Machine Vision Based Steering System for Agricultural Combines

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Abstract. Agriculture is vitally important to the economy and well being of the United States. Corn and soybeans are two of the most important crops in the Midwest. Automated agricultural guidance systems offer opportunities for reduced fatigue, improved safety, increased efficiency and a host of other improvements. A machine vision based guidance system for agricultural combines was developed at the University of Illinois. Three machine vision guidance algorithms were developed; the most successful algorithm utilized a single camera mounted at approximately operator eye level on the cab of the combine. The algorithm, called the Cab Mounted Camera Algorithm (CMCA), closely mimics the perceptive process used by the operator. The algorithm developed was used to automatically harvest a 4.6 ha (12.0 a) cornfield during both the day and at night. The indicated accuracy of the guidance system was statistically the same as the accuracy of the GPS used to record the position of the combine.

Keywords. Automatic control, automatic steering, automatic guidance, combine harvesters, corn, fuzzy logic, guidance, harvesters, harvesting, image processing, machine vision
Introduction

Agriculture today is driven by pressure to feed an increasing population with a declining farm work force at a lower cost. The drive to decrease costs and increase production has provided inroads for new technology in agriculture. The cost and production goals require technological innovations to maximize efficiency.

Precision agriculture is an example of an innovation that helps to increase efficiency, allowing the inputs to be matched to the conditions. Precision agriculture adds new information for the operator, but adds another system for the operator to manage. The operator is one of the greatest obstacles to increased vehicle performance (Fitzpatrick et al., 1997). The additional load on the operator, coupled with advancements in vehicle technology, has lead to new interest in vehicle automation.

Vehicle automation has been simplified by improvements in vehicle technology. The increasing use of electrohydraulics has greatly facilitated increasing vehicle control. Advancements in technology make guidance more practical today than when it was first proposed (Callaghan et al., 1997). Increased emissions requirements have forced most agricultural machinery companies to move towards electronically controlled engines and transmissions. The controller area network (CAN-bus) provides a foundation for information exchange between various vehicle systems (Reid et al., 2000).

Sensor and computer costs have declined while power and functionality have increased. The price of GPS receivers has decreased, while the accuracy has increased. Other industries, including maritime, aviation and shipping, have placed an increased reliance on differential GPS. Embedded vehicle controls are used for a myriad of automotive applications, helping to decrease cost and increase performance.

Automation alone is not the solution; precision agriculture alone is not the solution. Together, however, automation and precision agriculture create a synergy that increases the effect of both applications. Precision agriculture and automation use many of the same technologies, albeit in different ways. GPS allows the precision agriculture system to georeference field data; for automation, GPS provides a highly accurate, drift free location signal. Machine vision can be used to supply crop condition information and the relative position of the crop. Together, precision agriculture and automation allow for complete input management.

Researchers in academia and industry have developed automated (driver assistance) or autonomous (driverless) vehicles. Billingsley and Schoenfish (1997) developed a series of machine vision based automatically guided tractors and used them to cultivate 1000 acres of Australian cropland. Agricultural machine vision guidance systems have been demonstrated under typical field conditions at speeds of up to 4.7 m/s on straight rows and 2.7 m/s on curved rows (Reid et al., 2000) (Figure 1). Bell (2000) demonstrated high accuracy (< 1cm mean error) tractor guidance along a predefined path utilizing a four-antenna carrier phase GPS system. Multisensor systems, such as Nagasaka et al. (2000), offer increased capability and redundancy. Nagasaka et al. developed rice paddy transplanting robot that used RTK GPS, a fiber optic gyro and an inclination sensor to demonstrate completely autonomous operation. The research projects demonstrated different guidance technologies and explored the feasibility of agricultural vehicle guidance.
Figure 1. A machine vision guided tractor was developed at the University of Illinois.

The objective of the combine guidance project was to develop a machine vision based automatic guidance system. Corn was selected as the primary crop of interest. Three guidance algorithms for corn were developed and evaluated during a two-year span. In 1999, the research system was used to collect initial field data. An algorithm was developed using the field data and tested in late 1999; a combination of poor crop condition and questionable guidance assumptions limited the performance of the system (Benson et al., 2000a). This paper covers the results from the most successful of the algorithms developed and tested during the 2000 harvest season. The algorithm, the Cab Mounted Camera Algorithm (CMCA), is described below (see Algorithm Description, below).

