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Video Processing for Early Stage Maize Plant Detection

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Abstract

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Video Processing for Early Stage Maize Plant Detection

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Algorithms were developed to process video of maize rows and extract plant features to estimate density and spacing of early growth stage maize plants. The Otsu method was modified to compensate for varied amount of plant segmentation noise presented in different operating conditions. Three features were extracted and used to differentiate between weeds and maize plants: projected plant canopy area, plant length in the image row direction, and perpendicular distance of estimated plant centres from the mean crop row position. Algorithm performance was analysed across three tillage treatments, three growth stages, and three target populations varying from 27 000 to 81 500 plants ha^{-1}. Overall, the algorithm estimated the number of plants in 6·1 m crop row sections with a root mean squared error of 2·1 plants or 8·7% of the mean manual count of 24·1 plants per experimental unit. The mean measurement error was significantly different across tillage treatments, but no evidence of significant differences was found across growth stages and plant populations. The error variance at the vegetative growth stages with the seventh or eight leaf collar visible was significantly higher than that at the growth stages with the third or fourth leaf collar visible. No significant differences were found between mean measured and estimated plant spacing distances.

1. Introduction

The actual interplant distance in crop rows may be different from the targeted plant spacing. Even if actual average plant population over a large field matches with the targeted plant population, uneven plant spacing adversely affects the yield (Doerge *et al.*, 2002). Plant population and plant spacing variability have an important effect on maize yield (Nafziger, 1996). Doerge *et al.* (2002) reported that every 2·5 cm reduction in maize plant spacing standard deviation resulted in yield increases of about 0·21 Mg ha^{-1}. Nafziger (1996) found that the maize plants on either side of a missing plant compensated for only 47% of the reduced yield in lower population fields (44 500 plants ha^{-1}) and 19% in higher population (74 000 plants ha^{-1}) fields, hence decreasing crop yield.

There are three main causes of variability in plant spacing: seed germination, planter seed placement, and plant death (Neilsen, 2001). Seed germination rates typically range from 90 to 95% (Nielsen, 2001). Planter performance depends both on planter maintenance and speed. Nielsen (1995) reported that when the planter speed varied from 6·4 to 11·2 km h^{-1}, the planted seed rate at higher speeds was significantly different than the planted seed rate at lower speeds. He concluded that a yield loss of at least 86 kg ha^{-1} occurs at every 1 km h^{-1} speed increase in the range of 6·4 to 11·2 km h^{-1}. Weather and pest-related damage may result in unevenly spaced plant survivors within a row (Nielsen, 2001). Owing to these factors, established plant population and spacing may be different from targets.

Bullock *et al.* (1998) reported that a farmer needs extensive knowledge of site-specific plant population and yield data for many years for variable rate seeding to be profitable. Manual stand counts are not feasible for a large field and are also susceptible to human error. In addition, except for high value crops, variable rate application (VRA) technology has not been as widely adopted as was originally anticipated by experts.

Bullock *et al.* (2002) presented an economic model showing that VRA fertiliser application is not yet profitable because two elements are still lacking: (1) the understanding of the relationship between yield and managed and unmanaged field variables; and (2) the absence of low cost, accurate field variable measurement technology. If plant population and spacing variability could be measured more extensively, the understanding of their effect on yield could be increased.

Birrell and Sudduth (1995) developed a combined harvester mounted mechanical sensor to map maize population at harvest which was an excellent estimator of hand-counted population (Sudduth *et al.*, 2000). Plattner and Hummel (1996) developed another maize population sensor using non-contact optical sensors at harvest. Shrestha and Steward (2003) demonstrated that machine vision can be effective in locating maize plants and measuring interplant spacing from videos of crop rows. In their work, a manually selected threshold was used to classify plant and background regions and no attempt was made to distinguish maize plants from weed plants.

Much of the work aimed at classifying plants by species or broader classes has had a purpose of providing information for selective or variable rate herbicide application. Researchers have investigated the use of leaf and canopy shape (Franz *et al.*, 1991; Guyer *et al.*, 1993; Woebbecke *et al.*, 1995) and canopy texture (Shearer & Holmes, 1990; Meyer *et al.*, 1998; Tang *et al.*, 2003) to classify weeds and crop species. Classification using diffuse reflectance spectra has yielded good results (Vridts *et al.*, 2002). Younan *et al.* (2004) investigated the classification of hyperspectral soil, weed, and crop reflectance spectra with several different approaches. Classification of maize plants and weeds is one component of maize population estimation, and good classification with low computation overhead should contribute to overall population and plant spacing estimates.

The overall goal of the statistical approach described in this paper was to generalise previous video-processing algorithms (Shrestha & Steward, 2003) to singulate maize plants in a wider range of field conditions with increased robustness. Statistical approaches were developed to distinguish between weed plants, and single, double and triple maize plants. The particular objectives of this paper were: (1) to develop an algorithm, which could be used in typical field conditions, to identify, locate, and count early growth stage maize plants using feature statistics; and (2) to validate the algorithm performance across varying tillage, growth stage, and population factors.

