corn plant objects by checking if any pixel in the right-most column of a processing unit belonged to a corn plant object. If a corn plant object was found on a border, then the program searched to the left for a plant gap, i.e., a region that had no vegetative object. Once a gap was found, the last column of a subsegment image was shifted left to where the gap was found, and the broken part of the split corn plant was included in the next processing unit. If a broken corn plant object was found in the right-most column of a processing unit that was generated by a mosaicking breakpoint, the broken part of the corn plant was shifted up or down by 40 pixels so that its shape was repaired (fig. 7).

When generating the mosaicked image, the coordinates of all mosaicking points in their original frames were stored. These coordinates were used so the distance across every mosaicked image fragment, a frame section added into the mosaicked image, between two adjacent mosaicking points.
Figure 6. The effect of using $M$-estimates for corn plant SCLZ detection. (a) Compared with the result of least-squares fitting in figure 5, both double exponential and Cauchy distribution data models resulted in the same lines that fit the corn plant center locations without skew. The scale factor ($\sigma$) in the Cauchy distribution was set as 15 pixels. (b) Identified corn plant center locations in image (a) after eliminating the objects (outliers) outside of SCLZ. (c) A case where line fitting failed when the data was modeled with a double exponential distribution function. (d) Line fitting succeeded when plant center location data in image (c) was modeled with a Cauchy distribution function.

Figure 7. The broken corn plant shown in figure 1 was repaired.

The algorithms were implemented using Microsoft Visual C/C++ 6.0 on a PC equipped with a 2.8 GHz Pentium 4 CPU. Ideally, planter design engineers do not want to miss any emerged plants in their data analysis, so manual correction could be accurately computed using the camera calibration matrix (Tang and Tian, 2008). In this way, the calibrated relationship between pixels and physical length was maintained in the mosaicked image and used to estimate interplant spacing. The interplant spacing, $S$, between two corn plant stem locations was defined as:

$$
S = \sqrt{\sum_{i=1}^{n} f_i^2 + \Delta X^2 + \Delta Y^2}
$$

where $\Delta X$ and $\Delta Y$ are the change in plant center locations along the $X$ and $Y$ directions of two sequential plants. When there are fragments between two sequential corn plants, $\Delta X$ is the summation of the width of each fragment $f_i$, $\Delta X_1$, and $\Delta X_2$, where $\Delta X_1$ is the distance in the $x$-direction between first plant center location to the first internal fragment leftmost column, and $\Delta X_2$ is the distance in the $x$-direction between the plant center location of the second plant to the left-most column of last internal fragment (fig. 8). All the variables in equation 14 have units of cm. The values of $\Delta X_1$, $\Delta X_2$, and $f_i$ were calculated using their calibrated coordinates, which were obtained from using their image coordinates in their original frames.

The algorithms were implemented using Microsoft Visual C/C++ 6.0 on a PC equipped with a 2.8 GHz Pentium 4 CPU.
functions for inserting and deleting corn plant stem center locations were also implemented in the software.

FIELD EXPERIMENTS

Spacing measurement accuracy was tested by using video captured in an experimental field in Iowa on 28 September 2007. The plants were planted on 10 September 2007 and were mostly at V3 growth stage during the experiment. The details of the video capture system were described by Tang and Tian (2008). Video was captured over two 41 m long corn row sections that had plant counts of 198 and 201 plants, respectively. In total, eight video clips were recorded from these crop rows; for every sampled crop row, there were two video clips recorded in one direction and two in the opposite direction. The interplant spacing of each tested crop row was manually measured by laying a measuring tape along the crop row. The distance of each corn plant from the beginning of the crop row section was recorded by a student. The camera was calibrated on-site immediately after the system was set up for recording.

After the video was processed and mosaicked images containing the crop row sections were produced (Tang and Tian, 2008), the algorithm identified the crop plants and the location of the crop plant center and produced a plant count estimate for the crop row section and individual plant spacing estimates. The automatically obtained plant count was compared with the manual plant count. Specifically, the corn plant misidentification ratio was defined as:

$$R_{\text{mis}} = \frac{E_{fp} + E_{ud}}{C_{\text{man}}}$$  \hspace{1cm} (15)

where

- $R_{\text{mis}}$ = misidentification ratio
- $C_{\text{man}}$ = manual plant stand count
- $E_{fp}$ = false-positive stand count error (plant counts accumulated where no plants exist)
- $E_{ud}$ = undetected stand count error (plants that were left uncounted).

To obtain the spacing measurement error of the system, both false-positive and undetected corn plants were manually corrected to ensure that the system-identified plants were the same as those identified manually. Although this manual process altered the original spacing data generated by the automated process, it was necessary to exclude plant identification error from spacing measurement error when conducting spacing measurement accuracy evaluation. Considering the purpose of spacing measurement accuracy evaluation, no manual correction of the plant center locations of those corn plants that were correctly identified by the system was allowed. After all plants were identified (automatically and manually) in a mosaicked crop row image, the interplant spacing estimates were exported and compared with the manual interplant spacing measurements. Linear regression was used to analyze the relationship between the manual and automated interplant spacing measurements.

RESULTS AND DISCUSSION

The algorithm achieved a mean misidentification ratio of 3.7% across both corn rows and all video sequences (table 2). Thus, on average only four corn plants in a stand of 100 plants needed to be manually identified after the automatic plant identification process. The system had an average $E_{fp}$ of 0.75 plants versus an average $E_{ud}$ of 6.6 plants over each crop row section. The false-positive plant identification errors were often generated by mosaicking errors leading to individual corn plants appearing twice in a mosaicked image, i.e., an extra fragment of the crop row image containing a corn plant was mistakenly mosaicked into the mosaicked image (fig. 9). Mosaicking errors usually occurred when the video sampling platform (in this case, a bicycle) traveled over bumpy soil surfaces caused by tractor tire treads or larger soil clods. There was only one case where an extra false-positive plant center was found within a single corn plant. This error was due to a tractor tire damaging and lodging a corn plant. The orientation of the lodged plant prevented the camera from observing its stem area, which led to the generation of multiple plant objects during the color segmentation process (fig. 10).

