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Precision Guidance of Agricultural Vehicles

By
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Introduction

Precision agriculture has created a technology revolution in production agriculture. It is common to find combine harvesters with on-board data collection systems for mapping yield and moisture content of harvested crop. The agricultural equipment industry is moving towards controller area networks for agricultural equipment communication systems. These are basic factors that have led to increased opportunity for automation of agricultural guidance.

The fundamental element of precision agriculture technology, the global positioning system (GPS) signal can be used for agricultural vehicle guidance. The location accuracy provided by several modern GPS systems are adequate for some agricultural operations requiring low location accuracy, but many agricultural operations (planting, cultivation, harvesting) require precise location. Furthermore, although GPS can locate the vehicle on the field, it can't provide information on obstacles or crops that the vehicle may encounter. For successful development, agricultural vehicle guidance must utilize local information and global information, implying the need for sensor fusion.

An agricultural vehicle guidance system can be conceptualized by the signal flow diagram shown in Figure 1. The posture of a vehicle is the position and orientation of a vehicle relative to some reference frame (Kanayama and Hartman, 1989). In simplest terms, a guidance system determines the current posture of a vehicle, compares it to a desired posture, and makes appropriate steering control to direct the vehicle toward the desired posture. Manual operator steering control also follows this conceptualization. The desired path is determined by the operator usually from visual cues like stationary objects at the edge of the field, previous swaths, or some kind of deliberately placed guidance marks (foam markers, guidance furrows, etc.). The operator observes the current posture of the vehicle and makes appropriate steering adjustments through the steering wheel.

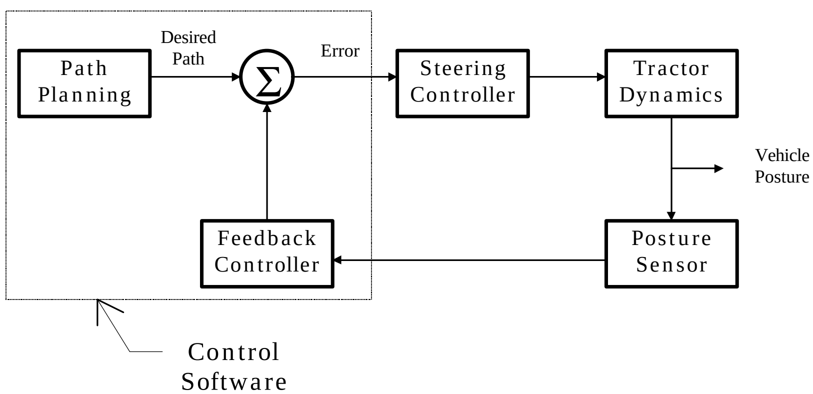

Figure 1. Signal flow diagram for automatic vehicle guidance system

Posture Sensing

A posture-sensing system must measure vehicle displacement, transverse velocity, and bearing relative to some reference frame (Grovum and Zoerb, 1970). Human operators use a significant amount of intelligence to combine visual and audio cues as well as sensations of vehicle motion to determine vehicle posture.

Three specific constraints that challenge posture sensor developers are the accuracy, speed, and stability required of an effective sensor. Auernhammer and Muhr (1991) give benchmarks for required accuracy of position sensors. They classify farming operations into rough (soil sampling, weed scouting), fine (pesticide application, soil cultivation), and precise (planting, plowing) navigation categories. Their suggested accuracy requirements for each of the navigation categories are 1 m, 10 cm, and 1 cm, respectively, although some researchers feel these values are too conservative (Nieminen and Mononen, 1994). Julian (1971) showed that fluctuations of less than 5 cm at the front wheel of front steered vehicles produce negligible deviations at the rear wheel so that trailed implements follow a true course. The required speed of a sensor is highly dependent on the type of field operation being performed. Field machinery has become larger and faster in recent years. Some commercial pesticide application equipment is operated at speeds approaching 25 km/hr. A small vehicle heading error will result in a large offset error as the distance traveled increases. Sensors with slow response or sampling times can propagate these type of distance-based errors. Gerrish and Surbrook (1984) suggested that the sensor speed should be based on the row spacing of the field crop, machine velocity, and maximum expected heading error. For field operations not based on crop row spacing, one must define a maximum allowable offset error. The third major posture sensing challenge is sensor stability. Some sensors exhibit output drift caused by time, temperature, or some other factor. Since field operations take time and can occur in taxing environmental conditions such as extreme heat and humidity, sensor drift can degrade the performance of a guidance system. There are currently three posture sensing technologies that give adequate posture sensing for autonomous or semi-autonomous vehicles; *dead reckoning*, *machine vision*, and *satellite-based triangulation systems*.

