Journal of Control Theory and Applications 2007 5 (4) 391–396 DOI 10.1007/s11768-006-6180-2

Modelling of an hydraulic excavator using simplified refined instrumental variable (SRIV) algorithm

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Abstract: Instead of establishing mathematical hydraulic system models from physical laws usually done with the problems of complex modelling processes, low reliability and practicality caused by large uncertainties, a novel modelling method for a highly nonlinear system of a hydraulic excavator is presented. Based on the data collected in the excavator's arms driving experiments, a data-based excavator dynamic model using Simplified Refined Instrumental Variable (SRIV) identification and estimation algorithms is established. The validity of the proposed data-based model is indirectly demonstrated by the performance of computer simulation and the real machine motion control experiments.

Keywords: Hydraulic excavator; Nonlinear dynamics; Data based model; Simplified refined instrumental variable algorithm

1 Introduction

The civil and construction industries currently deploy a large amount of manually-controlled equipment for a wide variety of tasks within the construction process, utilising a range of heavy hydraulic machinery including cranes, excavators, piling rigs and graders. Semi/fully-automatic functions are now starting to be adopted as a means of improving efficiency, quality and safety. The essential part of the above research fields is to design and implement a control system. Generally, system modelling is the first step in the development of a control system, and the dynamic model serves as an effective tool in designing the control system.

Much of the aforementioned work treats the control design as a problem in the continuous time domain; however, with increased computer power and decreased hardware cost, there is a growing trend toward digital control designs. In recent years, there have been a number of papers concerning the true digital control (TDC) design philosophy, in which the design of a control system is carried out overtly in discrete time. The TDC approach is based upon the simplified refined instrumental variable (SRIV) identification and estimation algorithms for data-based modelling [1∼3]. It has been successfully utilized in a range of difficult applications such as in [4∼6].

The present paper considers the application of the SRIV algorithm to a system modelling of the Lancaster University Computerised Intelligent Excavator (LUCIE), shown in Fig.1, which is being developed with the ultimate objective of executing common excavation tasks fully autonomously [7∼9]. Previous work [7] for LUCIE required a slow movement of the bucket to maintain accurate control. A reason that may partially explain this is that the dynamic model of the excavator employed for the controller was not the most appropriate or effective. By contrast, the present research utilizes the SRIV algorithm to build a data-based dynamic model of the excavator, which is expected to be able to fully describe the nonlinear dynamical behaviour of the excavator's hydraulic actuators and rigid body system. In this regard, one advantage of using SRIV is that it provides a rigorous model in the process of control parameters estimation, which may improve the joint control to ensure smoother, more accurate movement of the excavator arm. This is tested in both simulation and field tests.

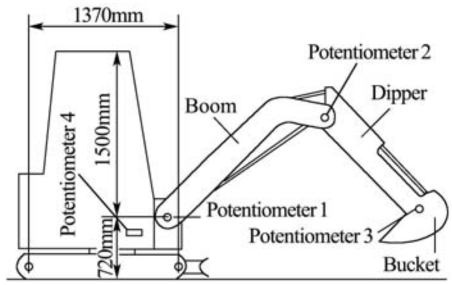


Fig. 1 The LUCIE excavator.

2 The simplified refined instrumental variable (SRIV) algorithm

The Simplified Refined Instrumental Variable (SRIV) algorithm [1∼3] is usually employed to estimate the parame-

Received 15 October 2006; revised 27 February 2007.

ters of the control models. To describe the SRIV estimation, the simplest Transfer Function (TF) model can be written in the form

$$\boldsymbol{y}(k)=\frac{\boldsymbol{B}(z^{-1})}{\boldsymbol{A}(z^{-1})}\boldsymbol{u}(k)+\boldsymbol{e}(k), \tag{1}$$

where $\boldsymbol{e}(k)$ is a zero mean, serially uncorrelated series of random variables with variance σ^2, which is introduced to allow for any unmeasurable stochastic inputs, disturbances or measurement noise that may affect the system between the input $\boldsymbol{u}(k)$ and the 'noise' output $\boldsymbol{y}(k)$ measurement.

The TF model shown in Eq.(1) is linear in the parameters of the $\boldsymbol{A}(z^{-1})$ and $\boldsymbol{B}(z^{-1})$ polynomials, as can be demonstrated by converting the equation into discrete time terms and solving for $\boldsymbol{y}(k)$ in the form

$$\begin{aligned}\boldsymbol{y}(k)=&-a_1\boldsymbol{y}(k-1)-\cdots-a_n\boldsymbol{y}(k-n)\\&+b_0\boldsymbol{u}(k)+\cdots+b_m\boldsymbol{u}(k-m)+\eta(k),\end{aligned} \tag{2}$$

where $\eta(k)=\boldsymbol{A}(z^{-1})\boldsymbol{e}(k)$.

An estimate $\hat{\sigma}^2$ of the noise variance σ^2 can be obtained from a recursive equation based on the squared values of a suitably normalized recursive innovation sequence [1, 10]. The standard errors on the parameter estimates can be calculated from the diagonal elements of the covariance matrix $\boldsymbol{P}^*(k)$ [11]. Hence, the SRIV algorithm provides an estimate of the uncertainty associated with the model parameters [12].