Methods and Materials

The combine guidance project used a Case\textsuperscript{1} 2188 rotary combine as the research vehicle. The vehicle was modified to incorporate an electrohydraulic steering valve, vehicle guidance sensors and the associated control equipment.

The vehicle control was split between a main guidance computer and a separate steering controller. Real time image processing was performed on the main guidance computer.

Four camera locations were used for combine guidance. In 1999, the primary cameras were located on the outside end of an eight row Case 1083 corn head. The cameras were mounted low on the head and could directly view the cut/uncut edge. For 2000, a third camera mount was installed directly over the cut/uncut edge while a fourth camera was installed above the cab of the combine. A schematic of the camera installations is shown in Figure 2.

\textsuperscript{1} Case IH is a trademark of CNH Global NV. Mention of trade name, proprietary product or specific equipment does not constitute a guarantee or warranty by the University of Illinois, and does not imply the approval of the named product to the exclusion of other products that may be suitable.
At the beginning of the 2000 harvest season, the existing Satloc (Scottsdale, AZ) GPS for the yield monitor was replaced with a Trimble (Sunnyvale, CT) Ag122 beacon GPS. A Trimble 4400 RTK GPS receiver was used to record the vehicle position during guidance. Additional information on the modifications to the combine is available in Benson et al. (2000b).

Developmental Model

The guidance algorithms were developed and evaluated using the same developmental model. The key steps in the model development model were a) feasibility study, b) image acquisition, c) off-line development, d) algorithm evaluation, and e) experimental guidance.

The feasibility study was used to evaluate potential ideas. Typically, the feasibility study was used to indicate whether the idea was worth further investigation. The feasibility study images were analyzed using software packages such as ImagePro (MediaCybernetics, Silver Spring, MD).

The feasibility study was performed with only a few images, typically less than ten. After showing the feasibility of the concept, field-ready hardware was assembled and used to collect harvest images. Still and video images were recorded while the combine was operated conventionally. A special data-recording program was used to record still images along with the GPS position and the actual steering angle.

The images were used to develop the algorithm off line. Off-line development increased the amount of development time available and reduced the wear on the vehicle. Still images simplified development and were used to develop the basic algorithms. Video images more accurately simulated the field conditions and were used to tune the algorithm.

The algorithm was evaluated in the field under normal field conditions. During the initial evaluation phase, the guidance algorithm was operated in an observer mode. During observer mode, the algorithm acquired and processed images, however, the control system was not active. The guidance system recorded raw and processed images along with the GPS position.
and steering information. The raw images provided additional images for development while the processed images provided a visual feedback of how the system performed. Recording the images, however, increased the amount of file transfer and slowed the system down.

After evaluating the algorithm and making any required modifications, the algorithm was used to guide the vehicle in the field.

The conceptual development model illustrated provided a consistent and repeatable basis for algorithm development and evaluation.

**Guidance Algorithm**

Machine vision was the primary guidance sensor for the combine guidance project. The camera location determines the scene; the scene determines the guidance algorithm. One potential guidance strategy for a machine vision-based harvester is to follow the cut edge from the previous run. A human operator, however, primarily drives the vehicle based on the relative position of the center snout and checks the outer rows occasionally.

The crop height and the width of the head complicate viewing the cut edge from the cab or body of the combine. Two options for viewing the cut edge from the head include: a) a camera located low on the head directly viewing the cut/uncut edge and b) a camera located above the cut/uncut edge. Algorithms were developed for both camera locations and evaluated in the field. The first system, a camera low on the head, encountered difficulties in sparse crop and due to shadows (Benson et al., 2000a). The second concept was initially feasible, however, image quality problems restricted the use of the algorithm.

A high mounted camera mimics the perceptive process the operator uses to drive the vehicle. From above the row, multiple rows are visible; a properly designed algorithm could help to reduce the impact of missing plants. A high mounted camera system could be developed with a single camera rather than the multiple camera systems required for the other options.