2. Methodology

Video of maize rows was collected across different field conditions. A video-processing algorithm was developed and processed video by sequencing video frames, extracting image row features, and classifying segmented vegetation into maize plants or weeds (*Fig. 1*). The Otsu method (Otsu, 1979) was modified and used for classification. This method is a well-known adaptive thresholding technique that selects a threshold maximising the ratio of 'between variance' to 'within variance' of two modes of a bimodal distribution. The overall algorithm was implemented in a Windows application software package using Visual C++ and Microsoft Foundation Classes (Microsoft, Redmond, WA). The application used an object-oriented architecture developed by Shrestha *et al.* (2003). Algorithm performance was analysed by comparing the results with manual measurements.

2.1. *Experimental design*

The effects of three factors on counting performance were investigated. These factors were: (1) tillage; (2) growth stage; and (3) plant population. Three tillage systems were investigated: 'till plant' which did not have tillage prior to planting, 'plough' for which a mouldboard plough was used, resulting in a minimum amount of crop residue on the soil surface, and 'spring disc' for which spring tillage was done using a disc or cultivator. Within each of the tillage treatments from two different years, three different maize plant densities were maintained. Video was collected as the plants varied in growth stages from V3 to V8, based on the growth stage system described by Ritchie *et al.* (1993) which defines the $V(n)$ vegetative growth stage as the stage when the n^{th} leaf collar is visible. Plant growth stages were classified into three levels namely V3–V4, V5–V6, and V7–V8 stages, to account for the existing variability in growth stages among the plants at the time of data collection. The three levels of population were 39 500, 54 000, and 74 000 plants ha^{-1}. The experiment was designed for full factorial interaction resulting in 27 different treatment combinations.

2.2. *Data collection*

Maize row video was collected at the Iowa State University Agronomy and Agricultural Engineering Research Center (Boone, Iowa) during summers of 2001 and 2002. A digital camcorder (TRV900, Sony USA, New York, NY), was mounted on a utility vehicle 0·60 m above the ground with a 0·30 m by 0·40 m field of

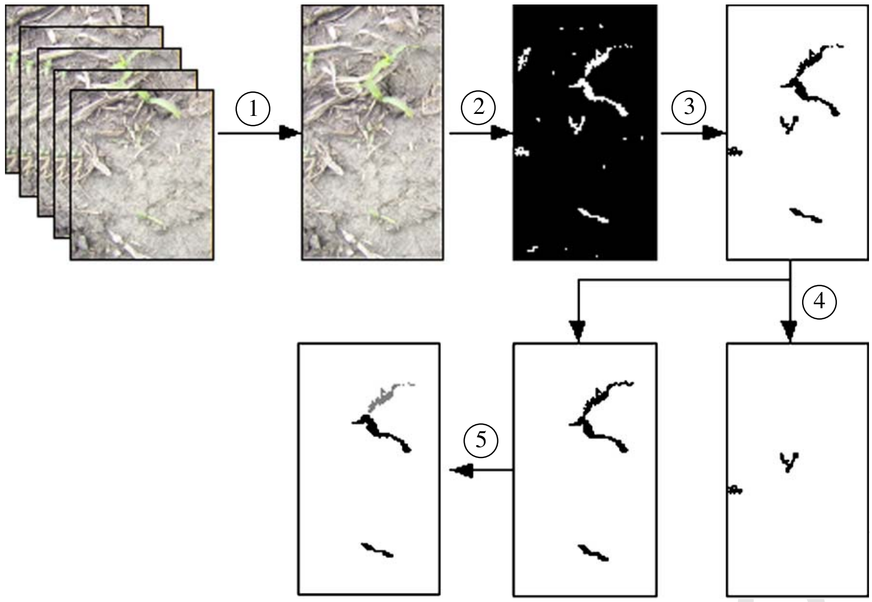

Fig. 1. Overall process consisted of: (1) frame sequencing; (2) segmentation; (3) plant identification; (4) plant type classification; (5) multi-plant separation

view. Each captured image size was 480×720 pixels with 24 bit colour resolution. The vehicle was driven over and parallel to 6·1 m maize rows sections planted 0·76 m apart with the camera directly over the plants at the speed of about 3·6 km h^{-1}. The shutter speed was fixed to 1/1000 s; frames were captured in progressive scan mode; and other camera settings were set to be automatically adjusted. In the field, the video stream was recorded on a digital video (miniDV) tape. In 279 row sections, the maize plants were counted manually to compare with automated counted results. In addition, the distance of each plant stem from the beginning of each row section was manually measured to the nearest 1 cm. Plant spacing was measured manually in 126 row sections.

2.3. *Algorithm development*

2.3.1. *Frame sequencing*

Frame sequencing is the process of determining the amount of spatial overlap in succeeding video frames (*Fig. 1*). Frame sequencing was necessary to discard duplicate information and prevent multiple counting of maize plants. An area correspondence algorithm developed by Shrestha and Steward (2003) was used to sequence video frames by estimating spatial shifts from one frame to another in both the frame column and row directions (*Fig. 2*). However, often the video frame columns were not parallel with the crop row. The angle between frame columns and the crop row was caused by: (a) camera misalignment with the centreline of the vehicle; and (b) vehicle yaw which introduced constant and variable frame-to-frame shift along image rows respectively. This frame-to-frame shift along image rows caused the plant centre location along image rows to vary when measured from the left edge of the composite image (*Fig. 2*). To estimate the plant centre location from the start of each row section, the distance parallel to the crop row had to be determined.

