Kinematic GPS for Closed-Loop Control of Farm and Construction Vehicles

Michael O'Connor, Gabriel Elkaim, and Dr. Bradford Parkinson,
Stanford University

BIOGRAPHY

Michael L. O'Connor is a Ph.D. candidate in Aeronautics and Astronautics at Stanford University. He received his S.B. in Aeronautics and Astronautics from MIT in 1992 and his M.S. from Stanford in 1993. He has worked on communication satellites for Hughes Aircraft Company in El Segundo, California.

Gabriel H. Elkaim is a Ph.D. candidate in Aeronautics and Astronautics at Stanford University. He received his BSE in Aerospace Engineering from Princeton University in 1990 and his M.S. from Stanford in 1995. He has worked for Schlumberger Wireline Logging and Testing in Montrouge, France.

Bradford W. Parkinson, Ph.D., is professor of Aeronautics and Astronautics at Stanford University, and Program Manager of the Relativity Gyroscope Experiment (Gravity Probe B). He served for six years as the first Program Director of the GPS Joint Program Office, and has been instrumental in GPS program development. Dr. Parkinson heads the NASA advisory council and is a Fellow of the AIAA and a member of the National Academy of Engineering.

ABSTRACT

Operating heavy equipment can be a difficult and very tedious task; control of an agricultural tractor requires the continuos attention of the driver, and farmers often work long hours during the critical times of planting and harvesting. Loaders and other ground vehicles are frequently used in situations which are unpleasant or even hazardous for the human operator. In the past, some efforts have been made to automate agricultural vehicles, but they have been largely unsuccessful due to sensor limitations.

This paper explores the use of kinematic GPS as the primary sensor in closed loop control of farm and construction vehicles. A single, low-cost GPS receiver can measure position to within a few centimeters and attitude to within 0.1°, and does not drift with time. The ability to provide accurate information about multiple vehicle states makes GPS ideal for system identification and control of dynamic systems. In this work, a ground vehicle control system was designed and simulated using realistic plant, sensor, and disturbance models. Optimal control methods were examined to deal with non-linear and time-varying vehicle dynamics. To validate this simulation, experimental data was taken at Stanford using a GPS-equipped electric golf cart.

This research builds upon previous work in developing GPS-based aircraft autopilots. It is significant because it is the first step towards 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 parameter identification and adaptive control that will operate for several hours without human intervention.

INTRODUCTION

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

Farming vehicle operation can be a trying and tedious task; speeds are very slow across large fields, and often fog, dust, or darkness limit visibility. Operating heavy

Presented at ION GPS-95, Palm Springs, CA, September 12-15, 1995.

equipment requires the full attention of the driver in a high noise and vibration environment. Further, farming operations during critical times such as harvest require long hours and are usually limited to daylight hours. Autonomous control has 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 an increased efficiency in farming techniques.

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 due to sensor limitations. Some 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. *Code differential* techniques are being used for geographic information systems [5-7] driver assisted control [8] and even automatic control of ground vehicles [9].

Using *precise differential carrier phase measurements* of the satellite signals, GPS navigation systems have demonstrated accuracy's of a few centimeters in vehicle positioning [10], and better than 0.1° in attitude[11]. This ability to accurately measure multiple states makes GPS ideal for system identification, state estimation, and automatic control of dynamic systems. Also, with aiding from a Pseudo-Satellite Integrity Beacon, navigation system integrity is impeccable [12].

This paper specifically focuses on the automatic

Figure 1 - Golf Cart

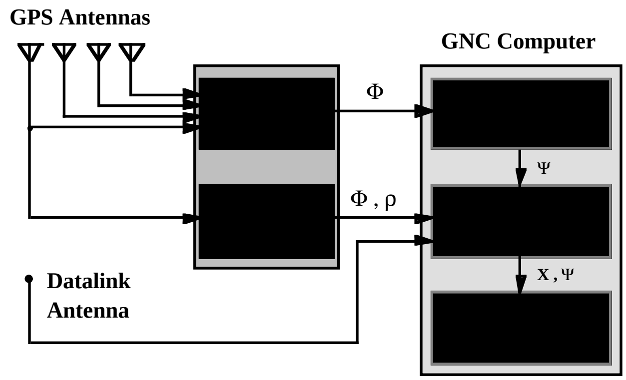

Figure 2 - GPS Hardware Architecture

control of ground vehicles using carrier-phase differential GPS as a 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 was used to study a recursive system identification algorithm to determine if important, time-varying vehicle parameters could be ascertained from sensor data in real time.

