Adaptive Control of Electrohydraulic Steering System
for Wheel-Type Agricultural Tractors

by

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Written for presentation at the
1999 ASAE Annual International Meeting
Sponsored by ASAE
Toronto, Ontario, Canada

July 18-21, 1999

Summary: This paper presents an adaptive steering controller for achieving consistent, sensitive, and accurate steering control with noisy and drifting control signals on an automated agricultural tractor. Conventional model-based PID controller is difficult to solve this problem because of too many disturbances and unknown factors. The authors have developed an adaptive steering controller consisting of an adaptive Kalman filter and an adaptive nonlinearity compensator for attenuating the effects of those disturbances and unknown factors. Both simulation and test results indicated that the method of using an adaptive Kalman filter and an adaptive gain compensator is an effective steering controller design approach for solve the programs generated by the noisy and drifting control signals such as tractor automated steering control.

Keywords: steering controller, electrohydraulic, off-road vehicle, adaptive control, Kalman filter
1. **INTRODUCTION**

Driving an agricultural tractor in field without overrunning crops is a skill and labor intensive task. The adoption of new agricultural technologies, such as precision agriculture, makes the maneuvering even more difficult. Meanwhile, the shortage and aging work force in agriculture results in decrease in skilled operators. Therefore, the development of automated or autonomous agricultural tractors is considered to be of societal importance. The rapid progress in guidance sensor and computer technologies makes it possible in developing reliable and affordable automated or autonomous agricultural tractors.

One of technical challenges in developing automated or autonomous tractors is the development of a reliable and accurate steering controller for its electrohydraulic steering system. Agricultural tractors are designed to perform various agricultural operations while travelling on field. It will result in unpredictable tractor dynamic behaviors due to unprepared terrain, operations, travelling speed, and tire stiffness. Such unpredictable dynamic behaviors will affect the steering control performance significantly, and make it difficult to design a rapid response and accurate steering controller due to too many disturbances and unknown factors.

This paper presents an adaptive steering controller for agricultural tractors with electrohydraulic steering. This controller consists of an adaptive Kalman filter and an adaptive gain compensator. Kalman filter is an optimal recursive data processing algorithm, and used to estimate system states based on its mathematical model. It can effectively eliminate the steering signal noise generated by the unpredictable tractor dynamics. In addition, the tractor electrohydraulic actuator is a typical nonlinear system. Among those nonlinear factors, the deadband contributes the most to the tardy and inaccurate in steering control. An adaptive gain compensator can provide an instant identification and compensation of deadband to ensure satisfactory steering performance. In light of the approach, this paper presents a dynamic model of the electrohydraulic steering system, an adaptive controller, including the PID base controller, the adaptive Kalman filter, and the adaptive gain compensator. This controller has been implemented both on a hardware-in-loop electrohydraulic steering simulator, and on an agricultural tractor platform. Results from both simulation and test indicate that this adaptive steering controller is capable of providing satisfactory steering control for automated or autonomous agricultural tractors.

2. **DYNAMIC MODEL OF ELECTROHYDRAULIC STEERING SYSTEM**

The dynamic behaviors of steering an agricultural tractor are mainly determined by the dynamics of tractor steering system, electrohydraulic actuating system, and all unpredictable disturbances. Therefore, the dynamic model of tractor steering should include sub-models of tractor steering dynamics, electrohydraulic system dynamics. The unpredictable disturbances are treated as noise of the system. The sub-model of electrohydraulic system dynamics will also play the key role in the adaptive gain compensation.

The model of tractor steering is developed based on the non-linear characteristics of the steering mechanism, which determines the steering linkage gain between the steering cylinder displacement, $y$, and the tractor front wheel steer angle, $\theta$. 
\[ \theta = \theta_1(y) + \theta_2(y) \]  

where: \( \theta_1(y) \) and \( \theta_2(y) \) are steering linkage geometric relationships to the steering cylinder displacement for a particular tractor.

From this kinematic steering linkage gain model, the dynamic steering model can be derived.

\[ I\theta = (T_s - T_r) - \xi_T \theta \]  

where: \( \theta \) and \( \dot{\theta} \) are angle velocity and acceleration of tractor front wheels; \( I \) is the inertia on the spindle axle; \( T_s \) and \( T_r \) are steering torque and resistance torque, and \( \xi_T \) is the damping ratio of tractor corresponding to the steering axle.

Use the format of a transfer function, the dynamic steering model can be represented as

\[ G_T(s) = \frac{\omega_T^2}{s^2 + 2\xi_T \omega_T s + \omega_T^2} \]  

where: \( \omega_T \) is the natural frequency of the tractor corresponding to steering; and \( s \) is the Laplace operator.

