2011 American Control Conference
on O'Farrell Street, San Francisco, CA, USA
June 29 - July 01, 2011

Iterative Learning Identification for an Automated Off-highway Vehicle

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Abstract— **This paper presents a new approach for identifying the lateral dynamics of an automated off-highway agricultural vehicle. A second order model is proposed to represent the vehicle lateral dynamics. An Iterative Learning Identification (ILI) method is used to identify the model parameters. Simulation and experimental results show the convergence of parameters with arbitrarily chosen initial estimations. The estimation results are compared to other traditional identification methods: least square estimation and gradient based adaptive estimation. The results highlight the practical benefit of the ILI approach- i.e. that it can be performed in a relatively small section of field and therefore done prior to actual usage or engagement with crops.**

I. Introduction

Agriculture has always been central to the development of human civilizations and will become critical in the next several decades as the world population surges. In addition to crop genetics, a large factor in the advancement of modern agriculture is the increased mechanization and automation of the entire agricultural process. A key facet of the overall mechanization is the improved functionality of modern machines that work to plant, monitor, harvest, and condition the fields of operation.

For several years, commercially available tractor machines have been capable of automatically steering themselves through pre-defined routes within fields by using global positioning systems (GPS). These remarkable systems are capable of centimeter-level line tracking in good conditions for a well-tuned control system that is integrated into the vehicle design. However, this level of performance degrades for so-called retrofit systems that effectively bolt-on to existing vehicles. According to previous studies in [1], [2], vehicle configurations and soil type and conditions will greatly affect the guidance performance. One possible solution to the problem is to perform a system identification test, and then design a robust controller based on the identified vehicle model. This paper details a method for identification of a vehicle lateral dynamics model. The assumption is that a vehicle-specific/ field-specific feedback controller can be readily designed once the vehicle model is well known; e.g. pole placement. Fig. 1 illustrates the current steering control approach used for this vehicle guidance system.

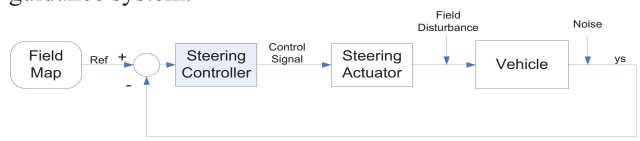

Fig 1. System configuration for an automatically steered agricultural vehicle

Vehicle lateral dynamics model identification (ID) can be based on vehicle parameter estimation, which includes vehicle mass, moment of inertia, and cornering stiffness [3]. However, these parameters are hard to measure and not always accessible. Another method of vehicle lateral dynamics model ID is open loop identification using a sinusoidal sweep [4]. A set of sinusoidal tests within a range of frequencies are analyzed to determine the system's frequency response. This open loop sinusoidal sweep approach is challenging in agricultural settings due to the limited area available to perform the necessary tests. The two integrators present in the vehicle dynamics suggest a spatial drift during open loop tests. Since land, and the resident crops, in an agricultural setting are very valuable the open loop sine sweep approach is limited. Closed loop identification is considered more appropriate for farm vehicle identification. Rekow ,et al [1] has used a Kalman filter to identify the model states online. In our study, we used the iterative learning identification method to identify the system model.

Iterative Learning Identification (ILI) is a novel approach for closed loop identification [5]- [7]. This method achieves identification by applying Iterative Learning Control (ILC) [8] concepts in the presence of measurement noise without any knowledge of the feedback controllers in the loop. The effectiveness of ILI has been previously demonstrated through numerical examples [5]- [7]. The current work is, to the knowledge of the authors, one of the first presentations of ILI implementation.

The rest of the paper is organized as follows. Section 2 gives a brief introduction to the vehicle model under consideration, which is a simplification of the well-known 'bicycle model' [9]. The choice of the model structure is important since ILI requires a fixed and known structure. Section 3 presents the ILI method used to identify the vehicle parameters. Results from simulated and experimental implementation on actual tractors are given in Section 4. A conclusion then summarizes the main points of the paper.

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II. VEHICLE DYNAMICS MODEL

A vehicle dynamics model can range from simple to very complex. For most vehicle control applications, it has been demonstrated that a relatively low order 'bicycle model' dynamics are usually sufficient for a linearized version of the plant. A 4^{th} order model is detailed in [10] to describe the lateral dynamics of a vehicle for automatic controller design. This model has been widely recognized for automatic vehicle designs [11]- [13]. The vehicle model is expressed as a transfer function from the front wheel steering angle, $u(s)$, to the lateral output, $y(s)$.