EXPERIMENTAL SETUP

The platform used for initial ground vehicle testing was a 1984 model Yamaha Fleetmaster electric golf cart pictured in Figure 1. The vehicle has a 1.55 meter wheel base, and is just under 2 meters 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 meters per second, and is controlled manually by the driver. Experiments took place on a grass field, and the vehicle was driven at a nominal speed of 2 m/s.

The GPS system used for vehicle position and attitude determination was identical to the one used by the Integrity Beacon Landing System (IBLS) [10], as shown in Figure 2. A 4-antenna, 6-channel Trimble Quadrex receiver produced 4 hertz carrier phase measurements for attitude determination. Measurements from a single-antenna 9-channel Trimble TANS receiver were used to determine vehicle position. An on-board Dolch computer with a Pentuim-90 running under LYNX-OS real time operating system performed attitude, position, and control signal computations.

The ground reference station consisted of a Dolch computer with a 9-channel TANS receiver generating carrier phase measurements, and a Trimble 4000ST receiver generating RTCM code differential corrections. Data was transmitted from the ground station to the vehicle through Pacific Crest 450-470

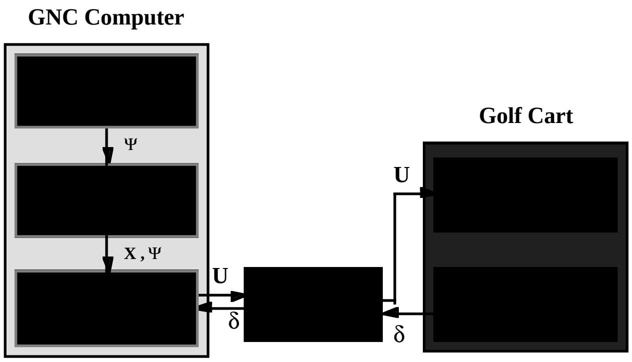

Figure 3 - Control Hardware Setup

MHz. radio modems over a range of less than one kilometer.

Vehicle steering angle was sensed and actuated by a modified Navico WP5000 boat autopilot. A Motorola MC68HC11 microprocessor board performed the communications between the computer serial port and the autopilot as shown in Figure 3. Analog steering angle was encoded from a potentiometer attached to the front wheels, and a pulse width modulated signal was sent to the steering motor. The maximum steering angle was +/- 30˚, and the motor commanded rate was limited to +/- 2.3˚/sec.

To achieve centimeter level accuracy quickly and reliably, a pre-defined location was surveyed using the IBLS software. To begin testing, the vehicle was taken to this location and its navigation solution was initialized. The integer residuals were checked after the initialization to help verify that the correct integers were 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 would still allow the user to operate with less expensive, more reliable single-frequency SPS equipment.

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 complex mathematical model of a dynamic system is not always appropriate to use [14], especially since controller and estimator design requires a simple (typically linear) model of plant dynamics.

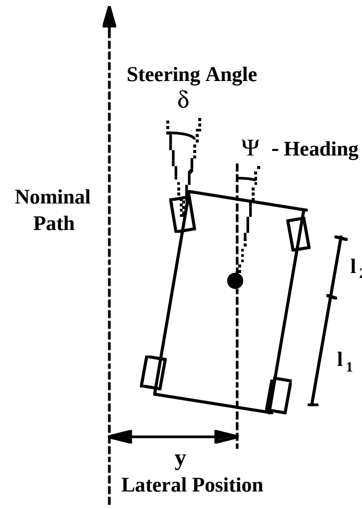

Figure 4 - Simple Vehicle Model

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

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. For this reason, a controller was designed for closed-loop straight line and U-turn driving based on a simple kinematic vehicle model with no estimator. The vehicle model used assumed no wheel