Dead Reckoning

Lawrence (1993) describes dead reckoning as essentially a motion memory system. "If a [vehicle] starts from a known location and travels in a known direction for a known time, its final position is known." On land vehicles, dead reckoning sensors can be as simple as wheel encoders which measure the rotation of the wheels of the vehicle or implement. If the wheel circumference is known, the distance traveled can be calculated. Unfortunately, these sensors are unable to detect wheel slippage and will, over extended periods of time, inaccurately predict vehicle movement. Several researchers have applied dead reckoning to agricultural land navigation (Gilmour, 1960; Harries and Ambler, 1981; Freeland, et al., 1992; Mitchell, 1995; Muhr et al., 1995). Patterson et al. (1985) developed a dead reckoning system for use on a trailed planter using wheel encoders. They tested their system in controlled laboratory conditions over a 38.1-m linear path. With proper alignment of vehicle and trailed implement, mean deviation of the implement position from the reference line at the end of this path was 12.95 cm. Inertial navigation is widely used for dead reckoning in the aerospace industry (Barbour et al., 1992). As a result of drift effects on long-term stability, inertial sensors are often limited to function as a back up to or integrity monitor of another primary posture sensing system. Yavnai and Bar-itzhack (1980), Afanasev and Neusypin (1992) and Borenstein (1995) have shown ways to compensate for some of these errors. The major limitation to widespread acceptance of inertial sensing technology for agricultural is the high cost requirement for accurate performance.

Machine Vision

Vision-based sensing utilizes a camera mounted on the vehicle to provide information on the vehicle motion relative to a guidance directrix in the field. There are several aspects of machine-vision based sensing. Different types of sensor modalities can be selected to measure the guidance information. Standard image sensors provide a color or monochrome response, but even special purpose cameras have been developed by combining standard sensors with optical filters (Reid and Searcy, 1987). Positioning of the sensor on the vehicle requires an understanding of the geometric relationship between the image sensor, the vehicle and the field-of-view that the sensor uses for guidance information. Machine vision methods require that a guidance directrix be observable by the image sensor for developing the control signal. Most previous research has looked at the use of row crops, soil tillage, and the edges between harvested and unharvested crops. Various methodologies of image processing have been investigated for extracting the guidance information. Finally, the processed images must produce an output signal that can be used to provide a steering signal for the vehicle.

Gerrish et al. (1984, 1985) investigated the potential of vision-based tractor guidance by studying the accuracy that could be achieved through automatic guidance, and by evaluating several images processing techniques to determine their applicability. This research led to the development of a vision-guided lawn tractor (Fehr and Gerrish, 1995). This work was later implemented on a Case 7110 tractor (Gerrish et al, 1997). A standard RGB sensor was used to measure crop vegetation from a position to the left of the cab at a height of 2.79 m and tilted downward 15 degrees below the horizon. During setup, the user selected pixels representing crop and soil material in the image for segmentation based on RGB values. The vehicle guidance signal was based on a single "look-ahead" point in the image. The position of the crop row at the single position in the image provided an offset that was used with a steering gain to directly control the wheel position. In their final system, the tractor was able to follow rows of corn plants in straight rows with an accuracy of 6 cm and 12 cm from a mean trajectory at speeds of 4.8 and 12.9 km/hr respectively.