Substituting a typical set of agricultural tractor parameters [14] into the model, assuming that the vehicle longitudinal velocity is fixed at 5 mph and the GPS receiver is placed 0.5 meter ahead of vehicle centre of gravity, the fourth order model is expressed in (1).

$$G(s) = 62.3202 \frac{(s+8.3455)(s+1.7497)}{s^2(s+39.2902)(s+10.8859)} \tag{1}$$

Agriculture vehicles usually operate in a relatively low frequency range as compared to on-highway vehicles due to their relatively low sampling frequency. Examining (1) shows that the fourth order vehicle model has two poles (-39.2902, -10.8859) and one zero (-8.3455) which characterize dynamics at least 4 times faster than the other poles (0,0) and zeros (-1.7497). Therefore, the 4^{th} order model in (1) can be further simplified by truncating the high frequency poles and zeros into a simple second order formulation in the format of (2).

$$G(s) = k\frac{s-a}{s^2} = \frac{b_1 s + b_0}{s^2} \tag{2}$$

where, b_1 and b_0 are positive constants which depend on the vehicle parameters and operating conditions; k = 2.1276, and a = -1.7497. The Bode plot comparison of the 4^{th} order model from (1) and the 2^{nd} order model from (2) is shown in Fig 2. From the plots, we see that the 2^{nd} order model is representative of the 4^{th} order model for low frequency operations. Previous investigation [4] have also demonstrated the suitability of a 2^{nd} order model for agricultural vehicle applications.

Section 3 will focus on the identification of parameters b_1 and b_0 in (2) with Section 4 illustrating the performance of the identification approach.

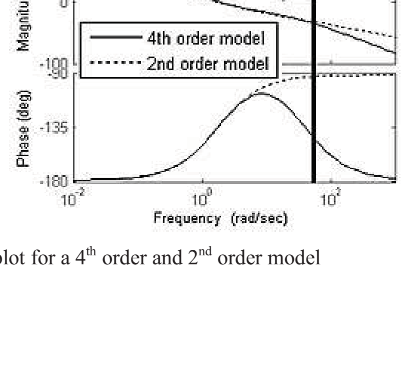


Fig. 2, Bode plot for a 4^{th} order and 2^{nd} order model

III. ITERATIVE LEARNING IDENTIFICATION

A. System Description

Iterative learning identification (ILI) was first discussed in [5], which showed the convergence analysis, and simulation results, for this parameter identification method. This identification method is then generalized to a linear continuous-time system in closed loop [7] and exhibits robustness against white measurement noise. Moreover, for our particular class of systems, ILI is advantageous since it can be applied repeatedly on a small section of land prior to vehicle operation. The closed loop identification scheme in [7] requires the user to specify both a reference signal *s(s)* (Fig.3) and a feedforward control input signal $u(s)$. However, in our experimental system (Fig. 6), only the reference signal s(s) (Fig. 3) can be specified. To accommodate our specific class of systems, the scheme of [7] is modified here and made specific to the plant given in (2).

Consider (2) in transfer function form,

$$y(s) = \frac{B^o(s)}{A(s)}u(s) = \frac{b_0{}^o + b_1{}^o s}{s^2}u(s) \tag{3}$$

where $b_0{}^o$ and $b_1{}^o$ are the unknown true parameters of the system, whose values are to be estimated. For the agricultural vehicle tested in the experiment, steered wheel angle *u(s)* is provided by the integrated AutoTrac™ wheel angle sensor. Tractor lateral position *y(s)* is measured by a StarFire™ RTK receiver, capable of 1 inch accuracy.