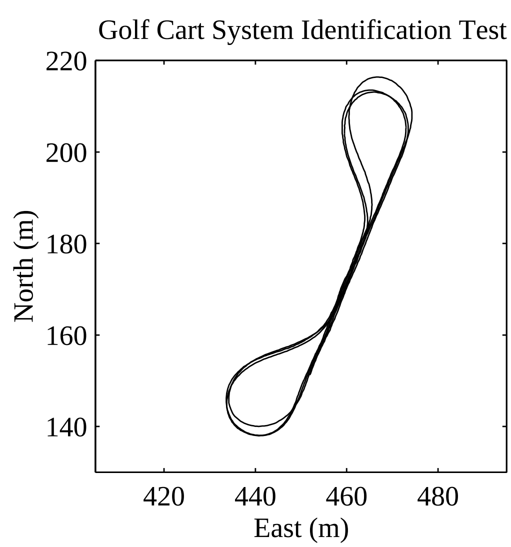

Figure 5 - Golf Cart Identification Passes

$$\begin{bmatrix} \dot{y} \\ \dot{\psi} \\ \dot{\delta} \end{bmatrix} = \begin{bmatrix} 0 & V_{Xo} & -\dfrac{V_{Xo} l_1}{(l_1 + l_2)} \\ 0 & 0 & -\dfrac{V_{Xo}}{(l_1 + l_2)} \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} y \\ \psi \\ \delta \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u$$

Figure 6 - State-Space Equations

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 4.).

This original controller was intentionally designed with no filtering of sensor data so the control signal would be noisy in response to noisy sensor measurements. Feed-forward U-turn trajectories were also designed to require large positive and negative control signals. Both of these were done to sufficiently excite the golf cart dynamics, providing 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 five-minute trial, complete with 6 U-turns as seen in figure 5. 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 1 state was needed to describe the control to steering angle transfer function, and 2 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. The equations describing this model are shown in figure 6.

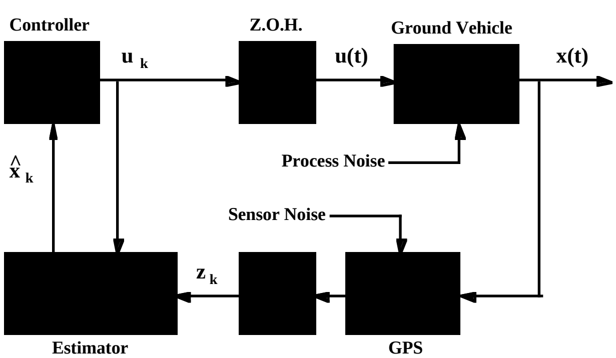

Figure 7 - Control Block Diagram

GROUND VEHICLE SIMULATION

Because the simple kinematic model described above matched the golf cart experimental data, it was used for the vehicle simulation and control system design in this work. Using this model, the controllable vehicle states are lateral deviation from desired position (y), heading (ψ), and steering angle (δ). The steering angle rate (u) was commanded by the control computer, and was physically limited by the motor to +/- 2.3 °/sec.

The technique used for vehicle automatic control was a discrete Linear Quadratic Regulator / Estimator, as shown in figure 7. The control gains (K) were chosen to minimize a quadratic cost function based on control inputs and state deviations from nominal [17]. The full vehicle state was appended to include the observable sensor biases ψ-bias and δ-bias for estimation purposes. The optimal estimator gains (L) were found using the assumed vehicle dynamic model and a model of disturbances based on the experimental data [18].

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

Table 1 - Simulated Measurements and Disturbances

	1−σ(noise)	1−σ(dist)
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

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

Figure 8 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 meter path. The initial errors on steering and heading biases were 0.2˚.

An extended simulation was run for a 10 kilometer path to gather statistical data. The results for true vehicle

