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System Identification and Adaptive Steering of Tractors Utilizing Differential Global Positioning System

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A real-time gradient-based method of identifying parameters defining the dynamic response of a farm tractor is presented. By use of a linear state-space model of the vehicle, four parameters are identified with carrier-phase differential Global Positioning System as the primary sensor for position and attitude, and a linear potentiometer is used to measure steering angle. The resulting real-time estimates of the vehicle parameters are used to redesign linear control gains. This adaptive estimation and control scheme achieves a 25% improvement in lateral error standard deviation over a conventional fixed-gain controller.

Introduction

THE advent of relatively low-cost, Global Positioning System-(GPS-) based centimeter-level position sensors has caused a profound change in the world of vehicle guidance and control. It is possible to determine accurately the position and orientation of a ground vehicle without sensor drift, using a single, high-integrity system.

At Stanford University, automatic tractor control using carrier-phase differential GPS (CPDGPS) is an outgrowth of research involving aircraft[1–4] and the need for high-accuracy (i.e., relative to accuracy that can be achieved by an expert human operator under ideal conditions) control of farm tractors on the modern farm. High-accuracy guidance and control of a tractor over an arbitrary trajectory makes it possible to reduce row overlap and therefore wasted time, fuel, and chemicals under a wider range of weather conditions. It also may provide relief to operators who must work a very difficult job under long hours and grueling conditions.

Through this research the sensitivity of the control algorithm to operational conditions has become apparent. Factors such as vehicle configuration or soil type and condition greatly influence the dynamic response of the vehicle to commanded inputs. This added uncertainty in the system introduces unaccounted-for errors that degrade the performance of the guidance and control system.

One possible solution to this challenge would be to recalibrate the vehicle prior to every operation. This approach is undesirable for two main reasons. Operational conditions can vary over time spans on the order of several minutes. Furthermore, the time necessary for and the complexity of performing a calibration run is not practical in a realistic setting.

Another possible response to accommodate changes in the system dynamics is to perform a system identification of the vehicle during model operation and develop a very robust controller from that model. The Observer–Kalman Identification (OKID) algorithm has been applied to the system in an attempt to provide a robust fixed-gain controller that works under a variety of conditions.[5] The OKID algorithm is an off-line system identification algorithm and therefore would have to be run periodically as a batch process for real-time use. A disadvantage of the OKID algorithm is its black-box approach to system identification. As a result, it is very difficult to infer physical meaning to any of the parameters. Although this is an attribute when little is known about the system, it is a liability when the user would like to introduce knowledge of the system before the identification.

In this work a gradient-based on-line parameter identification algorithm is used because it allows knowledge to be incorporated into the identification process while keeping the computation requirements suitable for real-time implementation. The objective is to identify a small number of parameters within a state estimation filter and then to use the estimated parameters to recalculate the controller and estimator gain.

System Model

The vehicle model is a slightly modified version of the model developed by Wong[6] and refined by O'Connor.[1] The lateral position y is influenced by the heading, which is influenced by the steering angle (see Fig. 1).

The Wong model accounts for all lateral tire forces and vehicle inertia. O'Connor simplifies this by assuming small lateral tire slips. This reduced model treats the coupling between the heading and the steering angle as a first-order lag and the actual steering angle slew rate as a first-order lag system of the commanded slew rate. The vehicle model is

$$\begin{bmatrix} \dot{y} \\ \dot{\Psi} \\ \dot{\Omega}_z \\ \dot{\delta} \\ \dot{\omega} \end{bmatrix} = \begin{bmatrix} 0 & v_x & p_2 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & -p_3 & v_x p_4 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & -p_5 \end{bmatrix} \begin{bmatrix} y \\ \Psi \\ \Omega_z \\ \delta \\ \omega \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ p_5 \end{bmatrix} \cdot u \tag{1}$$

where y is the lateral error from the desired trajectory, Ψ is the heading error, Ω_z is the yaw rate, δ is the steering angle, ω is the slew rate, v_x is the forward velocity, and p_2–p_5 are the unknown vehicle parameters. These parameters come directly from Ref. 1 and are based loosely on the Wong bicycle model,[6] with an assumption of small tire slip. O'Connor's parameter p_1 was defined as the derivative of the linearized lateral velocity with respect to heading. This parameter is verified theoretically and experimentally to be 1 by O'Connor.[1] Because this parameter already has been shown be invariant, it is left out of the model. For consistency with previous work, we retain the enumeration for the remaining parameters. A precise definition of what these parameters represent is presented in the Identification Algorithm section.