Reid (1987) began development of a vision-based guidance system for steering a tractor through row crops. Near infrared images were used to segment row crops into crop and soil using a Bayes classifier to segment each image. Segmented images were processed to produce sets of points representing crop row centers using run-length encoding and marking the center pixel of each run. Regression equations describing crop row locations in images were determined using an unsupervised classifier that clustered pixels based on vertical proximity to classified pixels or the distance to a projection of the regression line passing through classified pixels (Figure 2). Final classes representing crop rows were separated based on the number of points in each class and used to determine the vanishing point of crop rows. Brandon and Searcy (1992) designed and built a vehicle control system using distributed control techniques to steer a tractor through row crops. The algorithms developed by Reid (1987) were implemented for computing heading and offset errors. They observed a limitation to straight rows when the guidance signal from images was used directly, since the information came from positions well ahead of the vehicle. For curvature in rows, the control information was integrated into a trajectory planner to buffer control information until the vehicle reached the proper turning point. Testing demonstrated that the system could detect heading errors within 0.5 degrees and offset errors within 5 cm. A limitation of this early work was that machine vision systems were bulky and had limited capabilities. A simplified row crop guidance was developed later by Billingsley and Schoenfisch (1995, 1997) utilizing modern and low cost computer imaging hardware. The image processing of this system was fundamentally identical to (Reid, 1987) with the exception that the operator had to select the initial positions of row crops that were subsequently tracked and used to compute a vanishing point.

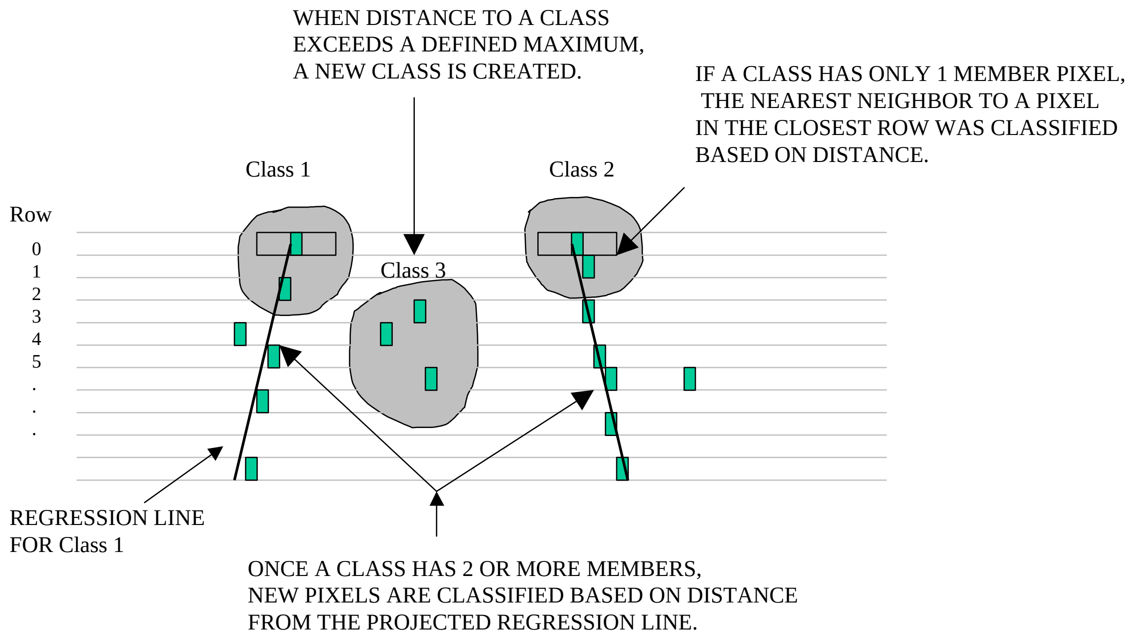

Figure 2. Method of computing regression lines using unsupervised learning (Reid and Searcy, 1992)..

More recently, Carnegie-Mellon and NASA, developed a guidance system for a New Holland hay windrower that uses machine vision to sense the edge of the uncut crop (Ollis and Stentz, 1996). The system uses a color camera on either side of the vehicle to track the edge of cut/uncut vegetation. The guidance signal is based on a vertical weighting of the crop edge and a calibration of the steering valve with the horizontal displacement of the crop edge in the image. An unsupervised classifier was used to segment the image into cut/uncut regions. Additional software was developed for compensation of shadows that are cast by the vehicle and for detecting obstacles based on their dissimilarity to cut/uncut classified crop.