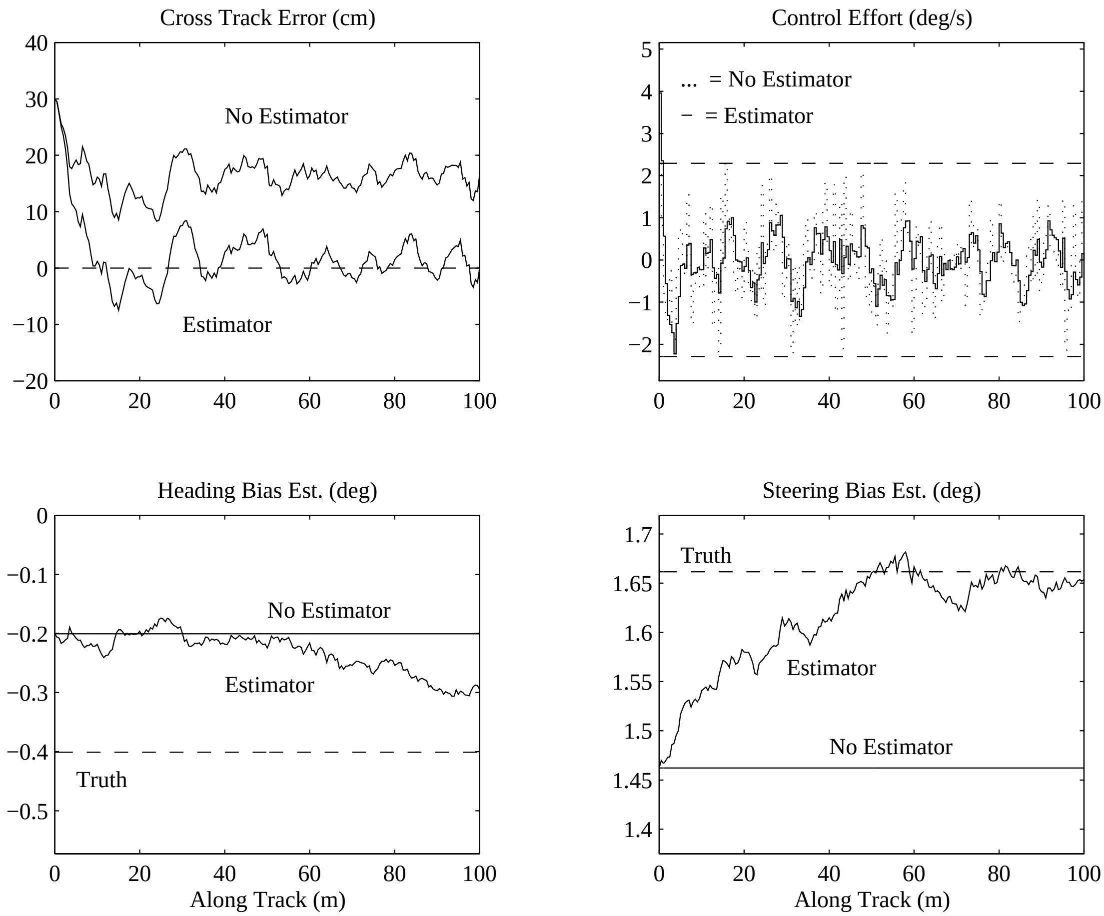

Figure 8 - Simulation Results

position error (y), control signal (u), and sensor bias estimate errors are shown in Table 2.

Table 2. - Simulation Statistical Results

	Estimator (Mean +/- 1-σ)	No Estimator (Mean +/- 1-σ)
Position y (cm)	0.0 +/- 3.1	16.3 +/- 2.7
Control u (deg/s)	.00 +/- .43	.00 +/- .92
ψ-Bias Error (deg)	.00 +/- .06	.20 +/- .00
δ-Bias Error (deg)	.00 +/- .03	.20 +/- .00

The simulation shows 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˚ bias in two sensors caused a 16.3 centimeter bias in the lateral position, which was held to a precision of around 3 centimeters. Estimating 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 the No Estimator case. During controller design, lateral position accuracy was traded-off for control effort because of the physical limit of the steering motor. Based on this, an estimator should allow more aggressive control design, since less control was required for the same system accuracy.

GOLF CART TEST RESULTS

The controller and observer gains from the simulation were used to perform closed-loop tests on the actual golf cart. The vehicle attempted to follow the same straight line for 12 separate trials. Hard limits on actuator authority caused instability in 2 of the 12 trials, but the golf cart successfully followed the line for 100 meters in the other 10. The raw measurements from the 10 successful runs are shown in Figure 9. Note that no "truth" was available for lateral position error since the only position sensor in use was GPS.