Camera rotation θ was estimated by taking the tangent of the ratio of total displacement in the X direction for each video segment X_T and total displacement in the Y direction Y_T (*Fig. 2*). The coordinates of each plant centre in the frame coordinate system were transformed into a coordinate system whose coordinates were parallel and perpendicular to the crop row. This transformation was accomplished with a rotational matrix:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \qquad (1)$$

where x' and y' were plant centre locations in the crop row coordinate system, and x and y were plant centre locations in the image coordinate system. All distance measurements were in pixels. Since interplant distances were manually measured along the crop row, this transformation was necessary to estimate actual interplant distances along the same direction.

2.3.2. *Plant and background region classification*

The plant and background region classification process can be divided into segmentation and plant identification steps (*Fig. 1*). After sequencing, the

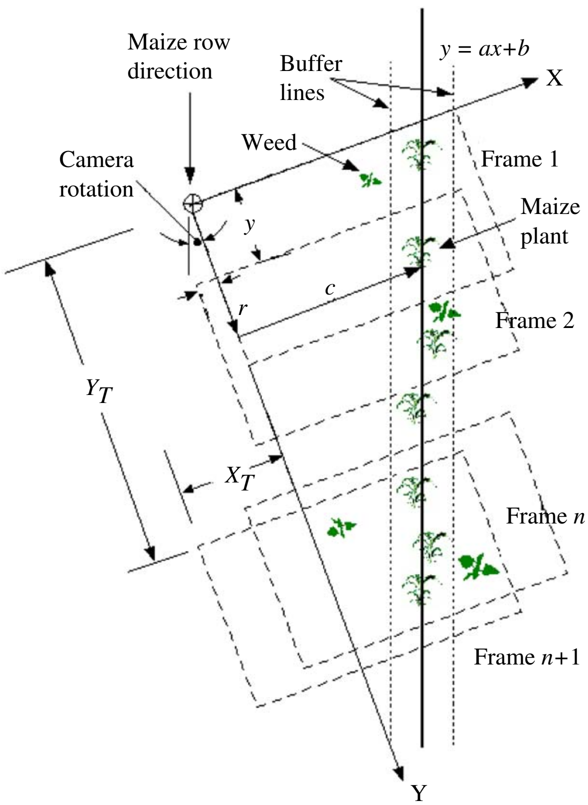

Fig. 2. Effect of camera rotation on video frame correspondence; dashed lines are image frames. The ratio of x/y is constant from frame to frame for camera rotation due to misalignment; this ratio varies from frame to frame for the camera rotation due to vehicle yaw; x and y, image scene shift amount from the last frame; X_T and Y_T, total displacement of each video segment; r and c, plant centre coordinates in two directions; a and b, coefficients of regression line passing through plant centres; n, nth image; X and Y, coordinate axis of camera

portion of each frame not overlapped with previous frames was segmented into vegetation and background regions using the truncated ellipsoidal method (Shrestha et al., 2001). Segmentation transformed the colour images into binary images with vegetation pixels set to one and background pixels set to zero. Plant identification was performed in a series of sub-steps namely feature extraction, region classification using these features, additional feature extraction from classified regions, and use of region features statistics for iterative separation of plants and background regions.

Two row features were extracted from each segmented frame row: (1) the total number of vegetation pixels; and (2) the median position of the vegetation pixels. An image row R_i was associated with the vegetation row class, V according to:

$$R_i \in V \Leftrightarrow |m_i - m_{i+1}| < V_i \,\&\, V_i > \bar{v} \quad (2)$$

where m_i is the median position of plant pixels in image row i, V_i is the number of vegetation pixels in row i and $\bar{v}$ is the mean number of vegetation pixels of all rows containing vegetation pixels in the composite image. This initial classification was based on the assumption that the number of noise pixels in a frame row associated with a background region would be less than that in a vegetation region. This initial classification of rows was followed by grouping consecutive plant rows into vegetation regions and consecutive background rows into background regions. Two features were determined for each vegetation region: (1) the total number of vegetation pixels or 'canopy area'; (2) the median vegetation location in two directions (labelled (r, c) in Fig. 2); in addition, region length in image rows was calculated for all regions.

Segmentation of vegetation typically resulted in some non-vegetative noise pixels incorrectly segmented as vegetation. Morphological dilation is effective in filtering unconnected, noise pixels but is also computationally expensive and thus was not used. Therefore, to reduce the computational burden, a statistical approach based on the Otsu method was developed to reclassify plant and background regions using the extracted features and minimise the effect of segmentation noise.

After the initial grouping of image rows into background and vegetation regions, the Otsu method was used to classify vegetation regions as either plants (weeds or maize plants) or noise by determining the optimal threshold to divide the bimodal distribution of each feature. For each video segment being analysed, the histogram of plant region lengths was constructed, and the variance ratio for each possible threshold value was calculated. The threshold that gave the maximum variance ratio was chosen as the optimum threshold. The Otsu method, however, was not independent of amount of noise present and produced a lower threshold when the number of noise pixels was high. Noise pixels resulted in many small length regions being initially classified as vegetation. The mean vegetation region length was used as the measure of the proportion of vegetation regions which were due to noise. Since noise regions were smaller than actual vegetation regions, the mean vegetation region length would decrease with increasing noise, where a large length often indicated the presence of many double and triple maize plants. The optimal region length threshold depended on plant growth stage and the population.

