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Carrier-Phase DGPS for Closed-Loop Control of Farm and Construction Vehicles

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ABSTRACT

Operating heavy equipment can be a difficult and very tedious task. Control of an agricultural tractor requires the continuous attention of the driver, and farmers often work long hours during critical times of planting and harvesting. Loaders and other ground vehicles are frequently used in situations that are unpleasant or even hazardous for a human operator.

This paper explores the use of carrier-phase DGPS as the sole position and attitude sensor in closed-loop control of farm and construction vehicles. A land vehicle optimal control system was designed and simulated using realistic plant, sensor, and disturbance models. To validate this simulation, a GPS-equipped electric golf cart was driven to high accuracy under automatic steering control. Golf cart experimental data were examined in post-processing to determine the feasibility of on-line system identification with GPS.

INTRODUCTION

Background

Ground vehicle automatic control has been a research objective for many years. Superior control for individual vehicles and cooperative efforts for multiple vehicles have myriad applications. Smart roads on which a driver merely programs a destination, construction vehicles that automatically build roads, agricultural vehicles that allow full resource utilization, and vehicles operating in hazardous environments are a few examples. In the short term, the largest application of autonomous vehicle control would be farm vehicles in which only high-level decisions would be made by a human operator.

Farm vehicle operation can be a trying and tedious task; speeds are very slow across large fields, and often fog, dust, or darkness limits visibility. Operating heavy equipment requires the full attention of the driver in a high-noise and -vibration environment. Farming operations during critical times such as harvest require long hours of labor, and high-precision operations such as bedding and cultivating are usually limited to daylight hours. Autonomous control could provide many potential benefits, such as allowing operation with limited visibility, more accurate control of row spacing, removal of a human operator from a chemically hazardous environment, and increased efficiency in farming techniques.

Previous Work

Autonomous guidance of agricultural vehicles is not a new idea. However, previous attempts to navigate and control ground vehicles for farming applications have been largely unsuccessful because of sensor limitations. Some guidance systems require cumbersome auxiliary guidance mechanisms in or around the field of interest [1, 2]. Others rely on a camera system requiring clear daytime weather and field cues that can be deciphered by visual pattern recognition [3, 4].

The ground vehicles described above typically operate in environments with good sky visibility. With the recent arrival of GPS, engineers now have access to a low-cost sensor that is well suited for use in vehicle navigation. GPS is already being used in a number of ground vehicle applications, including agriculture. Meter-level code differential techniques have been used for geographic information systems [5–7], driver-assisted control [8], and automatic control of ground vehicles [9].

Using precise differential carrier-phase measurements of the satellite signals, GPS navigation systems have demonstrated accuracies of a few centimeters in vehicle positioning [10] and better than 0.1 deg in attitude [11]. Also, with aiding from a pseudosatellite (pseudolite)-based Integrity Beacon Landing System (IBLS), navigation system integrity is impeccable [12]. This ability to measure multiple states accurately and reliably makes GPS ideal for system identification, state estimation, and automatic control of dynamic systems.

This paper specifically focuses on the automatic control of ground vehicles using carrier-phase differential GPS (DGPS) as the position and attitude sensor. A ground vehicle automatic control system using GPS was developed and simulated in software. This control system was implemented and tested experimentally on an electric golf cart. Experimental data were used to study a recursive system identification algorithm to determine whether important, time-varying vehicle parameters could be ascertained from sensor data in real time.

EXPERIMENTAL SETUP

The primary goal of this work was to experimentally demonstrate closed-loop control of a land vehicle using GPS as the sole sensor of position and attitude. This section describes the hardware used during the testing.

Vehicle Hardware

The platform chosen for the ground vehicle testing described in this paper was a 1984 model Yamaha Fleetmaster electric golf cart, pictured in Figure 1. The vehicle has a 1.55 m wheel base and is just under 2 m tall with the canopy attached. Four single-frequency GPS antennas are mounted to the top of the canopy. The top speed of the golf cart is around 5 m/s.

Fig. 1—Golf Cart

Vehicle steering angle was sensed and actuated by a modified Navico WP5000 ship autopilot. A Motorola MC68HC11 microprocessor board served as the communications interface between the computer and the autopilot, as shown in Figure 2. The microprocessor sent a pulse width modulated signal to the steering motor and encoded the steering angle from a feedback potentiometer—the only non-GPS sensor on the vehicle. The maximum steering angle was ± 30 deg, and the motor commanded rate was limited to ± 2.3 deg/s.