The University of Illinois also has an active program in vehicle automation in cooperation with Hokkaido University in Japan. Building on the work of Reid (1987), they have taken a system approach to guidance that integrates machine vision with other sensors required for automation.

The fundamental element of machine vision sensing is the algorithm for extracting the guidance information. There are opportunities for developing more robust methods for vision guidance. Industry will favor systems that are robust and automated and require little or no interaction from the operator. Reid and Searcy (1986) explored the use of the Hough transform for detecting the guidance signal. This method has advantages in that row crops transform to clusters of points in the image parameter space.

Pinto and Reid(1998) are considering the detection of the heading and offset as a pose recognition problem utilizing principal component analysis. The main goal of the vision part of a guidance system is to output the heading angle and the offset of the vehicle (Figure 3). In this research, this task was addressed as a pose recognition problem where each combination of heading angle and offset was considered a pose. A set of poses (images) was collected and used as a training set. The training stage of the algorithm used the principal component analysis (Hotelling Transform) to output a low-dimensional eigenspace on which each pose was represented by its projections. Given a new image, the pose (heading angle and offset) recognition was done by projecting the image onto the eigenspace and determining the closest training image projection. While this methodology requires substantial time in training, it offers fast and robust results in implementation.

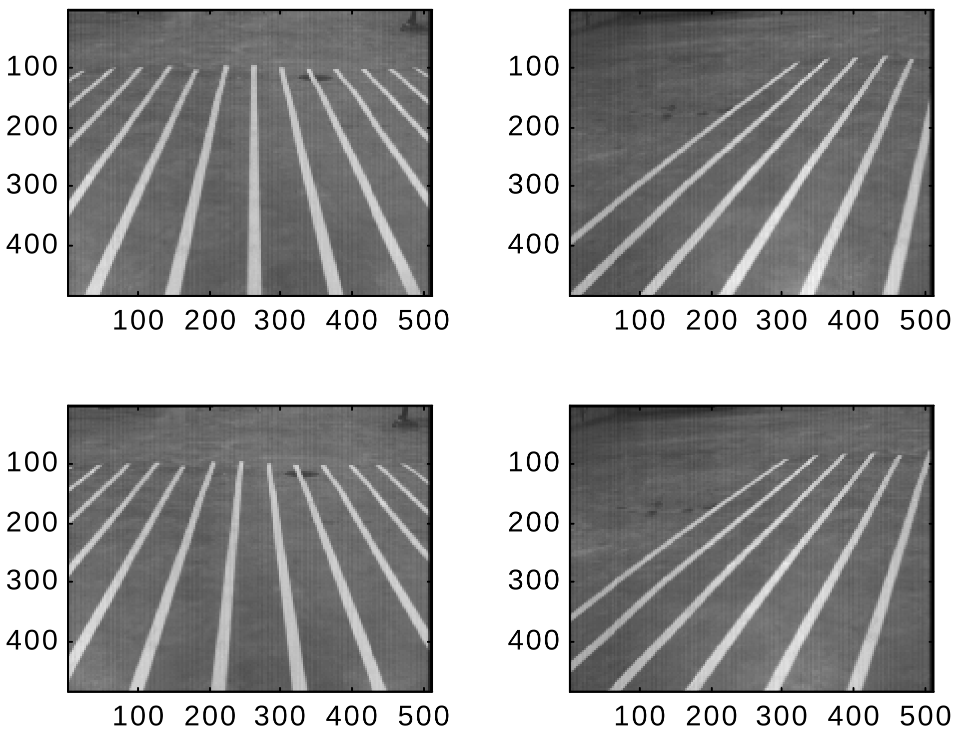

Figure 3. Four images representing row crop heading and offset as different poses. (top left) Offset = 0.0, and angle = 0; (top right) Offset = 0.0, and angle = -18; (bottom left) Offset = +9.0, and angle = 0; (bottom right) Offset = +9.0, and angle = -18.