The threshold obtained from the Otsu method was corrected for the amount of noise present using

$$T_{mod} = \frac{T_{Otsu}}{\log_{10}(\bar{L}_v)} \quad (3)$$

where T_{mod} is the threshold calculated with noise correction, T_{Otsu} is the threshold calculated from the Otsu method, and $\bar{L}_v$ is the mean vegetation region length. Noise tended to decrease the mean vegetation region length, so including $\bar{L}_v$ in the denominator of Eq. (3) counterbalanced the effect of noise on the Otsu method. The Otsu method with noise correction was also used to threshold the background region length and canopy area histograms.

Next, vegetation and background regions were reclassified iteratively. Vegetation regions with (1) lengths smaller than the region length threshold and (2) plant areas less than area threshold were reclassified as a background region. Similarly, background regions with lengths smaller than the threshold, were reclassified as vegetation regions. A line was fit to the plant centre locations using linear regression. A histogram of the perpendicular distances of the detected plant centre locations indicated the assumption of a normal distribution was justified. Second-order statistics were calculated using maximum likelihood estimation (MLE) (Hayter, 1996). Any plant with centre locations outside the 95% confidence intervals (CI)—called buffer lines—of the estimated crop row line were classified as stray plants or weeds (*Fig. 2*). The adjusted vegetation and background regions were again compared with threshold values and false regions were detected and reclassified. The reclassification procedure was repeated iteratively using constant thresholds from the modified Otsu method operating on the initial classification until the vegetation region count in succeeding iterations changed by less than 5%.

2.3.3. *Plant type classification*

After reclassification of vegetation regions, the region features—vegetation area and region length—were recalculated. At this point, each vegetation region contained either one or more weeds or maize plants. The size of weeds and maize plants were assumed to be normally distributed. However, the number and size of the weeds varied spatially. When both weeds and maize plants are present in an image, the feature distributions should be bimodal and separable. However, in instances when no weeds are present, the distributions will be unimodal, and the Otsu method of thresholding would give an erroneous threshold value. Therefore, separability, the ratio of 'between variance' to 'total variance,' was calculated as a measure of distribution bimodality (Otsu, 1979). Separability ranged from 0 to 1, with a low separability indicating a unimodal distribution due to a low number of detected weeds compared to maize plants. The threshold obtained from the Otsu method was multiplied by the separability value to obtain a modified threshold that was used to divide the feature histograms into weed and maize regions thus classifying the vegetation regions.

To further refine the weeds and maize plant classification, the second-order statistics of the length and area features for both the maize plant and weed distributions were estimated using MLE. If both the plant length and the canopy area of a vegetation region were less than the 95% CI of the estimated means of those features in the maize plant distribution, then it was classified as a weed. Similarly if a vegetation region had length and area features greater than the 95% CI of their mean in the weed distribution, then that region was reclassified as a maize plant. Once the maize plants and weeds were classified, any maize plant which had more than twice the average maize plant area was considered a double, and thrice the average maize plant area was considered a triple.

2.4. *Data analysis*

Plant estimation error, the difference between manual counts and estimates from the system, was calculated for each row section. The SAS (SAS Institute, Cary, N.C.) general linear model (GLM) procedure was used to test for significance differences in plant estimation error due to the main factors (tillage, growth stage, and population) and their interactions. This GLM procedure was used because the design was unbalanced after several row sections were removed from the analyses due to the acquisition of poor quality video for those sections. For factors having a significant effect on mean error, treatment least-squared means were compared using the Tukey test across levels of those factors. Homogeneity of error variances across the main factor level was tested using the modified Levene test (Conover *et al.*, 1981). Root mean squared error (RMSE) was calculated and used to represent the accuracy of the estimated plant counts relative to the manual plant counts. In addition, estimated plant counts were regressed using GLM on manual plant counts to investigate the calibration of the sensing system.

Plant locations were estimated relative to the end of the crop row section. Each of the plants detected by the algorithm was matched with the nearest plant that was manually measured. The location estimation error was calculated as the difference in distance along the crop row. GLM was used to test for treatment effects on mean location estimation error and error variance.

For plant spacing estimates, the interplant distances between every detected plant pair were converted from pixels into physical units. The second-order statistics of interplant distances were estimated for both manual measurements and algorithm estimates at each treatment combination except for the 74 000 plants ha^{-1} population level. Mean manually measured and algorithm-estimated interplant distances for each treatment combination were compared using student's *t*-tests.

3. Results and discussion

3.1. *Experimental treatments and video quality*

The sensing system could be used over a wide range of daylight conditions. While capturing video of some rows, however, the video camera was mistakenly set to manual aperture, so the camera could not make adjustments when the sky conditions changed resulting in saturated images. This led to saturated pixels in parts of the images resulting in poor plant segmentation performance. Therefore, the 56 row sections with saturated images were excluded from further analysis.