3 LUCIE and problem definition

The platform of LUCIE is based on a commercial manual hydraulic JCB801 mini tracked excavator. It has been refitted with electro-hydraulic servo valves, associated sensors and a computer-control system, to allow for the development of the new intelligent control systems. All of the movements are hydraulically driven, four potentiometers are fixed on the joints for angle measurement (refer to the numbered annotation in Fig.1). A specific property of the robotic excavator is that it is a directly driven manipulator with hydraulic actuators. The behaviour of hydraulically driven manipulators is dominated by the highly nonlinear, lightly damped dynamics of hydraulic actuators [13] and outside uncertainties such as the soil-tool interaction during digging. The design of a controller for such a system is therefore very much influenced by the behaviour of hydraulic actuators. Most research on robot control focuses on the nonlinear multi-variable dynamics introduced by the rigid body mechanisms of a manipulator [14]. This focus arises because most robots utilised in the manufacturing industry are equipped with electrical motors that can usually be regarded as ideal linear torque generators. However, this type of dynamics is not comparable with the highly nonlinear and complicated dynamics of a hydraulic actuator.

While kinematic models act on a purely geometric basis, dynamic models capture considerations such as force, acceleration, inertia and friction. The purpose of such models is to relate joint torques and external forces to the motions of the joints of the excavator. The forward dynamic model is used for simulation. It gives the joint torques and external forces and moments so that the motion of the entire machine can be predicted.

Vaha and Skibiniewski [15] have proposed a model based on the Newton-Euler method of dynamical modelling for robot manipulators. Lawrence [16] has used a similar formulation to model an excavator backhoe that has been modified for forestry applications. Sarata [17] has proposed a Lagrangian formulation of wheel loader dynamics and the machine is modelled as a three-link manipulator. The model captures the second-order effects of centripetal and Coriolis force due to the linkage mass and end effector load. These models are relevant chiefly for trajectory control when the bucket is moving through free space as opposed to contacting the terrain. The usual approach to control design for hydraulic actuators often leads to hydraulic motion system control mismatch. A standard approach [13] is based on a model that linearises hydraulic actuator dynamics around an operating point. This approach often gives a somewhat satisfactory result. However, an excavator needs to operate in the whole range of working action (i.e. the whole length of the hydraulic cylinder) and hence its performance may be severely degraded by inappropriate linearization during control design. What's more, in the case where the nonlinear characteristics of a hydraulic actuator cannot be ignored, a nonlinear control approach may be more appropriate. However, considering the system requirements for a hydraulic actuator, a data-based model approach using SRIV algorithm for controller design is suggested in this paper. The data-based model developed here is expected to fully describe the nonlinear dynamical behaviour of the excavator's hydraulic actuators and rigid body system without omitting any factors that may affect the motion. In addition, it should be kept as simple as possible so that design complexity is reduced while accurately describing the system's behaviour.

4 Modelling for the excavator joint dynamics

4.1 Data acquisition experiment

In this section, an experiment is designed to obtain data that are used to get the models of the excavator joint dynamics used in the next section. Because the aim of this experiment is to get enough correct data to ensure the data-based models obtained are able to describe the joint dynamics as realistically as possible, some rules must be followed to guarantee the validity of the experiment, as follows:

The experiment should excite all modes of the system that may be excited when the model is used, and over the full range of movement. For the joint arms of LUCIE, the drive-demand is from minimum to maximum and the arms move over their full motion range, from fully 'open' to fully 'closed'.

Beyond the rules discussed above, it should also be noted that the cross coupling of different joints of the machine is eliminated with the employment of Danfoss PVG 32 load-independent proportional valves which control the motion of the boom, dipper, bucket, cab slew, left track, right track, and dozer respectively. Additionally, during the whole experiment, the hydraulic pressure that drives LUCIE is kept constant, approximately 1.1×10^7 Pa and the sample time is chosen to be 0.1 second, which is within the capabilities of the on-line computer and is found to work well in practice. In the experiments, the boom, dipper and bucket are driven from the fully closed position to fully open position with the drive-demands from maximum negative voltage to maximum positive voltage, respectively, in the safe ranges.

4.2 Data-based model

After getting the data from the experiments described above, the discrete-time models of the joint dynamics are estimated from the experimental data using the SRIV algorithm.

For example, Fig.2 shows the response of the dipper, from an initial almost fully closed position, to a series of input voltages ranging from -100 to -1000 (A negative voltage scaled from 0 to -1000 causes the arm to open, whilst a positive voltage of up to 1000 reverses the direction. Large absolute value of input implies faster movement.). In each case, the dipper opens at a speed proportional to the input voltage until it reaches its maximum extended position. The data are stacked for clarity of presentation, with the slope of traces higher up the plot representing experiments with larger input voltages. Fig.3 shows the dipper closing case responses. Similar experiments are carried to the boom and bucket.