Basic assumptions of ILI are similar to those of its counterpart, ILC. We assume the system has the same initial condition for each trial. Additionally, we assume the trial itself has the same characteristics (inputs, outputs) for each trial. The trial duration is the time interval [0,T]. The trial index is denoted as *j*. At the start of the process (*j*=0) there is an initial set of estimated parameters which need to be specified. We define the denominator and numerator of the system at the j-th trial as:

$$A(s) = s^2,\ \hat{B}^j(s) = \hat{b}_0{}^j + \hat{b}_1{}^j s \tag{4}$$

Here we exploit process knowledge to identify only the numerator. The system denominator $A(s)$ is known, and is therefore fixed at all trials. Parameters of system numerator $\hat{B}^j(s)$, on the other hand, will be updated at each trial. We define the unknown parameter set at the *j*-th trail to be $\hat{\gamma}^j = [\hat{b}_0{}^j, \hat{b}_1{}^j]^T$.

B. Identification Steps

To construct an ILI scheme, we use the following procedure. First, choose a reference signal *s(s)*. Then, perform the following experiment at the *j*-th trial as shown in Fig. 3, and use the parameter update law to estimate the parameters for the *j+1*-th trial. The error signal $\varepsilon^j(s)$ is generated if the estimation of $\hat{B}^j(s)$ is known. The scheme for generating the error signal $\varepsilon^j(s)$ is shown in Fig. 3.

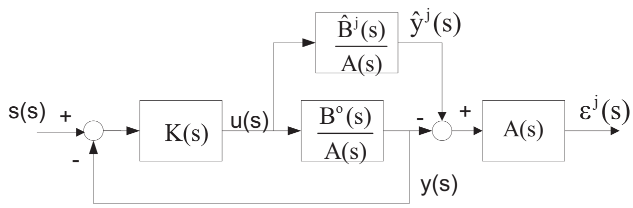


Fig. 3. Data generation scheme

The identification steps are:

1) Design a feedback controller $K(s)$ to stabilize the plant $\frac{B^o(s)}{A(s)}$. Then, choose a plant reference signal s(s), and inject it into the closed loop system.

2) Take the measured steered wheel angle *u(s),* and inject it into the estimated plant model from the *j*-th trial $\frac{\hat{B}^j(s)}{A(s)}$; this results in an estimated output $\hat{y}^j(s)$. The measured vehicle lateral output is denoted by *y(s)*.

3) According to Fig. 3, obtain the mismatch signal $\varepsilon^j(s)$

$$\begin{aligned}\varepsilon^j(s) &= [\hat{y}^j(s) - y(s)]A(s)\\ &= [\frac{\hat{B}^j(s)}{A(s)}u(s) - y(s)]A(s)\\ &= K(s)G_S(s)\hat{B}^j(s)s(s) - K(s)G_T(s)A(s)s(s)\end{aligned} \quad (5)$$

where $G_T(s) = \frac{\frac{B^o(s)}{A(s)}}{1+K(s)\frac{B^o(s)}{A(s)}}$, and $G_s(s) = \frac{1}{1+K(s)\frac{B^o(s)}{A(s)}}$

4) Project $\varepsilon^j(t)$ onto a finite-dimensional subspace of dimension 2, which has the same dimension as the unknown parameter set $\hat{\gamma}^j$. The projected error can then be written in vector form as:

$$\delta^j = [\delta_1^{\ j}, \delta_2^{\ j}] = U^T \varepsilon^j(s) \quad (6)$$

Matrix U is obtained by taking the QR decomposition of matrix V_s,

$$V_s = UR \quad (7)$$

where matrix V_s contains the differentiation of reference signal $s(t)$, and is illustrated in (8) . The dimension of V_s is chosen in accordance with the dimension of $\hat{\gamma}^j$.

$$V_s = \ s(s), s(s)s \quad (8)$$

The choice of projection matrix U is discussed in more detail in [6]. According to (7) and (8), matrix U can be calculated when s(s) is available.

5) Substitute (5) into (6), and rewrite (6) to separate the terms containing $\hat{\gamma}^j$ with the rest.

$$\begin{aligned}\delta^j &= U^T \varepsilon^j\\ &= U^T[K(s)G_s(s)\hat{B}^j(s)s(s) - K(s)G_T(s)A(s)s(s)]\\ &= U^T K(s)G_s(s)(\hat{b}_0^{\ j} + \hat{b}_1^{\ j} s)s(s) - U^T K(s)G_T(s)A(s)s(s)\\ &= U^T[K(s)G_s(s)s(s) \quad sK(s)G_s(s)s(s)]\hat{\gamma}^j\\ &\quad - U^T K(s)G_T(s)A(s)s(s)\end{aligned} \quad (9)$$