A total of 223 paired observations of manual and automated plant counts from row sections were analysed using linear regression (*Fig. 3*). The manual plant counts varied from 13 to 38 plants, which corresponded to populations of 27 000 to 81 500 plants ha^{-1}. The estimated slope of the regression line was 0·97 which was not significantly different from one with student's *t* statistic with 221 degrees of freedom (t_{221}) of 0·8809, and corresponding probability *P* of 0·1191. The estimated *Y*-intercept was 0·58 which was not significantly different than zero ($t_{221} = 0{\cdot}7632$, $P = 0{\cdot}2821$). The residual plot did not reveal any specific changes in variance across the range of manual counts. The linear model had a coefficient of determination (R^2) of 0·87 and an RMSE of 2·1 plants, which was 8·7% of the mean manual count of 24·1 counts per experimental unit.

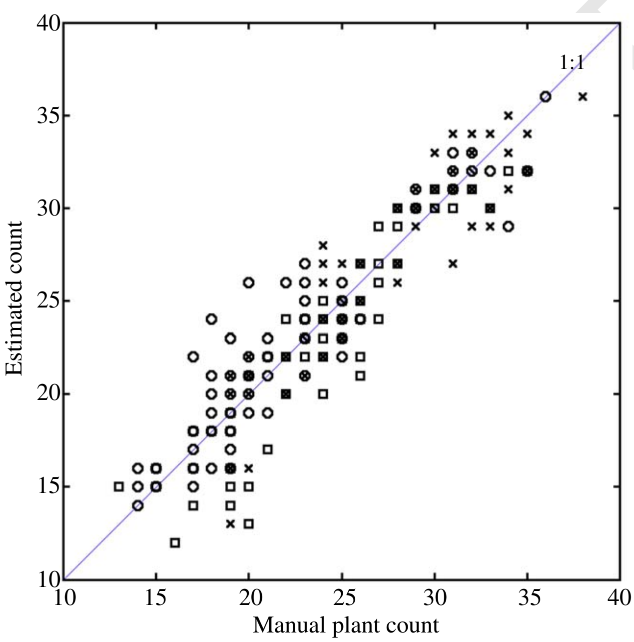

Fig. 3. Algorithm estimated maize plant counts related to manual counts for 223 6·1 m long experimental row sections differentiated by tillage treatment: ○, spring disc; ×, plough; □, till plant

This RMSE was somewhat higher than the RMSE reported by Shrestha and Steward (2003) because the algorithm was generalised and tested over a wider range of operating conditions. Much of the error was due to either large weeds or small undetected maize plants. The addition of other shape features to the weed and plant classification algorithm may be helpful in reducing error.

3.2. *Plant count estimation error analysis*

3.2.1. *Mean estimation error*

The mean plant count estimation error was significantly different across tillage treatments [$F_{2,216} = 6{\cdot}71$, the *F* statistic with 2 numerator degrees of freedom (df) and 216 denominator df; $P = 0{\cdot}0015$]. No evidence of significant differences across population ($F_{2,216} = 0{\cdot}62$, and $P = 0{\cdot}54$) and growth stage ($F_{2,216} = 1{\cdot}46$, $P = 0{\cdot}23$) treatments was found. For the spring disc tillage treatment, the algorithm overestimated the number of plants by 0·45 plants per experimental unit. However, for the plough tillage treatment, the automated count was 0·23 plants less than the manual count, and for till plant, the automated count was 1·03 plants less than the manual count (Table 1). The least square mean error associated with spring disc and till plant tillage treatments were significantly different.

The effect of tillage–growth stage interaction on mean estimation error was significant ($F_{4,216} = 3{\cdot}62$; $P = 0{\cdot}0071$), but no evidence of other significant interactions was found. The tillage–growth stage interaction indicates that the tillage system effect depends on growth stage. Further analysis showed that the plant size distribution pattern varied from one growth stage to another. When the plants were small and well spaced, the direction of leaf orientation was random, and actual plant length along the row more closely followed a

Table 1
Mean plant counting error across different tillage treatment

Tillage	*Mean error*
Spring disc	$-0{\cdot}45^{a*}$
Plough	$0{\cdot}23^{a,b}$
Till plant	$1{\cdot}03^{b}$

*Letters indicate groupings by Tukey–Kramer test.

uniform distribution and thus had a larger variance. In addition, when the plants were small, the difference between mean plant size and mean weed size was small. A larger variance and similarity between plant and weed sizes led to misclassification of some larger weeds as plants or some smaller plants as weed. However, at higher growth stages, the plant leaves were mostly spread out across the row direction; the plant length distribution pattern along the row direction was near normal; and the difference between mean weed and plant size was greater.

The effect of maize plant and weed size on counting error can be explained by examining hypothetical normal distributions of weeds and plants sizes at different growth stages (*Fig. 4*). Assuming a 95% confidence interval, the region under two normal distributions that overlap is the area of confusion (shaded region in *Fig. 4*). When maize plant and weed sizes are similar, as in case of the V3–V4 growth stages, the area of confusion is large. When the maize plant size is larger and the maize plant and weed sizes are different, the area of confusion is smaller as in case of the V5–V6 growth stage (*Fig. 4*). The average weed size was similar for all maize growth stages, but maize plant size increased substantially across growth stages (Table 2). The expected number of plants or weeds in the area of confusion is proportional to the area of confusion itself. Hence, with a larger area of confusion, it is expected that the classification error will be higher. This explanation matched with observations that at earlier growth stages, weeds were the main cause of error in