The measured lateral position was *zero mean* with standard deviation of 5.0 centimeters. The control effort was mean of -0.01 degrees/second with standard deviation of 1.26 degrees/second.

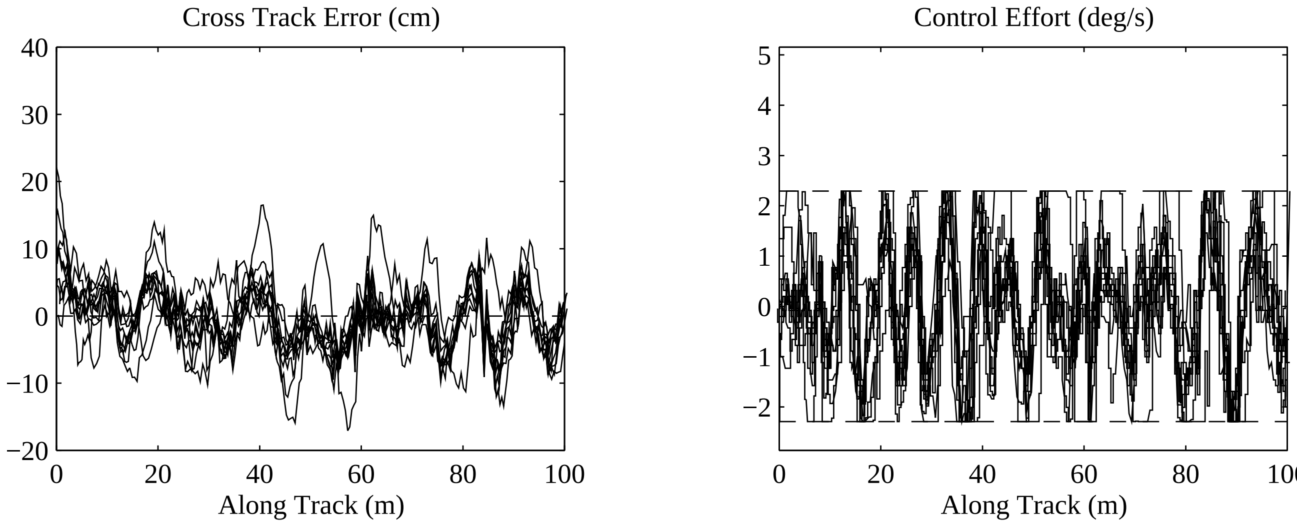

Figure 9 - Golf Cart Experimental Results

The experimental results show that more control effort was required and accuracy was poorer than predicted by the simulation. This is most likely due to an inexact disturbance model in the simulation, since the measurement performance of GPS is fairly well understood.

One 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 meter high positioning antenna relative to the wheel base was not corrected for. The data shows that the roll motion was on the order of +/- 1 degree over a few seconds, which corresponds to a lateral disturbance motion of about 4 centimeters.

PARAMETER IDENTIFICATION

In order to determine the feasibility of real-time parameter identification using GPS, the data taken during the first closed-loop control trial (Figure 5) was run through an Extended Kalman Filter [19]. The vehicle state included ψ, δ, and δ-bias. In addition, the state transition matrix parameter $-V_{xo}/(l_1+l_2)$ was appended to the state vector and 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 10. The time history of these values are plotted along with their "expected" values based on previous identification and golf cart dimensions. The parameter estimate