Denote

$$M = U^T \ \ G_s(s)K(s)s(s) \quad sG_s(s)K(s)s(s) \quad (10)$$

and the offset term

$$\bar{\delta}^j = -U^T K(s)G_T(s)A(s)s(s) \quad (11)$$

(9) can be rewritten as:

$$\delta^j = M\hat{\gamma}^j + \bar{\delta}^j \quad (12)$$

6) The parameter update law for $\hat{\gamma}^j$ can be developed as follows.

$$\hat{\gamma}^{j+1} = \hat{\gamma}^j + H\delta^j \quad (13)$$

The convergence of the estimation is guaranteed [6-8] when the learning gain H is given by:

$$H = k * M^{-1}, (k < 1) \quad (14)$$

where k determines the convergence speed, and it is a constant less than 1. M is defined in (10).

An examination of (13) indicates a similarity to the typical Iterative Learning Control update laws with learning gain *H* updating the parameters from iteration to iteration.

C. Determining Learning Gain H

According to (14) and (10), the learning gain *H* can be determined if we have a good estimation of matrix *M*. The unknown terms in the matrix *M* are $G_s(s)K(s)s(s)$ and $sG_s(s)K(s)s(s)$.

The scheme in Fig. 4 gives an estimate of these two terms without knowing the dynamics of the controller. This needs to be done prior to the ILI procedure. First, use the same reference signal *s(s)* that has been discussed in the ILI procedure. Then, measure the system input, which, in this case, is the steered wheel angle *u(s).* The representation of *u(s)* is given by

$$u(s) = \frac{K(s)}{1+K(s)\frac{B^o(s)}{A(s)}}s(s) = G_s K(s)s(s) \quad (15)$$

Taking the derivative of the input signal *u(s)* in the Laplace domain results in

$$su(s) = \frac{sK(s)}{1+K(s)\frac{B^o(s)}{A(s)}}s(s) = sG_s K(s)s(s) \quad (16)$$

From (15) and (16), the two unknown terms in matrix *M* are estimated over the time window [0,T]. Thus, the learning gain *H* can be determined based on the estimated *M* matrix.

The closed loop scheme in Fig. 4 is the same as the one in ILI scheme (Fig. 3). Therefore, a different experiment setup is not necessary for estimating the matrix *M*.

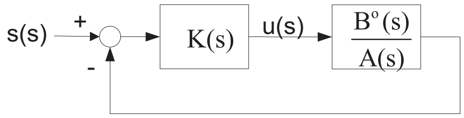


Fig.4. Estimation scheme for two unknown terms in matrix *M*

IV. Simulation and Experimental Results

A. Simulation Results

Ten iteration trials were performed with a time window of 16 sec by using the iterative identification method discussed in Section 3. A step input signal was selected for the reference *s(s),* and the feedback controller was a proportional-integral-derivative (PID) controller. The parameter updating results in Fig. 5 are starting at two different initial conditions. The true parameter values for b_0 and b_1 are 1.89 and 0.66 respectively. At iteration 6, the estimation percentage errors for both parameters are 0.69% and 1.5% respectively when the initial estimates are 1 and 1. Fig. 5 also shows that the estimated parameters are almost the same as the true parameters after six iterations for the given reference trajectory. Comparing the convergence result from different initial conditions in Fig. 5, the convergence result is relatively insensitive to the choice of initial values.

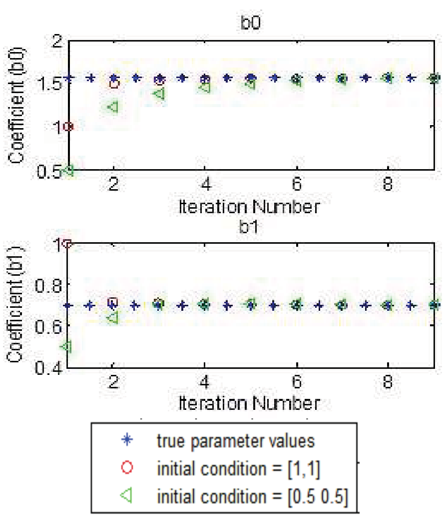


Fig. 5. Convergence of parameters in simulation with initial estimates [1,1] and [0.5 0.5]