GPS-based Systems

Global positioning (GPS) systems, although new to agriculture, have generated much of the potential growth in agricultural equipment automation by enabling the agricultural equipment industry and producers to see beyond the limitations of their previous paradigm that shunned technological advancement. GPS systems use multiple satellites to triangulate position. The current systems available consist of a constellation of at least 24 satellites placed in orbit such that a user at any point on the earth's surface will always have at least 4 satellites in view (Daly, 1993).

It is well known that several factors may limit the accuracy of satellite-based positioning systems, include clock errors, atmospheric errors, "multipath" signal reception and satellite position error. The most severe GPS errors result from selective availability (SA), the purposeful dithering of GPS signals by authorities, to prevent hostile parties from using the precision of GPS. This dithering can be imposed on either the timing information or ephemeris. Typical inaccuracies can be 100 m or more. There are methods of signal processing to minimize the effects of errors and increasing the number of satellites tracked reduces the impact of SA.

Differential GPS (DGPS) provides significantly better error correction. DGPS signals are available commercially from radio and satellite sources. Coast Guard stations provide a free radio-based correction signal. Good quality DGPS systems can locate positions, usually within 3 to 5 m and occasionally to within a meter. The most accurate DGPS systems use a technique called kinematic DGPS (KDGPS) which utilizes the GPS carrier signal. The KDGPS receiver calculates the distance between the receiver and the satellite based on the carrier frequency rather than the broadcast satellite position information. Mobile system accuracy can be as good as 2 - 20 cm.

A limitation of GPS is the speed and latency of position updates. Because of the computations that must be performed, position updates on low quality systems may occur only once every two seconds. However, most current technology comes standardized with 1 second updates with 10 Hz output available on newer systems. At high speeds, vehicles can travel a significant distance between updates making control difficult. The computation time also causes the position update to be latent, i.e. when the position reading is received from the sensor, it indicates the posture of the vehicle at an earlier time, not at the time of receipt. This introduces lag into sensor readings further complicating control.

Based on the current trends, the accuracy of GPS-based systems will continue to increase and the cost will continue to decrease. But even with extremely high accuracy, the role of GPS for posture sensing is its ability to provide global positioning information. Local sensors will always be valuable for providing information on the dynamic environment around the vehicle whether it is crop vegetation or the detection of obstacles.

Several studies have explored the use of GPS for vehicle guidance. The University of Illinois (Stombaugh et al, 1998; Stombaugh, 1997) utilized a 5 Hz real-time kinematic (RTK) GPS for guidance of a 2WD Case 7720 tractor. In order to eliminate lag in the system responses the GPS was mounted in front of the front wheels on a mask extending to a height above the cab. Straight-line tests of vehicle response showed that the lateral position error at 4.5 m/s was within 16 cm (95% confidence). O'Conner et al (1995; 1996) successfully developed a 4-antannane carrier-phase GPS system for guiding a John Deere 7800 tractor on prescribed straight row course with headland turns. Four single channel GPS sensors were mounted on the cab and the receiver produced attitude measurements at 10 Hz. The closed loop heading response was better than 1 degree and the line tracking standard deviation was better than 2.5 cm.

Sensor Fusion

The role of sensor fusion is clear for agricultural automation; no individual sensing technology is ideally suited for vehicle automation under all modes of use. The appropriate sensor will depend on the field status at the time of operation. But even under a given field operation, the availability of data from multiple sensors provides opportunities to better integrate the data to provide a result superior to the use of the individual sensor.

Noguchi et al (1998) developed a guidance system by the sensor fusion integration (Figure 4) with a machine vision, an RTK-GPS and a geometric direction sensor (GDS). An Extended Kalman Filter (EKF) and a statistical method based on two-dimensional Probability Density Function were adopted as a fusion integration methodology. To achieve the navigation planner based on sensor fusion integration, four types of control strategies were built by changing combination of three kinds of sensors; machine vision, the RTK-GPS and the GDS. The developed navigation planner involved a priority scheme of the control strategies using a knowledge-based approach. The average lateral error of the vehicle guidance based on the fusion of the RTK-GPS and the GDS indicated 8.4 cm. Because the lateral error was less than 20 cm which was the accuracy of the RTK-GPS, the developed sensor fusion methodology with the EKF seemed to perform with satisfactory precision.