The hydraulic actuator in tractor steering mechanism is a highly nonlinear system, and usually maneuvered by an electrohydraulic spool valve. Its system dynamics can be represented using linearized analysis of the non-linear relationship between the valve spool position and cylinder actuator displacement if such changes are small (Zhang et al. 1999).

\[ G_A(s) = \frac{K}{s} \frac{\omega_A^2}{s^2 + 2\xi_A \omega_A s + \omega_A^2} \]  

where: \( K \) is the nonlinear gain; \( \omega_A \) is the natural frequency; and \( \xi_A \) is the damping ratio of the electrohydraulic system.

Integrate these two sub-systems, an overall model of the electrohydraulic steering system can be obtained:

\[ G_S(s) = \frac{K_{NL}}{s} \frac{\omega_S^2}{s^2 + 2\xi_S \omega_S s + \omega_S^2} \]  

where: \( K_{NL} \) is a nonlinear gain which serves as the nonlinear compensator to the steering controller; \( \omega_S \) is the natural frequency; and \( \xi_S \) is the damping ratio of the integrated tractor electrohydraulic steering system. System identification study has verified that this model is capable of representing the non-linearity and dynamic behaviors of electrohydraulic steering system in an agricultural tractor efficiently (Wu et al. 1998).

The most challenging part is to estimate the operating state of tractor steering with consideration of the unpredictable noises. Among numerous noises, the disturbance caused by tractor dynamic response to the varying terrain, changing tire-ground stiffness, and different traveling speed has the most significant effect on steering dynamics. The noise from steer angle measurement and the pressure fluctuation in the hydraulic steering system are the other major noise sources to this
system. A white noise model has been developed to represent those unpredictable noises in this steering system dynamic model. A discrete linear system model can be used to describe those white noises.

\[
\begin{cases}
X_k = A_k X_{k-1} + W_{k-1} \\
Y_k = C_k X_k + V_k
\end{cases}
\]  

(6)

Where, \( X_k \) is a system state vector; \( A_k \) is a state transition matrix; \( W_k \) is the system noise vector; \( Y_k \) is a measurement vector; \( C_k \) is a measurement matrix, and \( V_k \) is the measurement noise vector.

Based on the state transition characteristics and measured value of system variables, as well as the current state variables, the state characteristics of the steering system can be estimated using the equation below (Bozic, 1994).

\[
X_k = A_k X_{k-1} + K_k [Y_k - C_k A_k X_{k-1}]
\]  

(7)

\[
K_k = P_{k|k-1} C_k^T [C_k P_{k|k-1} C_k^T + R_k]^{-1}
\]  

(8)

\[
P_{k|k-1} = A_{k-1} P_{k-1} A_{k-1}^T + Q_{k-1}
\]  

(9)

Where: \( X_k \) is predicted state vector, \( X_{k-1} \) is the predicted state vector at previous time step, \( K_k \) is the gain of the filter, \( R_k \) is the measurement noise covariance matrix, \( P_k \) is the error covariance matrix, \( P_{k|k-1} \) is the error covariance matrix at time \( k-1 \), and \( P_{k|k-1} \) is the prediction of error covariance matrix based on previous error.

3. STEERING CONTROLLER FOR THE AGRICULTURAL TRACTOR

This adaptive steering controller is developed based on a proportional-integral-derivative (PID) base controller (Fig. 1). The equation below is the transfer function of this base controller.

\[
G(s) = \frac{k_I}{s} + k_P + k_D s
\]  

(10)

Where: \( k_I \), \( k_P \), and \( k_D \) are respectively the integral gain, proportional gain, and derivative gain of the controller.

This base controller is capable of implement satisfactory steering control if the operating state of the system is accurately identified. Since a tractor is often perform different operations at varying terrain, changing tire-ground stiffness, and different traveling speed, it is desirable to adapting controller parameters accordingly. Equation (10) can be rearranged to providing a quick tuning guideline.

\[
G(s) = \frac{k_I}{s} \left( 1 + \frac{2\xi}{\omega_0} s + \frac{1}{\omega_0^2} s^2 \right)
\]  

(11)
Where:

\[
\omega_0 = \sqrt{\frac{k_I}{k_D}} \quad (12)
\]

\[
\xi = \frac{k_p}{2\sqrt{k_I k_D}} \quad (13).
\]

To ensure the satisfactory steering control performance under the worst cases, the base PID gain should be set at a minimum level based on the nominal system natural frequency \(\omega_0\).

\[
G(j\omega_0) = k_p \quad (14)
\]

The PID base controller can be used to compensate steering error for keeping the system stable near its natural frequency. Therefore, it is essential to obtain system's natural frequency under various operation conditions for stable steering. A tuning coefficient, \(\gamma\), is introduced in debugging the frequency range of the control system (Fig. 2). If the system is unstable only at a relative narrow frequency band, use a small tuning coefficient \((\gamma < 1)\), otherwise use a large tuning coefficient \((\gamma > 1)\) to estimate two break points the frequency band.