B. Experimental Results

This identification approach was tested on a full scale John Deere 8330 tractor equipped with a StarFire™ RTK receiver and an integrated AutoTrac™ steering system. Fig.6 shows the system on which experimental data was obtained. The automatic tractor is capable of following some designated trajectories, which allows us to choose some built-in test references. The chosen reference s(s) is a step lateral signal with an amplitude of 3 meters, equivalent to a crop row change, as shown in Fig. 7(b). During the tests, the longitudinal speed is fixed at 5 mph, and the measurements are recorded at 5 Hz. For consistency, the experiment is repeated for ten times with a time window of 16 sec. Fig. 7 shows the measured input signal (vehicle wheel angle) and output signal (vehicle lateral position) for the 10 iterations, and each input and output pair corresponds to one iteration.

Fig. 6. Experiments are conducted on a John Deere tractor with integrated AutoTrac™ (model 8330, Deere and Co.).

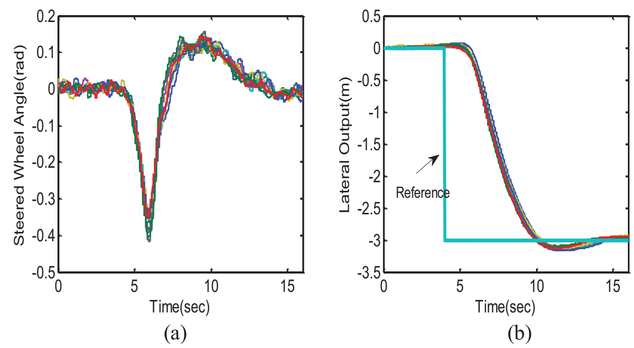


Fig.7. (a) Experimental Inputs (b) Experimental Outputs

The experimental parameter update results are shown in Fig.8. Each point represents the estimated parameter value at a particular trial. The trend of parameter convergence is clear from Fig. 8. The estimated parameter values are quite consistent after 6 iterations as the simulation results indicated. Fig. 8 also compares the parameter convergence results by starting at different initial value. As expected, the convergence result is not affected by the choice of initial values.

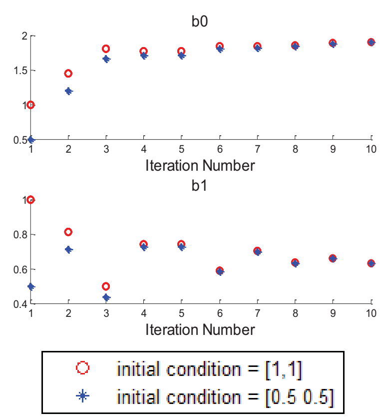


Fig.8. Convergence of parameters in experiment with initial estimate [1,1] and initial estimate [0.5 0.5] respectively

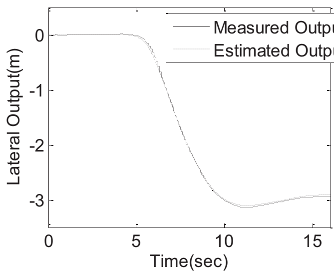


Fig.9. Comparison between the estimated output and the measured output using the model from ILI

The estimation result of parameters b_0 and b_1 are taken as the average of the parameter values when convergences are observed. In this case, at iteration 8,9 and 10. The estimated parameter values b_0 and b_1 are 0.6398 and 1.8733 respectively. We then construct the vehicle lateral dynamics model using (2) by substituting the estimated parameter values. Injecting the measured input to our estimated plant, we obtain the estimated plant output. The estimated output and the measured output are compared in Fig. 9. As evidenced, the transient behavior is captured quite well; this is sufficient information to supply a model-based controller design scheme.

C. *Comparison with Other Identification Approaches*

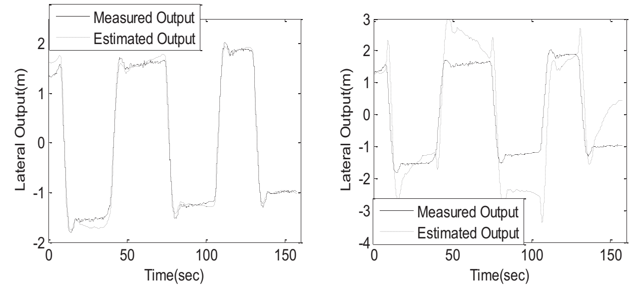
Since in this paper, we are identifying the unknown parameters in a transfer function; two conventional transfer-function domain parameter ID methods are compared with the ILI approach.