The conceptual guidance development module described above was used to develop the algorithm. Images were recorded while manually harvesting during 1999 (Figure 3). The images showed that it was not always possible to detect individual rows, however, it was possible to distinguish the center interrow space in most images. The image shown was originally acquired to investigate the feasibility of using machine vision to detect head utilization. The two problems, however, have different characteristics. Head utilization by nature is primarily concerned with a wide area close to the vehicle. Guidance, on the other hand, utilizes a narrower field of view and more distant information.
Algorithm Description

A flow chart for the CMCA is shown in Figure 4. An image was acquired from the image sensor, digitized by the frame grabber and extracted to memory. The images could be color or monochrome.

An adaptive segmentation module determined the segmentation levels based on a histogram of the image intensity. The adaptive segmentation module developed a histogram of a window in the image; the upper and lower segmentation levels were calculated based on predefined cumulative percentage goals. The histogram was used to map from percent goals to specific pixel values.
The image was processed from the bottom to the top, starting with segmentation, row-by-row filtering and then a SRI blob analysis procedure. The image was segmented into two classes based on the adaptive segmentation levels. If the pixel was within the two segmentation levels, the pixel was used for guidance (Equation 1). After segmenting the image, a low pass filter was used to remove noise. Several different filter types were used during the algorithm development stage, including gaussian, median and low pass. The low pass filter had the best combination of processing speed and image performance.

\[
P_c(i, j) = \begin{cases} 
0 & \text{if } p_x(i, j) > p_{xusl} \\
1 & \text{if } p_{xlsl}(i, j) < p_x(i, j) < p_{xusl} \\
0 & \text{if } p_x(i, j) < p_{xlsl} 
\end{cases}
\]  

(1)

Where \(i\) is the row index, \(j\) is the column index, \(p_c(i, j)\) is the pixel segmentation class, \(p_x(i, j)\) is the pixel level and \(p_{xusl}\) and \(p_{xlsl}\) are the upper and lower segmentation levels in pixels.

The blob analysis module began by run length encoding the row. Each run was checked to see if it was connected to a prior blob and assigned as appropriate. Blob analysis relies on the connectivity of points within the image; terminating processing early would change the relationship of points in the image. After processing the entire image, the blob statistics including the area, perimeter and form factor were calculated (Equations 2 and 3).

\[
FF(k) = \frac{P(k)^2}{4\pi A(k)}
\]

(2)

\[
CM(k) = \frac{A(k)P(k)}{(X_c(k) - GS(i-1))}
\]

(3)

Where \(k\) is the blob identifier, \(FF\) is the form factor, \(CM\) is the composite matrix, \(A(k)\) is the blob area, \(P(k)\) is the blob perimeter, \(X_c(k)\) is the x centroid and \(GS(i-1)\) is the guidance signal from the previous iteration.

A linear regression was run on the blob with the largest composite matrix. The operator could select whether to use the centroid or regression results for guidance. Typically, better results were obtained with the centroid than with the raw regression results.

The algorithm tracked the center inter-row space. During testing, especially in weaker stands of corn or dense leaf canopies, the system would periodically select a non-center row space. Improper row selection would cause the guidance system to veer suddenly and attempt to align the combine with an incorrect row. A fuzzy module was added between the blob calculations and the controller. The fuzzy module evaluated the output from the system and determined if the output was appropriate for the center row. A schematic of the fuzzy quality module is shown in Figure 5. The two inputs for the fuzzy evaluation module were the guidance signal and the absolute value of the percent change in the guidance signal. The guidance signal input was used to ensure that the value was within a reasonable range. From experience, the output did not vary significantly from image to image. The output from the module was a binary acceptance rating. If the output was acceptable, the results were used for guidance. If the results were not acceptable, then guidance was based on the results of the previous image.
Field Evaluation

The conceptual development model illustrated above was used to develop the CMCA. Evaluation and guidance data was collected for the CMCA and the other algorithms over 23.7 ha (58.9 a) of typical central Illinois corn fields. During the 2000 harvest season, there was widespread wind damage and stalk rot in central Illinois. The 4.6 ha (12.0 a) section used for automatic harvest was relatively free of damage.

Table 1. Field summary, harvest dates and yield for data collection and evaluation.