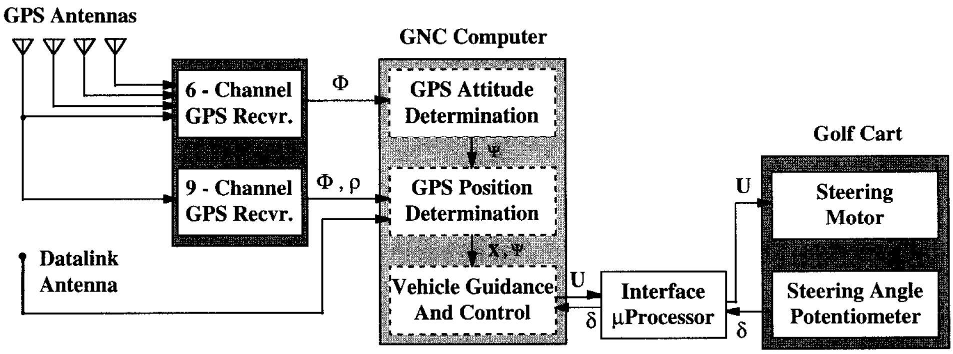


Fig. 2—Vehicle Hardware Architecture

GPS Hardware

The GPS system used for vehicle position and attitude determination was identical to the one used by the IBLS [10], also shown in Figure 2. A 4-antenna, 6-channel Trimble Quadrex receiver produced 4 Hz carrier-phase measurements for attitude determination. Measurements from a single-antenna 9-channel Trimble TANS receiver were used to determine vehicle position. Data collection and automatic control were performed using an on-board Dolch computer running with a Pentium-90 microprocessor. This computer performed attitude determination, position determination, and control signal computations in separate software processes using the LYNX-OS real-time operating system.

The ground reference station consisted of a Dolch computer, a single-antenna 9-channel Trimble TANS receiver generating carrier-phase measurements, and a Trimble 4000ST receiver generating RTCM code differential corrections. The RTCM corrections and raw carrier-phase measurements were transmitted from the ground station to the vehicle through Pacific Crest 450–470 MHz radio modems at 4800 bps. The reference station was approximately 500 m from the testing site.

VEHICLE MODEL IDENTIFICATION

The most difficult aspect of performing a meaningful ground vehicle simulation is arriving at a good model of vehicle dynamics and disturbances. Ground vehicle dynamic models range from very simple to overwhelmingly complex, and there is no single model that is widely accepted in the literature [13]. The most sophisticated mathematical model of a dynamic system is not always appropriate to use [14], especially since controller and estimator design requires a simple (typically linearized) model of plant dynamics.

Steering Linearization

Before performing experiments to identify the golf cart dynamics, calibration tests were run to linearize the steering angle sensor and the steering actuator. The calibration produced look-up tables that were implemented in software on the navigation and control computer.

Transfer Function Identification

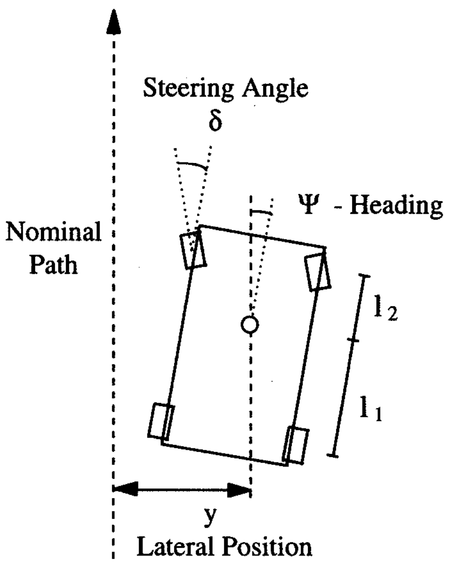
Open-loop tests using sinusoidal or random control inputs (standard system identification techniques [15]) posed a problem. Only a limited amount of data could be taken before the vehicle traveled to the end of the field of operation. To avoid this problem, a basic controller was designed for closed-loop straight-line and U-turn driving based on a simple kinematic vehicle model. The vehicle model used assumed no wheel slip, small steering and heading angles, constant velocity of the rear wheels, actuation through a single front tire, and no roll or pitch motion (see Figure 3).