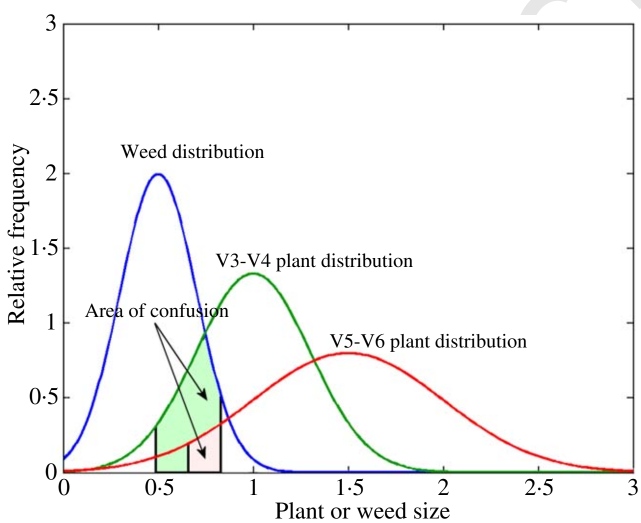

Fig. 4. Effects of difference between mean plant size and mean weed size distribution on plant counting accuracy; a larger area of confusion should lead to more misclassified plants; V3–V4, vegetative growth stage with third or fourth leaf collar visible; V5–V6, vegetative growth stage with fifth or sixth leaf collar visible

Table 2
Average plant and weed canopy size and overlapped plants count. *V*(*n*) growth stage indicates vegetative growth stage when nth leaf collar is visible

Growth stage	*Plant size, cm²*	*Weed size, cm²*	*Mean number of overlapped plants*
V3–V4	18·1 (11·0)*	12·5 (2·6)	1·1
V5–V6	31·8 (16·8)	10·3 (2·3)	2·9
V7–V8	36·25 (23·2)	14·8 (5·8)	7·8

*Numbers in parenthesis is the standard deviation.

plant estimation and at later growth stages, the overlapped leaves from neighbouring plants were the main source of error. Overlapped leaves tended to bias the mean plant length toward higher values. The estimation bias was proportional to the numbers of plants with overlapping leaves with those of neighbouring plants (Table 2).

The type and size of weeds varied across tillage treatments. The spring disc tillage treatment had many small weeds adjacent to the maize plants, whereas the till plant system had larger weeds. Larger weeds were similar in size to the maize plants making it difficult to separate weeds from maize plants based on their size. In addition, at the V3–V4 growth stage and low plant population density, plant leaf orientation was nearly random which increased the variance of plant length along the frame row direction. This variance was used to calculate the threshold used to separate plants from weeds. When plant length variance was larger, some of the large weeds were counted as maize plants, and the estimated plant count was biased higher than the manual count.

The amount of residue on the field surface was also different for different tillage systems. For the plough tillage treatment, the field had almost no residue or weeds. There were relatively few noise pixels in the segmented images, and the variability in plant size was lower. These cleaner surface conditions enabled more accurate estimation of actual plant size and better classification of small weeds from maize plants. For the till plant treatment, however, the field was covered with crop residue and only a few weeds were visible. Maize plant segmentation was better when the field was covered with residue than when the field had many small weeds. However, with the till plant system, there were many double plants growing close to each other. If there are many double plants in a row, the average plant length estimated by the algorithm was biased towards a higher value. This biasing caused the double plants to be classified as single plants and led to lower estimates than manual stand counts for the till plant treatment.

Table 3
Root mean squared error (RMSE) values for different tillage, growth stage, and plant population density combinations

Population, plants ha^{-1}	*Tillage*	*RMSE for growth stage*		
		V3–V4	*V5–V6*	*V7–V8*
39 500	Spring disc	1·04(5.6)	2·31(12·1)	3·17(17·2)
	Plough	—	—	3·51(18·0)
	Till plant	—	—	3·53(21·1)
54 000	Spring disc	1·39(6.4)	2·30(10·5)	—
	Plough	1·89(8.3)	1·56(6·6)	—
	Till plant	1·96(8.4)	2·19(9·8)	2·62(12·2)
74 000	Spring disc	1·83(5.8)	—	—
	Plough	2·21(7.0)	1·61(5·2)	—
	Till plant	1·59(5.2)	—	—

—, Data not available.
Number in parenthesis are RMSE as a percentage of mean plant count for a particular treatment combination; $V(n)$ growth stage indicates vegetative growth stage when *n*th leaf collar is visible.

3.2.2. *Error variance*

Plant count error variance was significantly different only across growth stages ($F_{2,216} = 15{\cdot}84$; $P < 0{\cdot}0001$) and no evidence of differences across tillage treatments and population was found. In particular, the error variance for the V7–V8 growth stage level was significantly higher than the error variance for V3–V4 or V5–V6 growth stages. No evidence of differences in the error variance between V3–V4 and V5–V6 growth stages was found. These results indicate that the uncertainty of population estimates increases as the canopy starts to close in the row. Canopy closure depends on both population and growth stage, but for the populations analysed in this data set, no population effect was observed.