<table>
<thead>
<tr>
<th>Farm</th>
<th>Location</th>
<th>Harvest Date</th>
<th>Area (ha)</th>
<th>Yield (t/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Farm 1</td>
<td>Urbana, IL</td>
<td>9/19/2000 – 9/28/2000</td>
<td>4.6 (11.2)</td>
<td>7.52 (119.9)</td>
</tr>
<tr>
<td>Farm 2</td>
<td>Urbana, IL</td>
<td>10/02/2000</td>
<td>10.0 (24.5)</td>
<td>7.64 (121.8)</td>
</tr>
<tr>
<td>Farm 3*</td>
<td>Fairmont, IL</td>
<td>10/25/2000 – 10/31/2000</td>
<td>13.9 (34.1)</td>
<td>8.05 (128.3)</td>
</tr>
</tbody>
</table>

* Used for guidance and evaluation

The CMCA was evaluated in the field under both mock and actual guidance situations. During mock guidance, the combine was manually operated with the guidance system active, but with the steering controller disabled. During actual guidance situations, the guidance system calculated the steering command and sent the command to the steering controller. The operator controlled the vehicle speed and threshing settings.

Mock guidance revealed two issues with the CMCA: a) the image processing system was relatively slow (< 1 Hz) and b) there was a tendency to select the wrong row. A representative processed image is shown in Figure 6.

Figure 5. CMCA fuzzy quality module schematic.

The guidance signal from the fuzzy quality evaluation module was converted to a desired wheel angle by a PID controller. The calculated guidance signal was sent to the separate controller via an RS-232 serial link. The separate controller and the guidance algorithm were asynchronous; the separate controller ran at a faster update rate than the main guidance system.
The nature of CMCA methodology slowed processing. Each additional line added significantly to the processing load. Reducing the size of the image from 320 x 243 pixels to 160 x 121 pixels decreased the resolution of the system, but increased the maximum speed of the algorithm from ~0.5 Hz to ~1.0 Hz. The tendency to select the wrong row meant that the vehicle would track through the field for a distance, select a new row, align the combine with the new row and continue through the field for a distance. The tendency to select the incorrect row was eliminated by adding the fuzzy evaluation module and reducing the height of the camera. The fuzzy parameters were tuned in the field to provide suitable performance and robustness.

Reducing the height of the camera relative to the crop had the effect of limiting the field of view. Limiting the field of view reduced the number of rows in the image. The same effect could have been generated by limiting the size of the processed region in software or by using a higher magnification lens. The reduced height camera location was approximately at operator eye level. Reducing the height of the camera reduced the field of view and improved performance.

The improved system was used to guide the combine through the field. The guidance work was performed at a cooperator’s farm (Farm 3) in Fairmont, IL. The field was roughly rectangular with the rows running North to South and a waterway serving as the East border. The average yield for the field was 8.05 t/ha (128.3 bu/A), with a typical range of 4.52 t/ha (72.0 bu/A) to 12.30 t/ha (196.0 bu/A). A small drainage ditch roughly split the field into a northern third and a southern two-thirds, with the yields generally being lower in the southern portion. The crop, however, was largely intact and in good shape for the season.

The maximum operating velocity of the combine was dictated by the speed of the image processing system. The maximum velocity was 0.8 m/s to 1.3 m/s. After reducing the size of the processing window, the algorithm was relatively slow.

The CMCA was used to harvest a 4.6 ha (12.0 a) portion of the field. The CMCA was used to guide the combine through 4.0 ha (10.4 a) during the day and 0.6 ha (1.6 a) at night. Eleven passes were recorded during the day; four passes were recorded at night. There were no changes made to the software for night operation and the factory lighting package was used to illuminate the scene.

The overall accuracy of the system was 0.6 cm with a 13.3 cm deviation. The average daytime accuracy of the system was 0.3 cm, with a 13.3 cm deviation. The average nighttime accuracy of the system was –2.4 cm, with a 12.9 cm standard deviation. The actual row positions were not known. A second order spline fit was used to extract the row parameterization from the data. A second order spline fit provided $R^2$ greater than 0.975 for each of the runs. The indicated average accuracy is a measure of how well the model represented the data; the
deviation measurements provide a better indication of how well the system could track a given path. The results are presented in Table 2.