This controller was purposely designed with no filtering of sensor data so the control signal would be noisy in response to noisy sensor measurements. Also, feed-forward U-turn trajectories were designed to require large positive and negative control signals. Both of these steps were taken to excite the golf cart dynamics sufficiently to provide rich data for identification of an appropriate vehicle model in post-processing.

After some problems with instability due to actuator hard limiting, the controller succeeded in guiding the golf cart for a 5 m trial, complete with six U-turns, as seen in Figure 4. Recursive transfer function system identification techniques based on the LMS algorithm [16] were used on the golf cart data to determine the appropriate discrete model order to use for control system design. By performing identification on increasing model orders until pole-zero near-cancellations occurred, it was found that only one state was needed to describe the control to steering angle transfer function, and two states were needed to describe the control to heading transfer function. Furthermore, the transfer functions found were consistent with the simple kinematic vehicle model described above.

GROUND VEHICLE SIMULATION

Because the simple kinematic model matched the golf cart experimental data, it was used for the vehicle simulation and control system design in this work. It is important to note that farm and construction vehicles will almost certainly require a more complex dynamic model for automatic control. The major differences are described in the discussion of parameter identification later in this paper. Using the kinematic model, the controllable vehicle states



Linearized Equations of Motion:

$$\dot{y} = V_{X0}\,\Psi - \frac{V_{X0}\, l_1}{(l_1 + l_2)}\,\delta$$

$$\dot{\Psi} = - \frac{V_{X0}}{(l_1 + l_2)}\,\delta$$

$$\dot{\delta} = u$$

Fig. 3—Vehicle Kinematic Model

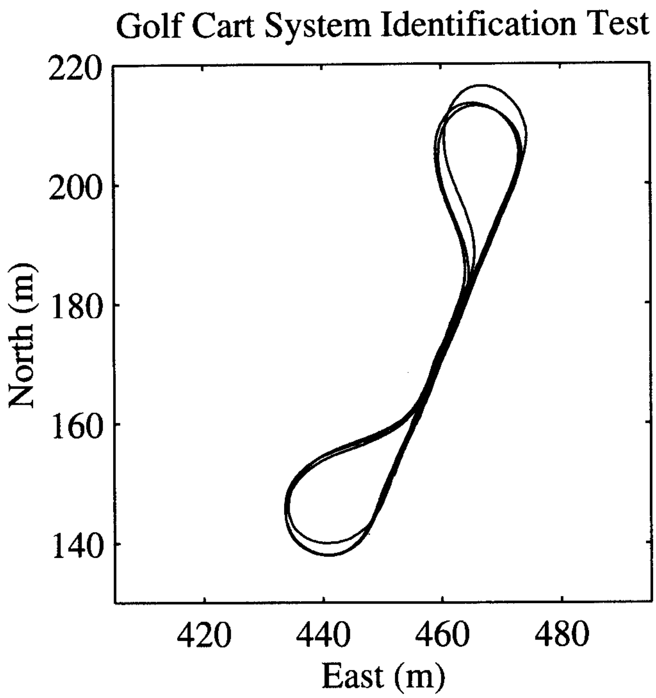


Fig. 4—Golf Cart System Identification Passes

are lateral deviation from desired position (y), heading (ψ), and steering angle (δ). The steering angle rate (u) was limited in the simulation to ± 2.3 deg/s to resemble the golf cart hardware.

Optimal Estimator and Controller

The technique used for vehicle automatic control was a standard discrete linear quadratic regulator/estimator, as shown in Figure 5. The control gains (K) were chosen to minimize a quadratic cost function based on control inputs and state deviations from nominal [17]. The optimal estimator gains (L) were found using the assumed vehicle dynamic model and a model of disturbances based on the experimental data [18]. Within the estimator, the vehicle state vector was appended to include the observable sensor biases, ψ-bias and δ-bias.

The estimator design and ground vehicle simulation both assumed random, uncorrelated measurement noise with normal distribution. The 1 σ measurement and discrete disturbance errors are shown in Table 1.

Two cases were explored in the simulation. In one case, the control signal sent to the vehicle was a linear combination of the *measured state* with sensor biases approximated and no filtering (No Estimator Case). In the second case, the control signal was a linear combination of the *optimally estimated state* (Estimator Case). The same controller gains, sensor noise, and measurement noise were used in both simulations.