A minimum RMSE of 1·04 plants was found for spring disc tillage treatment at V3–V4 growth stage and 40 000 plants ha^{-1}. Percentage wise, the RMSE was lowest at 5·2% of the mean for the till plant tillage treatment at V3–V4 growth stage and 74 000 plants ha^{-1} (Table 3) In general, RMSE was higher for later growth stages. At later growth stages, more plant leaves started overlapping neighbouring plant leaves. This introduced counting error in two different ways. First, the estimated plant length across frame rows was biased to be larger. Second, the larger range of plant sizes increased the variance. These factors increased the area of classification confusion leading to larger error variance. These results indicate overlapped crop plant leaves introduce higher error rates than weeds. However, quantitative relationships between the number and size of weeds and error were not established in this study, as these data were not recorded in the field.

3.3. *Spacing accuracy*

3.3.1. *Plant location estimates*

No significant effect on the mean plant location estimation error by any of the factors was observed. However, the overall mean absolute error was 57 mm. This systematic absolute error in plant location estimation was due to the analysis method. Each detected plant was matched with the nearest manually measured plant location. When a manually recorded plant was not detected by the algorithm, the nearest detected plant was assumed to be the corresponding plant, thus substantially increasing the spacing error (*Fig. 5*). However, misclassified weeds had no effect on location measurement accuracy, since weeds were not counted during manual measurements. At higher growth stages, more plant canopies were overlapped, and the probability of two plants being counted as one increased leading to an increase in location measurement error.

The variance in the location estimation error was significantly different across growth stages ($F_{2,3237} = 111{\cdot}03$; $P < 0{\cdot}0001$), but no evidence of a population effect was found. Error variance increased with increasing growth stages (Table 4) because plant centre locations were manually measured differently than the algorithm estimated them. Locations were manually measured to plant stems, but the algorithm estimated locations using the median position of each plant region along the crop row. When the plants were smaller in size, the plant leaves were smaller and more symmetrically spread out from the stem. At later growth stages, however, because of the larger, more asymmetrical canopy development, the leaf area centres were more likely to deviate further from the plant stem position, leading to an increased error variance.

3.3.2. *Interplant distance estimates*

No evidence of significant differences between the mean measured and estimated interplant spacing distance was found across combinations of all tillage treatments and two populations (Table 5). However, the modified Levene test for equal variance of manual and estimated interplant distances showed that the estimated variance was significantly higher than the measured plant spacing standard deviation ($P < 0{\cdot}001$ for all cases). The larger variance was primarily due to the algorithmic method of estimating plant centre locations.

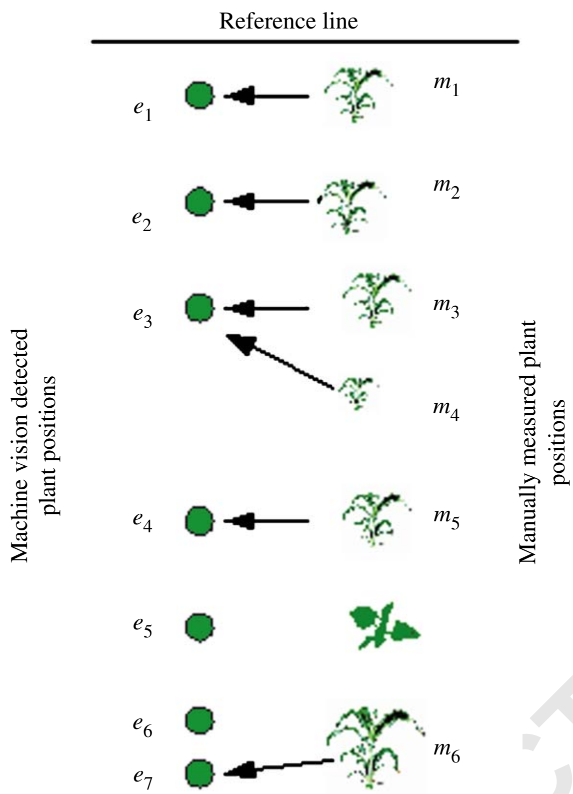

Fig. 5. Evaluation of location measurement; $m_1 \ldots m_6$, manual measurements of the plants from reference line at start of the row section; $e_1 \ldots e_7$, estimated position of plants; plant m_4 was not detected by machine vision and hence erroneously matched with e_3; e_5 was misclassified as a maize plant but does not affect error estimates

A diagram developed by Doerge *et al.* (2002) was used to visualise the manually measured and estimated interplant spacing. In this diagram, the distance from each plant to its two neighbouring plants along the crop row is plotted in a scatter plot (*Fig. 6*). After plotting the measured interplant distance for three tillage treatments and for a population of 54 000 plants ha^{-1}, it was observed that, the number of doubles were higher for the till plant tillage treatment. This result agrees with manual observations from videotapes and was one reason for the underestimation of plant population for this tillage treatment. The estimated plant spacing was also plotted in the same fashion. The manually measured and estimated plant distribution patterns were visually similar.