Table 2: The accuracy of the system as compared to a second order spline fit of the data.

<table>
<thead>
<tr>
<th>Run ID</th>
<th>Average (cm)</th>
<th>Standard Deviation (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-1.4</td>
<td>9.0</td>
</tr>
<tr>
<td>2</td>
<td>3.5</td>
<td>13.0</td>
</tr>
<tr>
<td>3</td>
<td>0.1</td>
<td>10.4</td>
</tr>
<tr>
<td>4</td>
<td>-0.4</td>
<td>10.4</td>
</tr>
<tr>
<td>5</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>6</td>
<td>0.3</td>
<td>9.3</td>
</tr>
<tr>
<td>7</td>
<td>-17.0</td>
<td>11.1</td>
</tr>
<tr>
<td>8</td>
<td>7.4</td>
<td>14.8</td>
</tr>
<tr>
<td>9</td>
<td>5.1</td>
<td>12.4</td>
</tr>
<tr>
<td>10</td>
<td>2.3</td>
<td>15.5</td>
</tr>
<tr>
<td>11</td>
<td>-0.6</td>
<td>13.3</td>
</tr>
<tr>
<td>N1</td>
<td>1.4</td>
<td>4.7</td>
</tr>
<tr>
<td>N2</td>
<td>0.0</td>
<td>4.2</td>
</tr>
<tr>
<td>N3</td>
<td>-2.5</td>
<td>8.4</td>
</tr>
<tr>
<td>N4</td>
<td>4.7</td>
<td>14.6</td>
</tr>
<tr>
<td>Day</td>
<td>0.3</td>
<td>13.3</td>
</tr>
<tr>
<td>Night</td>
<td>2.4</td>
<td>12.9</td>
</tr>
<tr>
<td>Total</td>
<td>0.5</td>
<td>13.3</td>
</tr>
</tbody>
</table>

The Fairmont, IL site was outside the range of the radio link from the RTK GPS base station to the combine GPS receiver. The output from the GPS was recorded for approximately two minutes with the system stationary. The GPS data was converted from latitude and longitude to Universal Transverse Mercator (UTM) projection to simplify measurements. At the Fairmont site, the dispersion for the GPS system 11.0 cm (Northing) and 1.4 cm (Easting). The difference between the system accuracy and the accuracy of the GPS was not statistically different at the 5% level for daylight operation (Table 3). During nighttime operation, there was a statistically significant difference in accuracy (in this case, the CMCA had a larger deviation). The difference between the daylight and nighttime operation was not statistically significant. The conclusion is that the guidance system was as accurate as the recording information available.

Table 3: Statistical significance of the indicated accuracy versus the deviation of the GPS position recording equipment.

<table>
<thead>
<tr>
<th>Comparison</th>
<th>Z</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daylight operation versus GPS</td>
<td>-1.53</td>
<td>0.9370</td>
</tr>
<tr>
<td>Night operation versus GPS</td>
<td>1.41</td>
<td>0.0793</td>
</tr>
<tr>
<td>Daylight versus Night operation</td>
<td>-2.24</td>
<td>0.9875</td>
</tr>
</tbody>
</table>
In the field, the performance of the system appeared to be related to the condition of the crop in view. In moderate to high yielding areas, the system rarely encountered problems. In low yielding areas, the CMCA could not reliably parameterize the crop rows. The CMCA utilizes the rows in view to determine the appropriate steering command for the vehicle, missing or damaged plants make it difficult to detect the row structure. To test the hypothesis that the CMCA performance and crop condition were related, the output from the fuzzy guidance module ("acceptability") was compared to the yield. The yield monitor and guidance output files were combined and GPS indicated position was used to align the data points. The average yield for the acceptable and unacceptable regions was calculated for each of the test runs (Table 4).

The comparison indicated that there was a statistically significant difference in yield between the acceptable and unacceptable regions. The overall results, however, mask the behavior on the individual runs. On 11 of the 14 runs, the yield was higher in the acceptance regions than the unacceptable regions. On three of the runs, the yield in the acceptable regions was lower than the yield in the unacceptable region.

Table 4. Statistical significance of the acceptability as compared to crop yield.