The measured states are lateral position error, heading error, and steer angle. The resulting observation equation is

$$z = \begin{bmatrix} y \\ \Psi \\ \delta \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} y \\ \Psi \\ \Omega_z \\ \delta \\ \omega \end{bmatrix} + V \tag{2}$$

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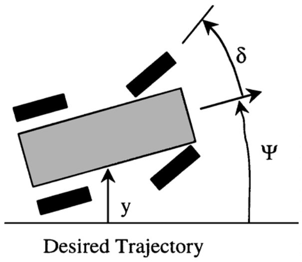

Fig. 1 Kinematic model.

The vehicle parameters (p_2–p_5) are unknown, vary over time, and are highly dependent on factors such as soil, implement, ballast configuration, and tire selection. Real-time identification of p_2–p_5, vital to improving controller performance, is the focus of this research.

Identification Algorithm

The identification algorithm is an extension of the least mean square (LMS) algorithm developed by Widrow and Hoff and presented in Ref. 7. The LMS algorithm utilizes gradient estimation techniques to minimize a quadratic cost function. The algorithm minimizes the variance in sequential innovations by adjusting the estimate of p_2–p_5. The algorithm presented here has been extended to this particular system.

The algorithm requires state estimates at every epoch. These estimates are generated with the standard linear Kalman filter:

Kalman Filter Step

Given

$$X_{k+1} = \Phi(\boldsymbol{p})X_k + \Gamma(\boldsymbol{p})u_k + w_k, \qquad Z_k = CX_k + v_k$$

$$E[w_k] = 0 \quad \text{and} \quad E[v_k] = 0 \tag{3}$$

$$E\left[w_k w_k^T\right] = Q \quad \text{and} \quad E\left[v_k v_k^T\right] = R$$

where $X \in \mathcal{R}^{n\times 1}$, $Z \in \mathcal{R}^{m\times 1}$, $\Gamma \in \mathcal{R}^{n\times i}$ and Φ and Γ are both functions of the unknown vector $\boldsymbol{p}$ (system parameters) and are evaluated with the most recent estimate of $\boldsymbol{p}$, n is the number of states modeled, m is the number of measurements included, and i is the number of inputs. Note that Φ and Γ are the discrete representation of A and B from Eq. (1). The optimal estimate of X_{k+1}, given X_k for a fixed Φ and Γ then is calculated in two steps.

1) Time Update:

$$X_{k+1}^{(-)} = \Phi(p)X_k^{(+)} + \Gamma(p)u_k, \qquad P_{k+1}^{(-)} = \Phi P_k^{(+)}\Phi^T + Q \tag{4}$$

2) Measurement Update:

$$L = P_{k+1}^{(-)}C^T \cdot \left(CP_{k+1}^{(-)}C^T + R\right)^{-1}$$

$$X_{k+1}^{(+)} = X_{k+1}^{(-)} + L \cdot \left(Z_{k+1} - CX_{k+1}^{(-)}\right) \tag{5}$$

$$P_{k+1}^{(+)} = (I - LC) \cdot P_{k+1}^{(-)}$$

Parameter Estimation Step

If Φ and Γ are not evaluated using their optimal values, there will be a mismatch in the dynamics of the filter and the dynamics of the system. The vehicle will behave differently than the model for a given input. This mismatch will cause a serial correlation in the innovation. The information that is provided by this correlation is leveraged to back out a better estimate of the parameters.

The performance cost function is defined as the mean squared error of the measurements.

$$J = E[e^T e]$$

where

$$e_k = \begin{bmatrix} e_k^y \\ e_k^\Psi \\ E_k^\delta \end{bmatrix} = (z_k - z_{k-1}) - C \cdot \left(X_k^{(-)} - X_{k-1}^{(+)}\right) = \Delta z_k - \Delta\hat{z}_k \tag{6}$$

with

$$\Delta z_k \equiv z_k - z_{k-1} \quad \text{and} \quad \Delta\hat{z}_k \equiv C \cdot \left(X_k^{(-)} - X_{k-1}^{(+)}\right)$$

If the identified parameters accurately represent the system dynamics, the error will contain only system noise, which introduces no bias.[8] Because J is simply the inner product of the measurement errors, it is sufficient to minimize the variance of each element within the error. This aids the identification process by decoupling the parameters from each other.

Identification of p_2

The parameter p_2 can be interpreted as the influence of yaw rate on the lateral velocity. Calculating the gradient of e^y with respect to p_2;

$$\frac{\partial\left(e_k^y\right)^2}{\partial p_2} = \frac{\partial\left(e_k^y\right)^2}{\partial e_k^y}\frac{\partial e_k^y}{\partial\Delta\hat{y}_k}\frac{\partial\Delta\hat{y}_k}{\partial p_2} = -2e_k^y\frac{\partial\Delta\hat{y}}{\partial p_2} \tag{7}$$

To a first-order trapezoidal approximation (T is the sample interval),

$$\frac{\partial\Delta\hat{y}_k}{\partial p_2} \approx \frac{T}{2}\cdot\left[\hat{\Omega}_k^{(+)} + \hat{\Omega}_{k-1}^{(+)}\right] \tag{8}$$

Therefore,

$$\frac{\partial\left(e_k^y\right)^2}{\partial p_2} \approx -Te_k^y\left[\hat{\Omega}_k^{(+)} + \hat{\Omega}_{k-1}^{(+)}\right] \tag{9}$$

From this result, Newton's method can be used for updating p_2:

$$p_2 \leftarrow p_2 + 2\cdot\mu_2\cdot Te_k^y\left\lfloor\hat{\Omega}_k^{(+)} + \hat{\Omega}_{k-1}^{(+)}\right\rfloor \tag{10}$$

where μ is a learning coefficient to be discussed latter.