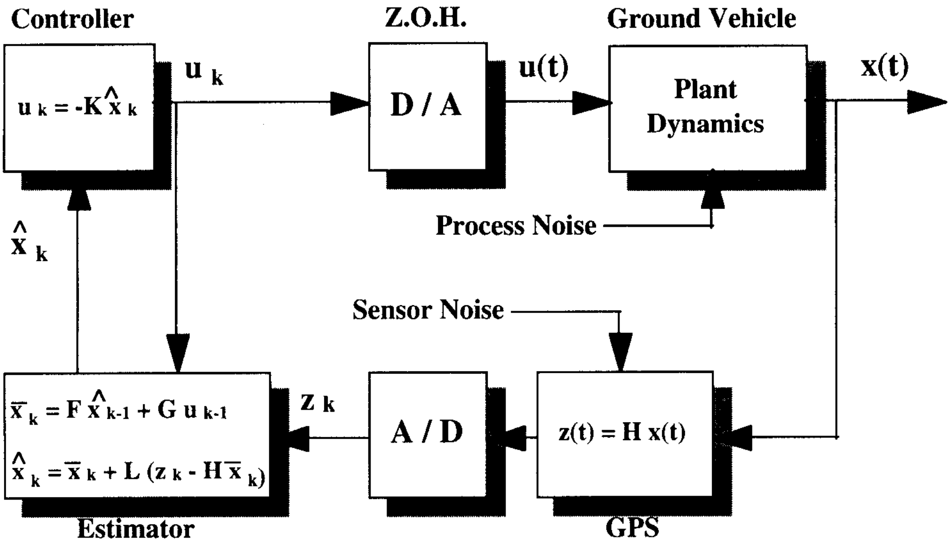


Fig. 5—Estimator/Controller Block Diagram

Table 1—Simulated Measurement and Disturbance Noise

Vehicle State	Measurement Noise (1 σ)	Disturbance Noise (1 σ)
Lateral Position y (cm)	2.0	0.1
Heading ψ (deg)	0.3	0.06
Steering δ (deg)	0.3	0.3
Heading Bias (deg)	—	0.006
Steering Bias (deg)	—	0.006

Simulation Results

Figure 6 shows the simulation results for both cases simulated with an initial lateral position error of 30 cm. Cross-track position error (y), actuator control effort (u), and estimated sensor biases are plotted for a typical 100 m path. The initial errors on steering and heading biases were 0.2 deg.

An extended simulation was run for a 10 km path to gather statistical data. The results for true vehicle position error (y), control signal (u), and sensor bias estimate errors are shown in Table 2.

The simulation showed that a fairly small sensor bias error can significantly affect the lateral position accuracy of the ground vehicle. This is especially true because the level of control being sought is so precise. A 0.2 deg bias in two sensors caused a 16.3 cm bias in the lateral position, which was held to a precision of around 3 cm. Estimating the vehicle state and sensor biases in real time eliminated the lateral position bias.

The amount of control used in the simulation was also quite different between the two cases. The control signal standard deviation in the Estimator Case was half the size of that in the No Estimator Case. This is important because controller design typically involves a trade-off between control effort and system performance. For farm and construction vehicles, small control effort is desired