\[
\omega_{1,2} = \omega_0 \left(\gamma \pm \sqrt{\gamma^2 - 1}\right) \quad (15)
\]

A parameter adaptive algorithm has been developed, which adjusts original parameters to match the current operational state while transforming parameters from an input parameter space \(C\) to an output parameter space \(K\) (Fig. 3). This algorithm can also be represented mathematically as a linear transformation \(\Phi\).

\[
K = K_0 + \Phi(C - C_0) \quad (16)
\]

Where, \(C_0\) is a base steering status on which the base controller has been tuned, \(K_0\) is the optimal controller parameters for this base status, and \(\Phi\) is the sensitivity of controller parameters to the base status. For example, \(C_0\) is the tractor steering on field under a content traveling speed of 4 km/h with the environmental temperature of 30°C. \(K_0=\{K_{i0}, K_{p0}, K_{d0}\}\) is a set of optimal parameters for the PID base controller tuned under that condition. Parameter sensitivity can be obtained from test. Figure 4 indicates error curves of the machine vision guided tractor on field with traveling speed of 3.2, 6.4, 9.6 and 12.8 km/h. It indicates that the steering system of this tractor has a natural frequency about 1Hz when it travels 6.4 km/h on field. This PID base controller uses traveling speed of 6.4 km/h on field as the base status in this research.

Since there are numerous disturbance, which may alter the natural frequency of the system, a Kalman filter has been developed to predict the system states in real time. This research interested in applying a discrete-time Kalman filter for smoothing the noisy steering signal from a visual guidance system in following crop rows in the field. Lho (1993) introduced an approach based on a system error model for smoothing noisy signal. Based on this approach, a Kalman filter vector can be designed based on the state variables determined by the error, error integer,
and error derivative of the steering angle. The system noise vector \( W_k \) can, therefore, be expressed as below.

\[
W_k = B_k w_k = \begin{bmatrix} \Delta t^2 / 2 \\ \Delta t \\ 1 \end{bmatrix} w_k
\]

(17)

Where: \( B_k \) is the vector of noise gain, and \( w_k \) is the noise in steering velocity.

In conventional Kalman filter design, it is required to first get a system noise covariance matrix and a measurement noise covariance matrix, but those matrices are difficulty to obtain in real time applications. However, it is possible to obtain an estimated error, which will support an adaptive Kalman filter and be capable of providing some information about the measurement error and system noise.

\[
E_k = Y_k - \hat{Y}_k
\]

(18)

Use the same method discussed in section 2, the following equations are capable of providing the estimated the measurement values and measurement errors

\[
\hat{w}_k = (B^T B)^{-1} B^T K_{k+1} \left( Y_{k+1} - CA_{k+1} \hat{X}_k \right)
\]

(19)

\[
\hat{v}_k = (1 - C_k K_k) \left( Y_k - CA_k \hat{X}_{k-1} \right)
\]

(20)

Since the right side of Eq (19) includes the observation and gain at next time step, and it is only possible to obtain the estimators \( \hat{w}_{k-1} \) and \( \hat{v}_{k-1} \) at this step. Therefore, a coefficient \( a \) is introduced to modify the covariance \( \sigma_{w_k}^2 \) and \( \sigma_{v_k}^2 \) by \( \hat{w}_{k-1} \) and \( \hat{v}_k \).

\[
\hat{\mu}_{w_k} = a \cdot \hat{\mu}_{w_{k-1}} + (1 - a) \cdot \hat{w}_{k-1}
\]

(21)

\[
\hat{\sigma}_{w_k}^2 = a \cdot \hat{\sigma}_{w_{k-1}}^2 + (1 - a) \cdot (\hat{w}_{k-1} - \hat{\mu}_{w_{k}})^2
\]

(22)

\[
\hat{\mu}_{v_k} = a \cdot \hat{\mu}_{v_{k-1}} + (1 - a) \cdot \hat{v}_k
\]

(23)

\[
\hat{\sigma}_{v_k}^2 = a \cdot \hat{\sigma}_{v_{k-1}}^2 + (1 - a) \cdot (\hat{v}_k - \hat{\mu}_{v_{k}})^2
\]

(24)

Where, \( \hat{\mu}_{w_k} \) and \( \hat{\mu}_{v_k} \) are the modified expectation value of \( w \) and \( v \).