<table>
<thead>
<tr>
<th>Run ID</th>
<th>Percent Too Low</th>
<th>Accepted</th>
<th>Too High</th>
<th>Yield Accepted</th>
<th>Not Accepted</th>
<th>Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>12.0%</td>
<td>86.4%</td>
<td>1.6%</td>
<td>8.01</td>
<td>6.48</td>
<td>7.63</td>
</tr>
<tr>
<td>2</td>
<td>0.8%</td>
<td>99.2%</td>
<td>0.0%</td>
<td>8.68</td>
<td>9.15</td>
<td>-3.01</td>
</tr>
<tr>
<td>3</td>
<td>3.1%</td>
<td>66.8%</td>
<td>30.1%</td>
<td>8.01</td>
<td>7.62</td>
<td>2.75</td>
</tr>
<tr>
<td>4</td>
<td>5.3%</td>
<td>91.5%</td>
<td>2.7%</td>
<td>9.27</td>
<td>9.26</td>
<td>0.02</td>
</tr>
<tr>
<td>5</td>
<td>5.0%</td>
<td>91.3%</td>
<td>3.7%</td>
<td>7.40</td>
<td>8.30</td>
<td>-4.29</td>
</tr>
<tr>
<td>6</td>
<td>3.1%</td>
<td>96.8%</td>
<td>0.1%</td>
<td>7.64</td>
<td>7.99</td>
<td>-1.07</td>
</tr>
<tr>
<td>7</td>
<td>4.3%</td>
<td>95.6%</td>
<td>0.1%</td>
<td>8.76</td>
<td>6.53</td>
<td>3.35</td>
</tr>
<tr>
<td>8</td>
<td>3.8%</td>
<td>95.7%</td>
<td>0.5%</td>
<td>7.78</td>
<td>7.72</td>
<td>0.21</td>
</tr>
<tr>
<td>9</td>
<td>8.8%</td>
<td>91.1%</td>
<td>0.2%</td>
<td>8.11</td>
<td>6.99</td>
<td>1.38</td>
</tr>
<tr>
<td>10</td>
<td>21.2%</td>
<td>77.9%</td>
<td>0.9%</td>
<td>7.69</td>
<td>6.75</td>
<td>2.49</td>
</tr>
<tr>
<td>11</td>
<td>9.1%</td>
<td>90.2%</td>
<td>0.7%</td>
<td>7.53</td>
<td>7.13</td>
<td>1.55</td>
</tr>
<tr>
<td>N1</td>
<td>12.5%</td>
<td>83.7%</td>
<td>3.8%</td>
<td>10.03</td>
<td>10.02</td>
<td>0.27</td>
</tr>
<tr>
<td>N2</td>
<td>1.6%</td>
<td>92.1%</td>
<td>6.3%</td>
<td>9.68</td>
<td>9.27</td>
<td>1.82</td>
</tr>
<tr>
<td>N3</td>
<td>7.2%</td>
<td>92.3%</td>
<td>0.5%</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>N4</td>
<td>7.3%</td>
<td>92.3%</td>
<td>0.4%</td>
<td>6.67</td>
<td>6.11</td>
<td>2.74</td>
</tr>
<tr>
<td>Total</td>
<td>7.0%</td>
<td>89.2%</td>
<td>3.8%</td>
<td>7.96</td>
<td>7.42</td>
<td>7.12</td>
</tr>
</tbody>
</table>

The conclusion that can be drawn from the results presented in Table 4 is that yield and acceptability are related. In general, the yield in the acceptable region is higher than the yield in the unacceptable region. The inconsistency observed implies, that yield (or crop condition) is not the sole factor that determines guidance parameter extraction performance ("acceptability").

**Discussion**

The CMCA was able to successfully provide a guidance signal for combine guidance. In the field, the system guided the combine through a typical field at a satisfactory level of accuracy.

In contrast to the results from the prior year, the images from the elevated cab mounted camera contained sufficient contrast to reliably segment the images. With the elevated cab mounted camera, there was a consistently detectable difference between the standing crop and the
interrow spaces. The difference allowed the images to be robustly segmented under both natural sunlight and artificial light.