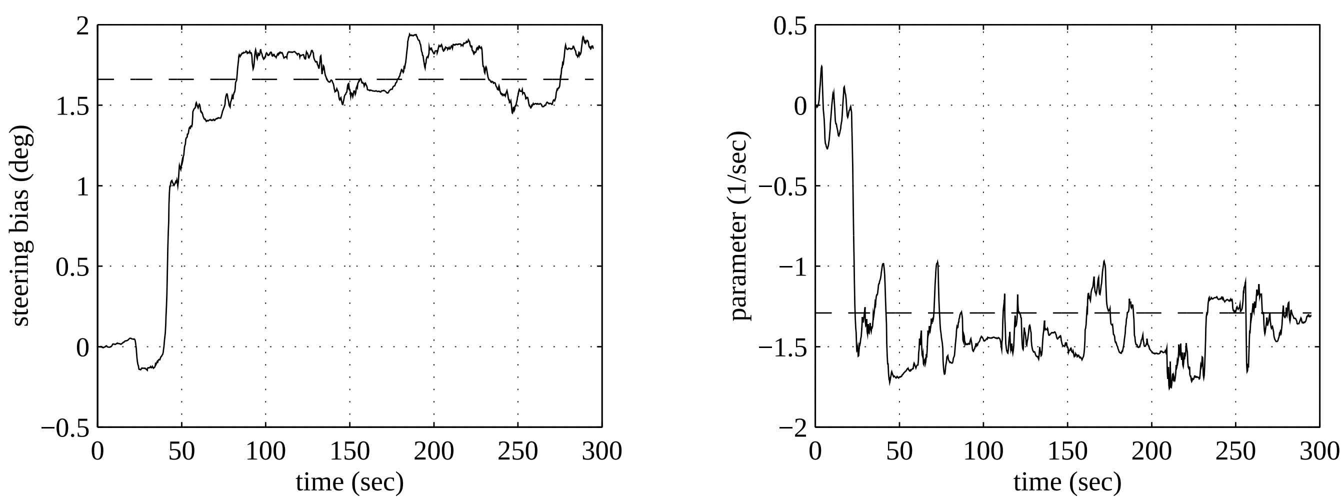

Figure 10 - Extended Kalman Filter Results

converged within about 25 seconds, and the steering bias within around 60 seconds.

CONCLUSION

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 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, pre-determined path.

(3) Using a slow actuator and sensors with significant biases, a vehicle was controlled along a path *with no steady lateral position bias and a 5 centimeter lateral position standard deviation.*

(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 to deal with changing vehicle dynamics in more complex field settings.

The structure and repeatability in the experimental path-following data suggests that we could improve performance significantly by correcting for the positioning antenna moment arm. Also, we feel the experimental results presented here could be improved with a stronger actuator.

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. It is the authors' hope that the control methodology discussed here can be extended to more complicated dynamic systems. Once an accurate vehicle model is developed, and reduction of that model to one sufficiently linear for control system design is achieved, optimal control methods can be applied to implement autonomous control.

The implication is that GPS could be used with a real-time parameter identification algorithm to create a control system that is able to adapt to changing vehicle conditions. Future research is intended to further explore this possibility in the automatic control of ground vehicles.

ACKNOWLEDGMENTS

The authors would like to thank several groups and individuals who made this research possible. At Stanford, Dave Lawrence, Stu Cobb, Boris Pervan, Clark Cohen, Chris Shaw, Konstantin Gromov, Andy Barrows, and Jock Christie were all extremely helpful. Trimble Navigation provided the GPS equipment used to conduct the experiments. Funding was provided by the FAA for research related to GPS, and by Deere and Company.

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. 1340-1345.
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, Sept. 1989.
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, Sept. 1992. Publ by SAE, Warrendale, PA, pp. 1-17 921650.
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. 323-335.
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, Sept. 1994, pp. 1077-1080.
7. Lawton, Kurt. 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. 459-464.
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. Lawrence, D., Pervan, B., Cohen, C., Cobb, H. S., Powell, J. D., and Parkinson, B.W. *A Real-Time Architecture for Kinematic GPS Applied to the Integrity Beacon Landing System*, Proceedings of the 51st Annual Meeting - Institute of Navigation, Colorado Springs, CO, June 1995, pp. 271-280.
11. Cohen, C. E., McNally, B. D., and Parkinson, B. W. *Flight Tests of Attitude Determination Using GPS Compared Against an Inertial Navigation Unit*, National Technical Meeting -

Institute of Navigation, San Francisco, CA, Jan 1993.

12. Pervan, B., Cohen, C., Lawrence, D., Cobb, H. S., Powell, J. D., and Parkinson, B.W. *Autonomous Integrity Monitoring for GPS-Based Precision Landing Using Ground-Based Integrity Beacon Pseudolites*, Proceedings of ION - GPS '94, Salt Lake City, UT, Sept. 1994, pp. 609-618.
13. Owen, G. M. *A Tractor Handling Study*. Vehicle System Dynamics, Vol. 11, 1982, pp. 215-240.
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. 249-268.
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.