Test results from steering control on the electrohydraulic steering simulator indicated that the nonlinearity of electrohydraulic steering control valves have a significant effect on the sensitivity and accuracy of steering control. Among all the nonlinear factors, the deadband made the most significant contribution to steering performance. Figure 5 shows the steady-state characteristic of steering rate control and their drifts as the temperature varies. To ensure sensitive, accurate, and consistent steering control, an adaptive compensator is desirable. Figure 6 shows an adaptive gain compensator developed in this research, which consists of a deadband compensator and a deadband drifting compensator. The deadband compensator is actually a modulated inverse valve transfer obtained at the standard operation condition as discussed earlier. The drifting
compensator would take a coefficient $k$, which is determined based on the detected deadband to compensate the deadband drifting.

4. RESULTS AND DISCUSSIONS

The validation tests in this research consisted of on simulator and on tractor tests. A hardware-in-loop electrohydraulic steering simulator (Wu et al. 1998) and a CASE MAGNUM\textsuperscript{1} 8920 Tractor were used in the validation tests. The validation of the adaptive Kalman filter was completed on the electrohydraulic steering simulator. Steering signals used in this validation test were collected from in field steering operation of from the tractor equipped with a machine vision guidance system. Figure 7 shows the improvement on steering using an adaptive Kalman filter. The results indicated that the use of an adaptive Kalman filter is capable of reducing steering error by 60%. More importantly, the Kalman filter is capable of eliminating the jerk when the steering direction changes, which can improve tractor the steering performance significantly. Test results also indicated that the steering error level would keep reducing during the initial transient (Fig. 8). It was due to the high nonlinearity caused extreme initial errors at beginning, and such extreme errors could easily be compensated since each estimation was performed based on a filtered previous signal. This feature is advantageous to improve both stability and dynamic performance of the steering control.

This adaptive PID steering controller has been tested on both the electrohydraulic steering simulator in laboratory and on the tractor platform on the field with rows of crop. In on-simulator test, steering control performance was evaluated by the sensitive and accuracy of the steering control responding to a step input steering signal. Figure 9 shows the response behavior of the displacement of the hydraulic steering actuator following a step displacement command. The results indicated that the adaptive controller is capable of compensating the deadband effectively, and achieving accurate position control corresponding to demanded displacement.

In field test, the controller performance was evaluated by the steering error while the tractor was traveling on either straight rows or on curved rows. The results indicated the Kalman filter based adaptive controller was capable of effectively reducing the front wheel steer angle on both the straight and curved rows (Figs, 10, 11). It means that the steering was much more consistent and stable with the adaptive steering controller than with a conventional PID controller.

5. CONCLUSIONS

An adaptive steering controller has been successfully developed for automated steering control of agricultural tractors. This adaptive steering controller consists of an adaptive Kalman filter and an adaptive nonlinearity compensator. This controller has been validated both on an steering simulator using steering signals collected from field steering operation and on an agricultural tractor platform in the field with straight and curved rows of crops. The adaptive Kalman filter is capable of estimating smoother steering signal, which resulted in a significant improvement on steering control consistency and accuracy. The adaptive gain compensator is capable of compensating the system nonlinearity effectively, and resulted in a greatly improved steering

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control sensitivity. Both simulation and test results validated this adaptive steering controller, and proved that the adaptive controller can balance the control stability and steering dynamic performance effectively. All the above results indicated that the method of using an adaptive Kalman filter and an adaptive gain compensator is an effective steering controller design approach for solving the problem generated by the noisy and drifting control signals such as tractor automated steering control.

6. ACKNOWLEDGEMENT

This research was supported by USDA Hatch Funds, Illinois Council on Food and Agricultural Research (98-069 AE), and the Case Corporation. Mr. Dennis Mohr, Mr. Eric Benson, and Mr. Jeffrey Will assisted in preparing the tests. The mentioned support is gratefully acknowledged.

Reference


Figure 1. Block diagram of steering controller for a machine vision guided agricultural tractor.

Figure 2. Frequency characteristic of the proportional-integral-derivative base controller.
Figure 3. Parameter transformation from an input parameter space \( C \) to an output parameter space \( K \), which adjusts the original parameters to match the current operational state.

Figure 4. Steering control errors on the same pathway with the same control parameters under different traveling speeds.
Figure 5. The steady-state characteristic of steering rate control and their drifts as the temperature varies.

Figure 6. The block diagram of adaptive gain compensator.
Figure 7. Comparison of steering rate error using non-filter, conventional Kalman filter, and advanced filter from steering controls on the electrohydraulic steering simulator.

Figure 8. Estimation error of steering rate using adaptive Kalman filter.
Figure 9. Dynamic response the adaptive steering controller to a step-input steering signal on an hardware-in-loop electrohydraulic steering simulator.

Figure 10. Comparison of steering error from an adaptive steering controller and a conventional PID control on field following straight rows of crops.
Figure 11. Comparison of steering error from an adaptive steering controller and a conventional PID control on field following curved rows of crops.