Combinations of sensors provide data for crop management in addition to guidance functions. The combination of various sensors with GPS provides opportunities for mapping crop responses as the vehicle performs field tasks. Noguchi et al (1998b) developed an intelligent vision system for autonomous vehicle field operations. Fuzzy logic was used to classify the crops and weeds.   A Genetic Algorithm (GA) was used to optimize and tune the fuzzy logic membership rules. Field trials confirmed that the method developed was able to accurately classify crop and weeds through the entire growing period (Figure 5). After segmenting out the weed, an artificial neural network was used to estimate crop height and width. The R^2 for estimation of the crop height was 0.92 for the training data and 0.83 for the test data. Finally, a geographic information system (GIS) was used to create a crop growth map.

Sensor fusion can also be used to improve lower quality sensors to higher precision. Will et al (1998) tested a commercially available system that integrates basic GPS with inertial guidance and vehicle radar to provide a high precision DGPS system through use of an EKF. Although the system suffered from offset inaccuracies, it had high precision and could even navigate during periods of GPS sensor loss. This demonstrates the value of sensor fusion techniques can be integrated to provide superior sensor performance.

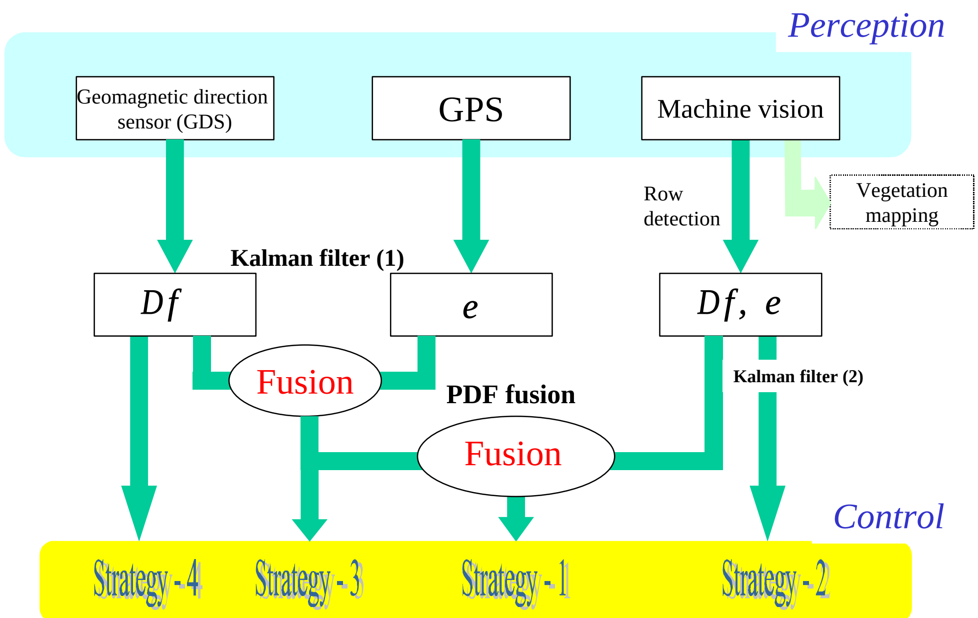

Figure 4. Concept of the sensor fusion integration for vehicle guidance from Noguchi et al. (1998a).

Steering Controller

The steering controller is the actuator that converts a control signal from a feedback controller to an appropriate mechanical adjustment in steering angle. The earliest steering controllers were comprised of a mechanical linkage from a furrow follower directly to the tie rods on the vehicle steering linkage (Willrodt, 1924; McKee, 1925). Later researchers like Ovshinsky (1954) used electrical systems to turn the vehicle steering wheel. Automation for precision agriculture will lead to more precise maneuvering, more consistent performance, higher efficiency, and less labor costs in operation.