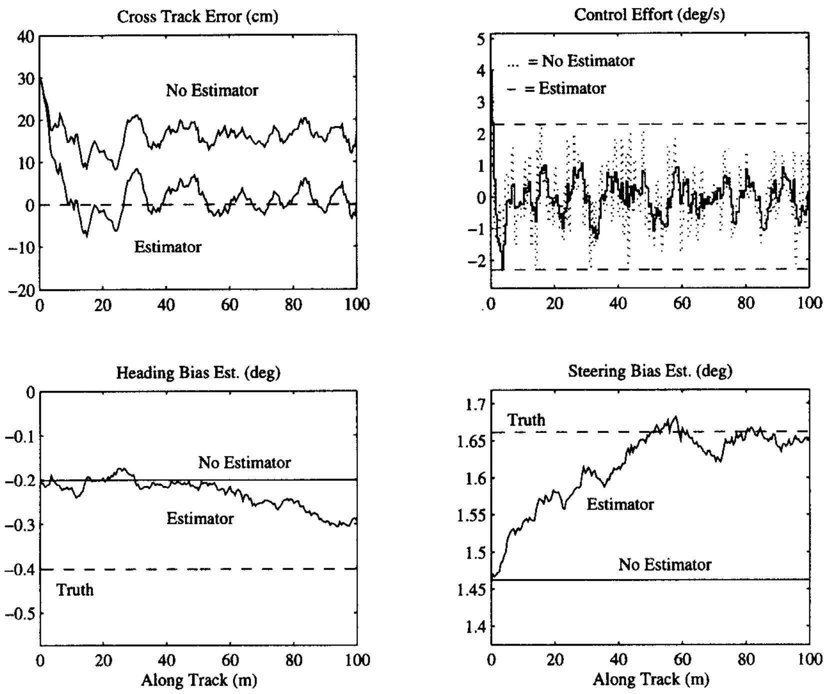


Fig. 6—Simulation Results

Table 2—Simulation Statistical Results

	Deviation From Truth (Mean ± 1 σ)	
	No Estimator	Estimator
Lateral Position y (cm)	16.3 ± 2.7	0.0 ± 3.1
Control u (deg/s)	0.00 ± 0.92	0.00 ± 0.43
ψ-Bias Error (deg)	0.20 ± 0.00	0.00 ± 0.06
δ-Bias Error (deg)	0.20 ± 0.00	0.00 ± 0.03

to provide smooth vehicle motion and avoid actuator hard limiting, while small lateral position errors are needed to successfully perform vehicle operations. By reducing the noise in the control signal, an estimator allows for more aggressive control law design.

GOLF CART TEST RESULTS

After running the simulations, the controller and observer gains from the Estimator Case were used to perform closed-loop tests on the actual golf cart. This section describes the golf cart experimentation.

Testing Configuration

To achieve centimeter-level position accuracy quickly and reliably, a predefined location was surveyed using the IBLS software. To begin testing, the vehicle was taken to this location and its navigation solution initialized.

The integer residuals were checked after the initialization to help verify that the correct integers had been obtained. A final system for safe, reliable ground vehicle navigation and control will probably require a better method of integer cycle ambiguity resolution. Using an integrity beacon near the field of operation would allow rapid integer determination; provide an additional ranging signal for navigation system accuracy and integrity; and still allow the user to operate with less expensive, more reliable single-frequency SPS equipment.

During the tests, the golf cart forward velocity was controlled manually. An estimate of forward velocity was displayed to the driver, who attempted to regulate to a nominal speed of 2 m/s. Experiments took place on "The Oval"—a large grass field on the Stanford campus.

Test Results

The vehicle attempted to follow the same straight line for 12 separate trials. A simple, linear control law combined with physical hard limits on actuator authority led to instability in 2 of the 12 trials, but the golf cart successfully followed the 100 m line for the other 10 trials. A perfect measurement of true vehicle position error was not available, so the carrier-phase DGPS measurements from the 10 successful runs are shown in Figure 7. Note that these measurements are a combination of navigation system error (measurement error) and vehicle position error.

The measured cross-track position had a zero mean and a standard deviation of 5.0 cm. The control effort had a mean of -0.01 deg/s and a standard deviation of 1.26 deg/s.

The experimental results show that more control effort was required and accuracy was poorer than predicted by the simulation. This is probably due to an inexact disturbance model in the simulation, since the measurement performance of the GPS system is fairly well understood. The repeated pattern in the cross-track position error for the 10 trials suggests that the disturbance is strongly correlated with vehicle position.

The most likely cause of the disturbance noise was the roll motion of the golf cart. Although the roll angle of the vehicle was measured, the resulting motion of the 2 m high positioning antenna relative to the wheel base was not