<table>
<thead>
<tr>
<th>Row Location</th>
<th>Direction</th>
<th>$E_{fp}$ (plants)</th>
<th>$E_{ud}$ (plants)</th>
<th>$R_{\text{mis}}$ (%)</th>
<th>Mean of $E_s$ (cm)</th>
<th>RMSE of $E_s$ (cm)</th>
<th>Mean (STD) of $E_s$ (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iowa-1</td>
<td>Forward</td>
<td>1</td>
<td>7</td>
<td>4.0</td>
<td>0.07</td>
<td>2.0</td>
<td>0.20 (0.40)</td>
</tr>
<tr>
<td></td>
<td>Backward</td>
<td>0</td>
<td>13</td>
<td>6.5</td>
<td>0.17</td>
<td>1.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Forward</td>
<td>1</td>
<td>6</td>
<td>3.5</td>
<td>0.43</td>
<td>1.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Backward</td>
<td>0</td>
<td>8</td>
<td>4.0</td>
<td>0.14</td>
<td>1.3</td>
<td></td>
</tr>
<tr>
<td>Iowa-2</td>
<td>Forward</td>
<td>1</td>
<td>2</td>
<td>1.5</td>
<td>-0.12</td>
<td>2.1</td>
<td>0.11 (0.46)</td>
</tr>
<tr>
<td></td>
<td>Backward</td>
<td>1</td>
<td>5</td>
<td>3.0</td>
<td>-0.10</td>
<td>1.8</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Forward</td>
<td>2</td>
<td>7</td>
<td>4.6</td>
<td>0.19</td>
<td>1.9</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Backward</td>
<td>0</td>
<td>5</td>
<td>2.5</td>
<td>0.21</td>
<td>1.7</td>
<td></td>
</tr>
<tr>
<td>Overall mean</td>
<td></td>
<td>0.75</td>
<td>6.6</td>
<td>3.7</td>
<td>0.12</td>
<td>1.7</td>
<td>0.12 (0.18)</td>
</tr>
</tbody>
</table>
Plant identification errors were dominated by undetected corn plants. When plants were damaged (usually by pests or traffic) or were considerably smaller than the average plant size, the likelihood of not being detected increased. There were four damaged plants, which were either lodged or pressed down by tractor tires. These plants were often undetected because their centers were difficult for the algorithm to recognize (fig. 10). The system was capable of detecting individual corn plant centers when plant canopies were interconnected but their stems were still located clearly apart from each other. In case of doubles, where two seeds were planted closely at one location, the system was not able to split the plants (fig. 11).

The undetected plant error varied from two to 13 plants across eight video sequences (table 2). This variation was found to be related to the smoothness in the mosaicking video frames, i.e., the consistency in the distance between mosaicking breakpoints. When pushing the video sampling platform over rough soil surfaces, depending on the walking velocity of the operator, a considerable degree of camera motion dynamics could occur, which in turn could cause more frequent mosaicking breakpoints. Since mosaicking breakpoints were used to define processing units, a higher frequency of mosaicking breakpoints led to shorter processing units and consequently led to less reliable plant centerline detection. Thus, either a video sampling platform with more mass or a much slower travel velocity should be used when acquiring crop row video with a lightweight sampling platform over rough soil surfaces.

When compared with the manual interplant spacing measurements, the interplant spacing data of eight measurements over these two crop rows generated by the system had a mean error of 0.12 cm with a standard deviation of 0.18 cm and an overall RMSE of 1.7 cm, which was 8.3% of the mean interplant spacing. There was no evidence of a significant difference in interplant spacing error due to travel direction when recording crop row video clips (F1, 6 = 0.078, P = 0.79). The interplant spacing error over these two crop rows was normally distributed with a few outlying errors (between 5 and 8 cm) at the tails of the distribution (fig. 12). When algorithm interplant spacing estimates were regressed onto manual plant spacing measurements, the linear model had a coefficient of determination (R2) of 0.96 (fig. 13). There were 12 data points out of 1588 measurements with values greater than 50 cm, which were produced by three larger interplant spaces within the tested rows. Since these 12 data points were much larger than the majority of the data, they substantially affected the linear model performance. After removing these outlying data, the linear model had an R2 of 0.86 (fig. 13). There were three interplant spacing estimates with errors greater than 13 cm (fig. 13). Upon closer observations, it was determined that these errors were due to errors in mosaicking video frames.
CONCLUSIONS

An image processing algorithm for individual corn plant and plant center identification in mosaicked crop row images was developed. The algorithm utilized multiple layers of information (plant color, shape, and crop row geometry) to construct a series of image processing procedures for interplant spacing measurement. Based on the results obtained from the field experiments, we can conclude:

- Using multiple sources of scene information, the corn plant identification algorithm was effective in identifying corn plants and their stem center locations in mosaicked crop row images. Specifically, the algorithm achieved a mean plant misidentification ratio of 3.7%. Most of the identification errors were primarily due to damaged plants or errors in mosaicking.
- When compared with manual interplant spacing measurements, the system estimated interplant spacing with an error (RMSE) of 1.7 cm or 8.3% of the mean spacing for V3 growth stage corn plants. Interplant spacing estimation error was primarily due to the inherent uncertainty of the corn plant center detection algorithm and external factors such as mosaicking error and crop damage.

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