Identification of p_3 and p_4

The parameter p_3 is the time constant associated with the lag between the actual yaw rate and the steady-state yaw rate, whereas p_4 defines the yaw acceleration achieved from a given forward speed and steer angle. The gradients of e^Ψ with respect to p_3 and p_4 are

$$\frac{\partial\left(e_k^\Psi\right)^2}{\partial p_3} = \frac{\partial\left(e_k^\Psi\right)^2}{\partial e_k^\Psi}\frac{\partial e_k^\Psi}{\partial\Delta\hat{\Psi}_k}\frac{\partial\Delta\hat{\Psi}_k}{\partial p_3} = -2e_k^\Psi\frac{\partial\Delta\hat{\Psi}_k}{\partial p_3} \tag{11a}$$

$$\frac{\partial\left(e_k^\Psi\right)^2}{\partial p_4} = \frac{\partial\left(e_k^\Psi\right)^2}{\partial e_k^\Psi}\frac{\partial e_k^\Psi}{\partial\Delta\hat{\Psi}_k}\frac{\partial\Delta\hat{\Psi}_k}{\partial p_4} = -2e_k^\Psi\frac{\partial\Delta\hat{\Psi}_k}{\partial p_4} \tag{11b}$$

Again using a simple trapezoidal integration,

$$\frac{\partial\Delta\hat{\Psi}_k}{\partial p_3} \approx -\frac{T^2}{4}\cdot\left[\hat{\Omega}_k^{(+)} + \hat{\Omega}_{k-1}^{(+)}\right] \tag{12a}$$

$$\frac{\partial\Delta\hat{\Psi}_k}{\partial p_4} \approx \frac{T^2}{4}\cdot v_x\cdot\left[\hat{\delta}_k^{(+)} + \hat{\delta}_{k-1}^{(+)}\right] \tag{12b}$$

resulting in update equations of

$$p_3 \leftarrow p_3 - \mu_3\cdot e_k^\Psi\cdot T^2/2\cdot\left[\hat{\Omega}_k^{(+)} + \hat{\Omega}_{k-1}^{(+)}\right] \tag{13a}$$

$$p_4 \leftarrow p_4 + \mu_4\cdot e_k^\Psi\cdot T^2/2\cdot v_x\cdot\left[\hat{\delta}_k^{(+)} + \hat{\delta}_{k-1}^{(+)}\right] \tag{13b}$$

Identification of p_5

The parameter p_5 represents the lag between the actual steer-angle slew rate and the steady-state rate.

This parameter manifests itself within the steering angle error, e^δ. The gradient is

$$\frac{\partial\left(e_k^\delta\right)^2}{\partial p_5} = \frac{\partial\left(e_k^\delta\right)^2}{\partial e_k^\delta}\frac{\partial e_k^\delta}{\partial\Delta\hat{\delta}_k}\frac{\partial\Delta\hat{\delta}_k}{\partial p_5} = -2e_k^\delta\frac{\partial\Delta\hat{\delta}_k}{\partial p_5} \tag{14}$$

The trapezoidal integration is slightly different because of the addition of the zero-order hold on the input:

$$\frac{\partial \Delta \hat{\delta}_k}{\partial p_5} \approx -\frac{T^2}{4} \cdot \left[\hat{\omega}_k^{(+)} + \hat{\omega}_{k-1}^{(+)} - 2u_{k-1}\right] \tag{15}$$

leaving the final update equation as

$$p_5 \leftarrow p_5 - \mu_5 \cdot e_k^{\delta} \cdot T^2/2 \cdot \left[\hat{\omega}_k^{(+)} + \hat{\omega}_{k-1}^{(+)} - 2u_{k-1}\right] \tag{16}$$

Discussion of μ_2–μ_5

In each of the update equations (10, 13a, 13b, and 16) there are learning coefficients μ. The OKID algorithm is gradient based. The change in each of the parameters is directly proportional to the estimated gradient. The learning coefficients scale the size of the steps to be taken. A large learning coefficient will result in rapid learning. Unfortunately, with rapid learning there is little noise rejection and the variance through time of the parameter estimates is large. When μ takes on a value larger than a critical value, the algorithm diverges. The value of this critical learning coefficient is determined from the eigenvalues of the input correlation. The evaluation of this critical value is covered very well by Widrow and Stearns.[7] In practice, the values to use for the learning coefficients often are determined empirically.