4. Conclusions

A video-processing algorithm using maize plant region features in video frame sequences from a commercially available digital camcorder was effective in detecting early growth stage maize plants for population sensing. In addition, this research showed that interplant distances measured in pixels from video frames can be used to effectively estimate interplant distance. With statistical separation of weed and maize plants, the overall maize plant count root mean squared error (RMSE) was 2·1 plants or 8·7% in 6·1 m row sections across the range of conditions. Plant count estimation error was dependent on tillage treatment, and error variance increased with increasing growth stage. Variance in location estimation error increased as growth stage increased. No evidence of significant differences was found between mean measured and

Table 4
Mean distance in cm between manual plant location and nearest plant counterpart of algorithm estimated plant locations (standard deviation in parenthesis)

Population, plants ha^{-1}	*Tillage*	*Mean distance, cm for growth stage*		
		V3–V4	*V5–V6*	*V7–V8*
39 500	Spring disc	−0·46 (4·65)	−0·23 (7.62)	1·27 (9·35)
	Plough	—	—	1·55 (10·77)
	Till Plant	—	—	0·76 (12·47)
54 000	Spring disc	0·30 (4·55)	−0·05 (6·73)	—
	Plough	−0·10 (4·11)	0·41 (7·29)	—
	Till plant	−0·05 (4·75)	0·38 (7·24)	0·23 (9·09)

—, Data not available.
V(*n*) growth stage indicates vegetative growth stage when *n*th leaf collar is visible.

Table 5
Interplant spacing for different plant population and tillage treatments

Population, plants ha^{-1}	*Tillage*	*Interplant spacing, cm*		*t-Statistic*	*Probability*
		Measured	*Estimated*		
39 500	Spring disc	31·75 (24·64)[+]	31·50 (26·16)	0·095	0·538
	Plough	32·77 (26·42)	32·26 (30·73)	0·131	0·552
	Till plant	37·08 (28·96)	37·08 (35·05)	−0·038	0·485
54 000	Spring disc	27·69 (19·81)	27·69 (20·57)	−0·002	0·499
	Plough	26·67 (17·27)	26·67 (19·05)	0·166	0·566
	Till plant	27·94 (21·59)	27·94 (23·88)	0·054	0·522

[+] Figures in the parenthesis represent standard deviation.

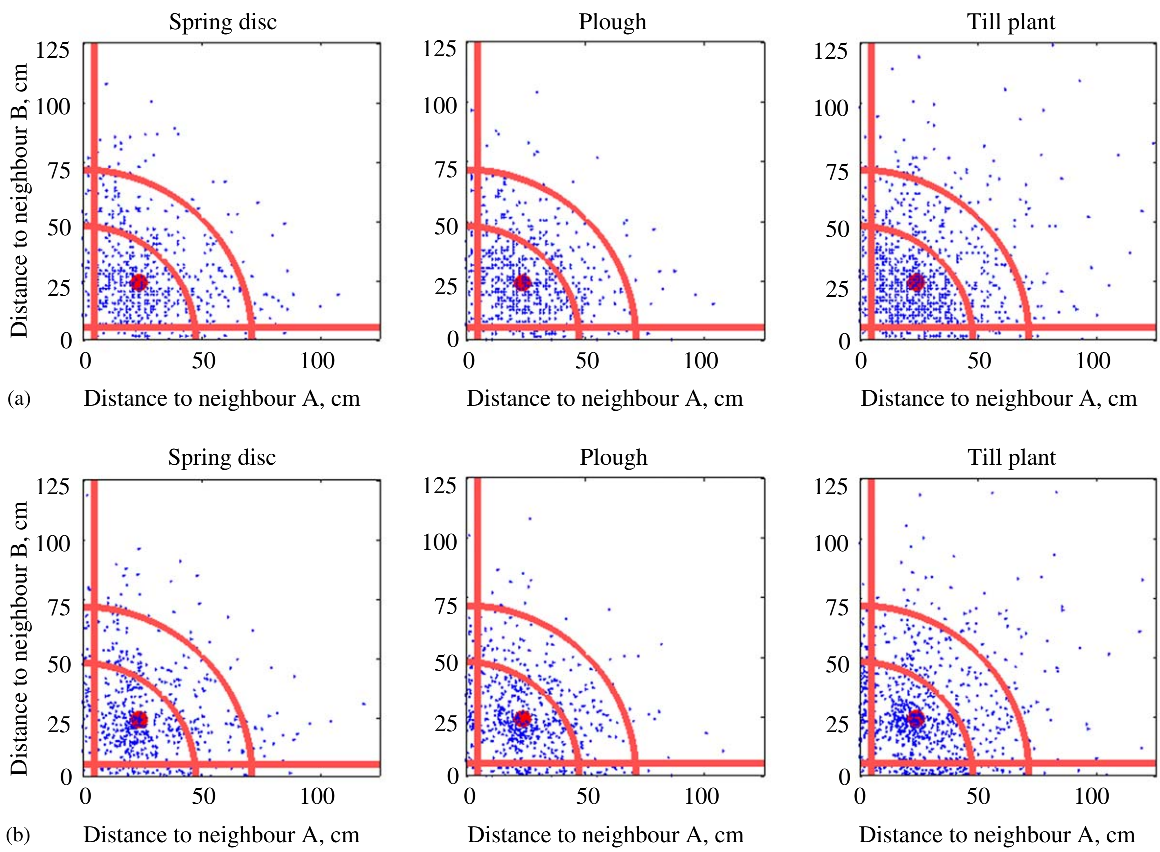

Fig. 6. Diagrams indicate the distance from a plant to it two nearest neighbours for (a) manually measured and (b) estimated interplant distance. Points below horizontal line or left of vertical line represent double plants; points nearest origin are triple plants; points between two arcs represent one skipped plant and point outside of the two arcs represent multiple skips

estimated interplant distances for all treatment combinations.

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