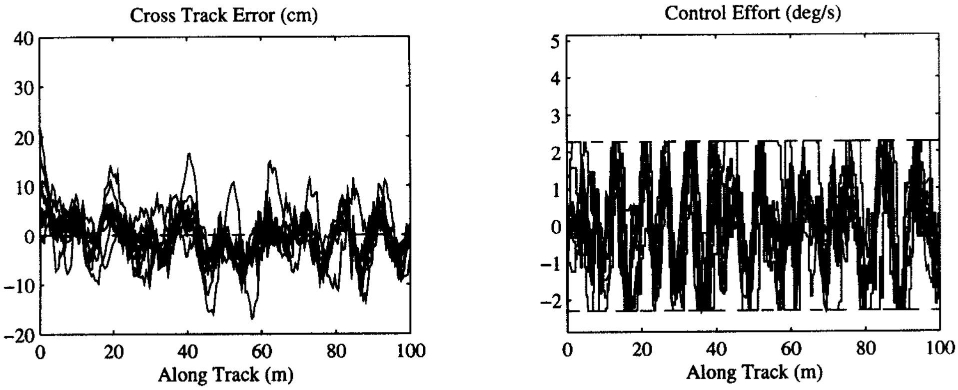


Fig. 7—Golf Cart Experimental Results

corrected for. The data show that the high-frequency roll motion was on the order of ± 1 deg, which corresponds to an unexpected lateral disturbance motion of about 4 cm. Also, the areas where large roll motion occurred correspond to the areas of large lateral position errors.

PARAMETER IDENTIFICATION

The dynamic model used to represent the electric golf cart will almost certainly be inadequate for simulation and testing of farm and construction vehicles in realistic settings. The most likely differences will come from wheel slip, disturbances from towed implements, and vehicle inertia properties, all of which can vary with time. Extending the research described in this paper to more complicated land vehicles will require good modeling, and may even require an algorithm to identify relevant, changing vehicle parameters in real time. Since carrier-phase DGPS is able to measure multiple vehicle states very accurately, it is an ideal sensor for parameter identification.

To determine the feasibility of *real-time* parameter identification using GPS, the data taken during the first closed-loop control trial (Figure 5) were run through a sequential extended Kalman filter [19]. The vehicle state included ψ, δ, and δ-bias. The state transition matrix parameter $-V_{x0}/(l_1+l_2)$ was appended to the original state vector and was estimated along with the state.

The parameter and steering bias values were initially set to zero to see how the filter would converge. The results of the identification are shown in Figure 8. The time history of these values is plotted, along with their "expected" values based on previous identification and golf cart dimensions. The parameter estimate converged within about 25 s, and the steering bias within around 60 s.

CONCLUSION

This research is significant because it is the first step toward a safe, low-cost system for adaptive, highly accurate control of a ground vehicle. It is anticipated that the implementation of these ideas will take place in three steps: (1) driver-in-the-loop control using a graphical display; (2) driver-assisted automatic control, with an on-board operator making only high-level decisions; and (3) vehicle autonomous guidance and control with on-line param-

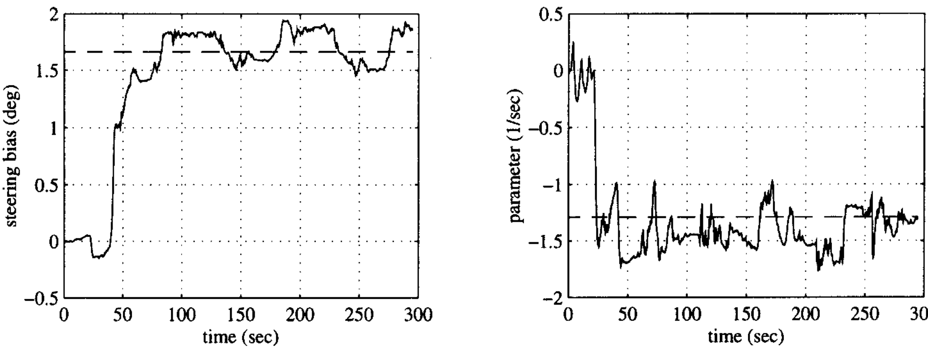


Fig. 8—Extended Kalman Filter Results

eter identification and adaptive control that will operate for several hours without human intervention.

The results presented in this paper are promising for a number of reasons:

1) A ground vehicle control system was simulated and demonstrated using GPS as the *only* sensor for position and heading. One additional sensor—a simple potentiometer—was used to measure steering angle.
2) A constant gain controller based on a very simple vehicle model successfully stabilized and guided a golf cart along a straight, predetermined path.
3) Using a slow actuator and sensors with significant biases, a vehicle was controlled along a path with no steady cross-track position bias and a 5 cm cross-track position standard deviation. The structure and repeatability in the experimental path-following data suggest that performance could be improved by correcting for the positioning antenna moment arm.
4) The ability to estimate vehicle dynamic parameters *in real-time* has been demonstrated using an extended Kalman filter on experimental data. This suggests that adaptive control may be feasible for dealing with changing dynamics on a more complicated vehicle or in more complex field settings.