An adaptive estimation method is also applied to identify the system parameters. Using the same model structure shown in (2), gradient based adaptive estimation is performed with a continuous update law (17) [15]:

$$\dot{\hat{\theta}} = -\Gamma \phi e_n \qquad (17)$$

where, $\hat{\theta}$ is the estimated parameter set, Γ is a scaling matrix, e_n is the normalized estimation error, and vector ϕ is called the regressor vector.

In the experiment, the reference is chosen as series of step maneuvers, since one single step maneuver is not sufficient excitation for estimating a second order system. This experiment is performed 5 times, and the averaged parameter estimation results are compared with the ones we obtained using ILI scheme in Table1. From Table 1, the estimated system gain and zero are close to the ones estimated from ILI. This indicated that the estimated vehicle models are quite consistent. The estimated output and the measured output are compared in Fig.10 (a). The transient response again is captured quite well. The time used for the parameters to converge is about 157 sec. However, if the longitudinal velocity is fixed, the testing area needed for this 157 sec test is comparatively bigger than the 16 sec test using ILI method.



(a) (b)

Fig.10. (a) Comparison between the estimated output and the measured output using the model from gradient estimation
(b) Comparison between the estimated output and the measured output using the model from LSE

Least Square Estimation (LSE) has also been applied and compared with the ILI method. The estimation of parameter set $\hat{\theta}$ is obtained through (18) [16]

$$\hat{\theta} = \Phi^T\Phi^{-1}\Phi^T y \qquad (18)$$

where, $\hat{\theta}$ is the estimated parameter set, Φ is the regressor matrix, and y is the measured output.

Both a single step and series of step maneuvers references have been tried for LSE. The estimation results are similar by using these different references, and the averaged estimate results are also included in Table 1. Fig. 10(b) compares the estimated output and the measured output for series of step maneuvers. The estimated model from LSE is a non minimum-phase system, which is clearly not true for the tractor model. One of the main reasons for the insufficiency of LSE is that the reference signal does not contain enough information. Simulation results also indicated a non minimum-phase system using the same reference with a SNR 30. However, when the selected reference is a chirp, using the same setup, the parameter estimation error is less than 10 %. It has also been indicated in [17] that when the reference signal does not contain enough information, the identification results are likely to be unfaithful.

TABLE I
ESTIMATED PARAMETERS USING THREE DIFFERENT IDENTIFICATION ALGORITHMS

Identification Algorithm	System gain and zero		Model Parameters	
	‘k’	‘a’	‘b_0’	‘b_1’
ILI	0.6398	-2.9279	1.8733	0.6398
Gradient	0.5941	-2.9830	1.7722	0.5941
LSE	-3.510	0.6150	2.1585	-3.510

V. CONCLUSION AND DISCUSSION

This work presented the framework for Iterative Learning Identification (ILI) and, to the knowledge of the authors, presented one of the first implementations of ILI on an experimental system. The ILI was demonstrated to be successful in identifying model parameters for an agricultural tractor vehicle. While there are other approaches available for parameter identification, there were significant key benefits in this application which made ILI particularly attractive. As mentioned, the field available for identification is limited. Contrary to a gradient based adaptive approach, which is suitable for on-line parameter identification, the ILI can be carried out on a small field section. Additionally, the ILI is capable of identifying system parameters with a step signal which is easily available from the current AutoTrac™ system. As a result, it provides better estimation results than a batch least squares type off-line identification.

While ILI has been shown to be a very viable technique in this work there is room for improvement. Future directions for the ILI approach include a better understanding of convergence speed and steady state convergence error. Using techniques from available ILC results, alternate update designs for (13) will be developed. This may include, for example, a stabilizing filter (e.g. Q-filter) type of technique [8] for low signal-to-noise ratio conditions.

ACKNOWLEDGEMENT

The authors would like to express our sincere thanks to Matt Potter, Jeff Westphal, Swaroop Mannepalli, Ryan Burnley and Richard Erwin from Deere & Company, who were extremely helpful in technical oversight, tractor and test equipment setup, and software tools supporting. This work has been funded by Deere & Company.

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