While the system was capable of moderate performance, the algorithm processing speed was a significant limitation. With reduced sized images and limited data recording, the system ran at 1.8 to 2.0 Hz. The vehicle, however, continues to move during the time between guidance updates. The slower the vehicle controller, the further the vehicle moves before the next control signal is calculated. The slower the controller is, the more effect processing errors and image errors have on the system. An example of an image error would be missing plants or rows. Processing errors included incorrect row selection or a segmentation error.

The fuzzy evaluation system and the relatively slow processing speed magnified the effect of processing or image errors. In the event of an image or processing error, the output was disregarded and the output from the previous iteration was used. In the field, gaps or missing plants would typically be present in several images in a row. The net effect was the same controller output would be held for several iterations, which typically translated into a second or more. When a proper image was received, the a relatively large steering correction would be required to bring the vehicle back on course. With a faster processing system, new guidance signals would be calculated faster and the overshoot would be minimized.

The limited processing speed forced the operator to reduce the speed of the combine. Typical manual operating speeds would range from 1.8 m/s to 2.7 m/s, depending on field conditions. With the guidance system active, the maximum speed of the combine was processing limited to 0.9 m/s to 1.3 m/s.

The net effect is that an improvement in speed would improve the field performance of the system. The algorithm used a blob analysis procedure that required evaluating the pixel connectivity. For every row, the connectivity of each blob had to be determined. Evaluating the connectivity increased the processing time. Improvements in coding efficiency, dedicated image processing hardware or a simpler processing methodology could speed processing. The current speed limitations are a short-term restriction, not a long-term barrier to future implementation.

In the field, the crop condition clearly affected the performance of the system. Simply put, if there is no crop, a machine vision system cannot provide a guidance signal. In the field, every time a low spot or weak area was encountered, the performance of the system began to decline. In the weak areas, the operator had to take control of the combine on several occasions. Obviously, it is not ideal to require the operator to periodically retake control of the system.

What sorts of alternatives are there to forcing the operator to retake control? At some level, we can define what an acceptable crop condition is. Crop condition problems can be isolated events (a few missing plants in a row) or larger problems (a depression or wet area). The size and nature of the problem dictates the solution.

Small, isolated crop condition problems could be compensated for under the existing model. If only a few plants in a row are missing or damaged, it may be possible to extract a guidance signal from other portions of the image. To increase the speed of the processing algorithm, the window size and field of view were reduced to a minimum. An alternative would be to change the field of view and restrict the size of the processing region within software; if there was a problem, the size or location of the processing region could be changed to facilitate guidance signal extraction. Larger crop condition problems may require other solutions. Increasing the size or location of the processing region for a fixed camera may not ensure satisfactory
guidance signal extraction. A multisensor system combining machine vision and GPS and/or inertial sensors could provide a guidance signal in the event of poor crop condition.

Shadows had an impact on system performance. The lighting conditions in the field were such that the combine shadow did not appear in the image if the harvest pass was conducted from North to South. If the combine operated from South to North, the shadow of the vehicle appeared as a dark spot in the image. The majority of the runs were conducted from North to South for two reasons: a) to avoid the shadow and b) the grain wagons were located at the southern edge of the field. One run, Run 3, was conducted South to North. The presence of the shadow threw off the performance of the guidance signal extraction (as demonstrated by acceptability). The acceptability of Run 3 was over 10% less (66.8%) less than the other runs. This suggests that shadowing is a potential problem.

Vehicle shadows are an issue with a cab mounted camera system. The shadow of the vehicle, specifically the cab, can be seen in the images under certain ambient illumination conditions. The shadow obscures the difference between the crop and the interrow space, making it difficult to reliably segment the images.

**Conclusion**

A combine guidance system was developed at the University of Illinois at Urbana-Champaign. Three different machine vision algorithms were developed, tested in the laboratory and evaluated under typical Illinois field conditions. The most successful algorithm mimicked the operator’s perceptive process and used a single camera mounted on the cab at approximately eye level. The algorithm, called the Cab Mounted Camera Algorithm or CMCA, was used to automatically guide the combine over 4.6 ha (12.0 a) of a typical Illinois cornfield. The system was able to guide the combine during day or night operation; however, large changes in illumination affected the performance of the system. The accuracy of the system was within the accuracy of the position recording equipment.

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