Steering controller design needs for agriculture differ from that of on-highway vehicles due to operating conditions of the vehicle in the field. Agricultural equipment often operates on unprepared, changing and unpredictable terrain, ranging from asphalt to spongy topsoil in the field. In this case, steering controllers should be able to provide appropriate steering actions in response to the variations in equipment operation states, travelling speed, tire cornering stiffness, ground conditions, and many other parameters influencing steering dynamics.

Since most modern agricultural vehicles employ some form of hydraulic steering system, recent developments in automatic steering controllers are merely modifications to the existing hydraulic system. As an example, Van Der Lely (1985) holds a patent for an automatic guidance system that uses fluid power to actuate the steering linkage. Laine (1994) analyzed E/H control techniques for a parasitic steering valve. US equipment manufacturers are standardizing on electrohydraulic (E/H) steering systems for agricultural vehicles.

The steering controller design depends on many factors other than E/H steering elements and vehicle dynamics, including ground condition and vehicle speed. Erbach *et al.* (1991) stated that neither negligible nor constant friction could produce significant and unpredictable sideslip. Grovum and Zoerb (1970) developed an agricultural vehicle steering dynamic simulation model. Julian (1971) developed transfer function model for the turning (yaw) rate of a tractor. O'Connor *et al.* (1996) developed a steering controller based on a set of linear motion equations. Lee (1997) used a "model-following" control method to modify both the steady state and the transient lateral response characteristics of a small-size Variable Dynamic Testbed Vehicle (VDTV) for both compact-size and mid-size vehicles. Sliding mode control and estimation theory has been used to estimate vehicle steering states for a steer-by-wire system (Krishnaswami and Riozzoni, 1995). Automation for precision agriculture requires a steering controller with stable and fast response. Additional research is needed to improve the design of steering controllers to compensate for the high degree of non-linearity and many unknown factors involved in steering agricultural equipment.

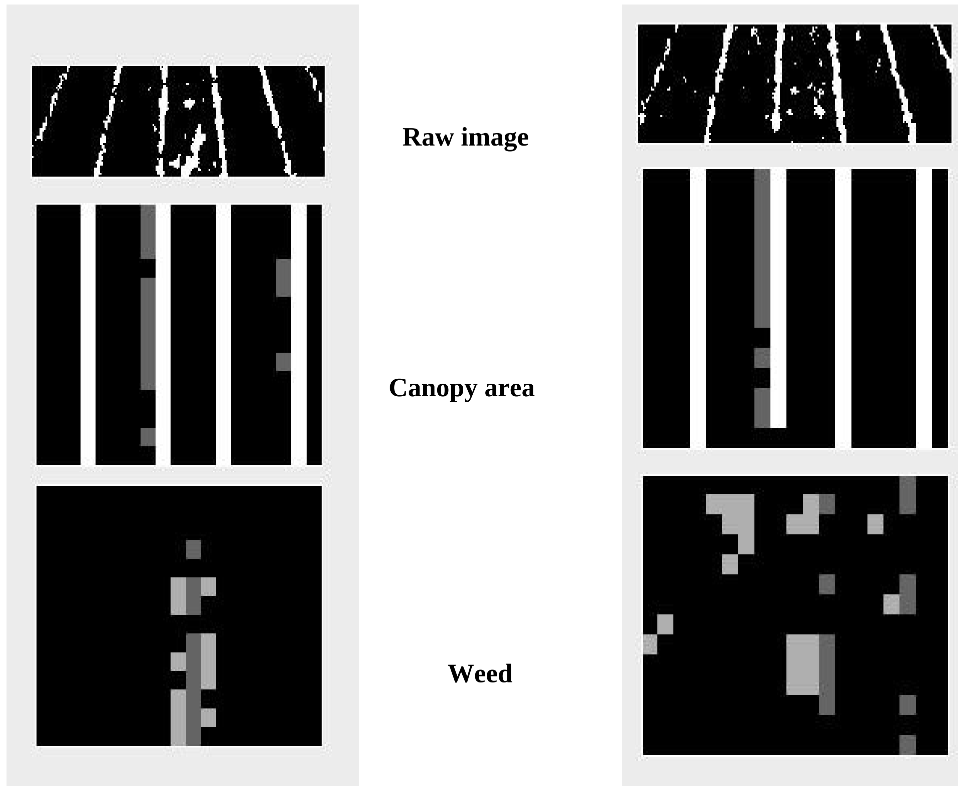

Figure 5. Machine vision classification of crop and weeds using machine vision and GPS. (Noguchi et al, 1998b).