It will be a big step to perform automatic control of a large farm or construction vehicle, since these vehicles typically have more complex dynamics and larger physical disturbances acting on them than do other vehicles. This paper has described a control methodology that was employed successfully to control a simple land vehicle to high accuracy. This same methodology, combined with a more sophisticated dynamic model and possibly real-time parameter identification, should be sufficient to control more complicated vehicles. Further research is currently under way to explore this possibility.

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REFERENCES

1. Young, S. C., Johnson, C. E., and Schafer, R. L., *A Vehicle Guidance Controller*, Transactions of the American Society of Agricultural Engineers, Vol. 26, No. 5, 1983, pp. 1340–45.
2. Palmer, R. J., *Test Results of a Precise, Short Range, RF Navigational/Positional System*, First Vehicle Navigation and Information Systems Conference—VNIS '89, Toronto, Ont., Canada, September 1989, pp. 151–55.
3. Brown, N. H., Wood, H. C., and Wilson, J. N., *Image Analysis for Vision-Based Agricultural Vehicle Guidance*, Optics in Agriculture, Vol. 1379, 1990, pp. 54–68.

4. Brandon, J. R. and Searcy, S. W., *Vision Assisted Tractor Guidance for Agricultural Vehicles*, International Off-Highway and Powerplant Congress and Exposition, Milwaukee, WI, September 1992. Pub. by SAE, Warrendale, PA, pp. 1–17.
5. Lachapelle, G., Cannon, M. E., Gehue, H., Goddard, T. W., and Penney, D. C., *GPS Systems Integration and Field Approaches in Precision Farming*, NAVIGATION, Vol. 41, No. 3, Fall 1994, pp. 323–35.
6. Pointon, J. and Babu, K., *LANDNAV: A Highly Accurate Land Navigation System for Agricultural Applications*, Proceedings of ION GPS-94, Salt Lake City, UT, September 1994, pp. 1077–80.
7. Lawton, K., *GPS System in a Box*, Farm Industry News, Vol. 28, No. 8, July/August 1995, p. 10.
8. Vetter, A. A., *Quantitative Evaluation of DGPS Guidance for Ground-Based Agricultural Applications*, Transactions of the American Society of Agricultural Engineers, Vol. 11, No. 3, 1995, pp. 459–64.
9. Crow, S. C. and Manning, F. L., *Differential GPS Control of Starcar 2*, NAVIGATION, Vol. 39, No. 4, Winter 1992–93, pp. 383–405.
10. Cohen, C. E. et al., *Autolanding a 737 Using GPS Integrity Beacons*, NAVIGATION, Vol. 42, No. 3, Fall 1995, pp. 467–86.
11. Cohen, C. E., Parkinson, B. W., and McNally, B. D., *Flight Tests of Attitude Determination Using GPS Compared Against an Inertial Navigation Unit*, NAVIGATION, Vol. 41, No. 1, Spring 1994, pp. 83–97.
12. Pervan, B. S., Cohen, C. E., and Parkinson, B. W., *Integrity Monitoring for Precision Approach Using Kinematic GPS and a Ground-Based Pseudolite*, NAVIGATION, Vol. 41, No. 2, Summer 1994, pp. 159–74.
13. Owen, G. M., *A Tractor Handling Study,* Vehicle System Dynamics, Vol. 11, 1982, pp. 215–40.
14. El-Gindy, M. and Wong, J. Y., *A Comparison of Various Computer Simulation Models for Predicting the Directional Responses of Articulated Vehicles,* Vehicle System Dynamics, Vol. 16, 1987, pp. 249–68.
15. Norton, J. P., *An Introduction to Identification*, Academic Press, 1986.
16. Widrow, B. and Stearns, S. D., *Adaptive Signal Processing,* Practice-Hall Signal Processing Series, 1985.
17. Bryson, A. E. and Ho, Y. C., *Applied Optimal Estimation*, Hemisphere Publishing Corp., 1975.
18. Kalman, R. E., *A New Approach to Linear Filtering and Prediction*, Trans. ASME. Ser. D.J. Basic Eng., Vol. 82, pp. 35–45.
19. Gelb, A., *Applied Optimal Estimation*, Analytic Sciences Corp., 1989.