Experimental Results

The OKID algorithm was implemented on the farm tractor shown in Fig. 2. The vehicle was equipped with CPDGPS to measure both position and attitude (roll, pitch, and yaw) to within 2 cm and 0.1 deg (1 σ), respectively. Position was measured using a high-integrity CPDGPS and attitude was measured using the four-antenna system. Note that the attitude system determines its measurement via internal baselines. It does not require a fixed reference station to provide position measurements at each antenna. This means that the attitude system is not dependent on the positioning system.[9] Also, the attitude antennas are mounted on a very rigid frame, eliminating any attitude baseline variations. A linear potentiometer was fitted to the steering linkage to measure the front wheel angle. An Intel Pentium-based personal computer running the Lynx real-time operating system provided the control.

The adaptive estimator was run for approximately half an hour and allowed to converge. The feedback controller used the estimated parameters to calculate linear quadratic regulator (LQR) control gains and the subsequent control signal in real time. These feedback gains were used to regulate about several curved rows (shown in Fig. 3), utilizing Bell's curved trajectory control algorithm.[10] This control algorithm is essentially an LQR in which the future reference states are generated for N steps. These reference states then are backpropagated to the current epoch to generate a series of feedforward control inputs. This algorithm is repeated at every epoch, and only the current epoch's control input actually is used to control the vehicle.

For the test, the tractor was fitted with a six-row hitched cultivator, a relatively large and heavy tool that noticeably affected the tractor's handling. As a comparison, a fixed controller developed by Bell et al.[10] was used over the identical trajectory. This controller was developed by utilizing the fixed parameters identified by O'Connor[1] on the same tractor but without any implement and on firm ground. Table 1 shows the performance of each controller on each row. Figure 4 shows a histogram of the overall distribution of lateral errors. The lateral error distribution shown in Fig. 4 is both narrower and more regular. This indicates less searching by the regulator because of improperly modeled dynamics. Both Table 1 and Fig. 4 show a 25% improvement in the lateral error distribution. This is attributed primarily to the large effect on the steering effectiveness (parameter p_4) that the heavy implement has on the vehicle.

Fig. 2 Test tractor.

Table 1 Lateral error comparison

	Fixed controller		Adaptive controller	
Row no.	Mean, cm	Std. dev., cm	Mean, cm	Std. dev., cm
1	2.40	5.08	3.17	3.46
2	2.16	3.81	1.59	2.78
3	3.00	4.38	3.88	3.46
4	2.83	3.91	1.38	2.74
5	2.15	4.63	3.88	3.11
6	2.35	4.26	1.39	3.00
Average	2.48	4.35	2.55	3.10

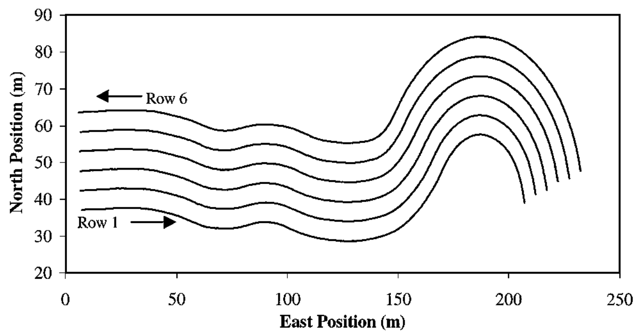

Fig. 3 Test trajectory.

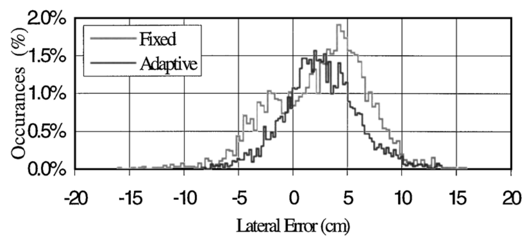

Fig. 4 Lateral error histogram.

Conclusions

A real-time parameter identification technique has been developed for an autonomous farm tractor. The 25% controller accuracy improvement illustrates the potential of system identification for an autonomous farm tractor. This improved controller exhibited fewer large deviations from the requested trajectories, thus requiring less controller energy. This may help to reduce wear and tear on the vehicle. It may also provide the ability to reduce operational costs to the user by reducing wasted time and chemicals. This work has also demonstrated the viability of CPDGPS for real-time vehicle dynamic model identification. An accurate model of vehicle dynamics was generated using differential GPS as the primary sensor. This model was generated autonomously and was able to recalibrate for different vehicle setup with no direct operator input, a feature that definitely would be attractive to any commercial end user.

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