Some advancement in hardware for control needs to occur in the agricultural equipment industry. Most researchers purchase off-the-shelf computing systems to develop their systems. But realistic vehicle systems are likely to be modular with a distribution of the steering and sensor functions to a dedicated computer systems.

Path Planning

Path planning is important for agricultural vehicle control. In most recent path planning research (Nelson, 1989; Kanayama and Hartman, 1989), the focus was on moving a vehicle from a current posture to a desired posture with little concern for the exact path chosen. In contrast, for parallel swathing field operations, the postures and the path are important. Each path must remain parallel to the previous path but one implement width to the side.

Future developments are needed to integrate path planning and crop management utilities in a single framework. Geographic information systems (GIS) are a logical platform for developing path planning since they already contain basic information about fields that the automated vehicle will traverse.

Safety Issues

Safety is a complicated issue in relation to vehicle automation research. Machinery related accidents have been reported to account for 10% of 200,000 farm accidents in 1993 in the US with a number of injuries being fatal (Murphy and Morrow, 1996). A safe automation system can eliminate accidents that occur during the operation of the machine like accidents that result from the operator being overworked, fatigued or taking risks due to environmental pressures to complete the task. Additionally, unskilled or low-skilled operators could be assisted by safety systems. The operation of machinery near environments where others might wander near an operating machine could also be accommodated.

As vehicle automation becomes a reality, there is hope for a reduction in the number of fatalities and accidents that occur during vehicle operation. However, on the way towards developing an automated or autonomous vehicle, there are safety issues of an “operatorless” vehicle that must be addressed. The barriers against the development of autonomous machinery already exist in some places in the US due to poor decisions on the operation of equipment not properly developed for automation. California has laws in place prohibiting vehicles without an operator as a result of a common practice in vegetable harvesting regions to have a slow moving tractor for transporting vegetables run “operatorless” while workers are harvesting vegetables around the vehicle. During the last year alone, 3 people have died and 2 others suffered crushing injuries due to an “operatorless” vehicle running over them. (Anonymous, 1998).

Murphy and Morrow (1996) reviewed sensor technologies that were available or needed development to improve vehicle safety by sensing human presence. Combinations of sensor technologies were implied as the potential solution to human presence detection.

Monta and Kondo (1998) point out that in the near future, it is likely that a combination of agricultural robots and humans will work in the field together. They developed a safety system that detects the presence of humans and develops a function defining the “degree-of-danger” (DD) in the environment surrounding the robot. The DD function is an input to a control system to regulate manipulator speed, decreasing the speed as the distance between the working end of the manipulator and the detected human presence decreases. There are several challenges for safety systems in mobile robots or even automatically guided machinery conveying a human. One challenge will be to have a large enough sensing range to cover the required envelope for detecting the degree-of-danger. This envelope will take on different sizes and shapes based on the tractor-implement configuration. Another challenge for these sensors is to have sensitivity to the presence of humans and obstacles. Ollis and Stenz (1996) sensed human and obstacle presence based on occurrences that were not classified as crop during segmentation. This provides one type of check for obstacles, but safety regulations will encourage the adoption of sensors that more thoroughly identify human obstacles.

As manufacturers adopt the controller area network capabilities, the communication of safety related information should become easier and have a common set of standards for implementation. In the US, some of these capabilities are likely to be driven by the construction equipment industry and later adopted for agricultural equipment. With the development of mobile computing networks, it will be possible to improve the safety to operators by providing remote control and operation capability.

Summary

The future of automatic guidance and autonomous agriculture is optimistic because of the convergence of technologies brought to the forefront by precision agriculture. The possibilities are further enhanced by the trends in equipment industries to add electronic capabilities to agricultural machines in the form of controller area networks, electro-hydraulics, and safety sensing systems. Research challenges will be in the successful fusion of these technologies to provide safe, productive, and economical tools for agriculture.

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