In common with other hydraulic systems [18], it is clear that the dipper angle behaves as an integrator, with an almost constant rate of change for a given input signal (see Fig.2). This is confirmed by a model identification exercise utilising $\boldsymbol{R}_T^2$ and Young Identification Criterion (YIC) [2] ($\boldsymbol{R}_T^2$ and YIC are two main statistical measures to provide a guide to selecting the most suitable model structure for the control system design.), where the TF model in each case is found to be of the following first order form:

$$\boldsymbol{y}(k) = \frac{b(z^{-1})}{1-(z^{-1})}u(k). \tag{3}$$

Here, $y(k)$ represents the dipper angle, $u(k)$ is the input voltage and b is a numerator parameter estimated for each experiment in turn. It is important to stress that the linear model (3) is based on a time invariant parameter b and, therefore, only holds for a specified input voltage. For example, in the dipper opening case, when $u(k) = -200$, then the SRIV algorithm determines that $b = -0.0073$ and $\boldsymbol{R}_T^2 = 0.9978$, i.e. over 99% of the variation in the data is explained by the simple TF model (3). Indeed, as illustrated in Fig.4, the response of the model (solid trace) closely matches the data (dots) of the experiment.

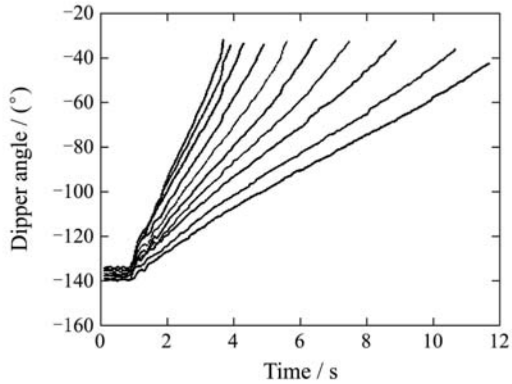


Fig. 2 Dipper opening responses for different drive-demands.

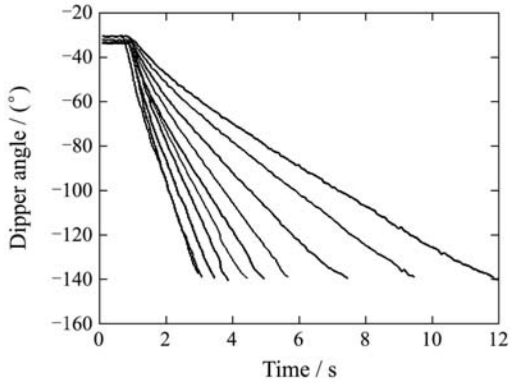


Fig. 3 Dipper closing responses for different drive-demands.

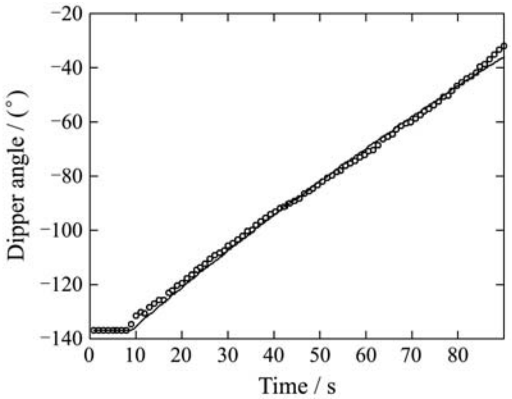


Fig. 4 Estimated transfer function model of dipper opening case against a constant input drive-demand.

Furthermore, plotting the value of b against the input voltage, as in Fig.5, reveals a nonlinear relationship that is straightforwardly represented with a nonparametric model. A 7th-order polynomial is fitted using MATLAB© and shown as the solid trace in Fig.5. It indicates the relationship between the values of b against the input drive-demands in the dipper opening case. Similarly, a 6th-order polynomial is fitted and shown as the solid trace in Fig.6 to indicate the relationship between the values of b against the input drive-demands in the dipper closing case.

Therefore, by combining Figs. 5, 6 and the equivalent polynomials for the dipper opening and closing experiments, with the TF models (3), the dynamic relationship between dipper motion and any specified input voltage may be determined. Furthermore, similar TF models may be obtained for the opening and closing experiments of the boom and bucket, with unity pure time delays for all cases. In this manner, a nonlinear simulation model is developed for LUCIE.

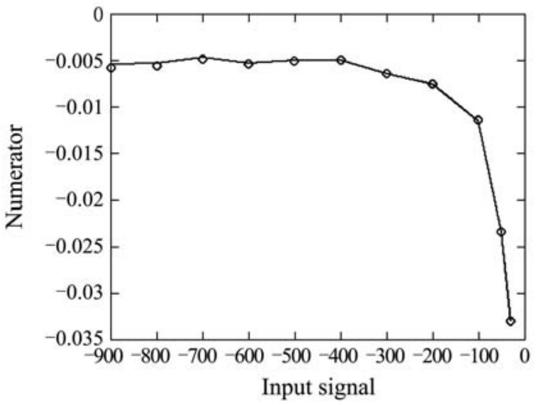


Fig. 5 Numerator parameters b for Eq. (3) fitted to experimental dipper opening data, plotted against the input drive-demand (dots); estimated curve (solid).

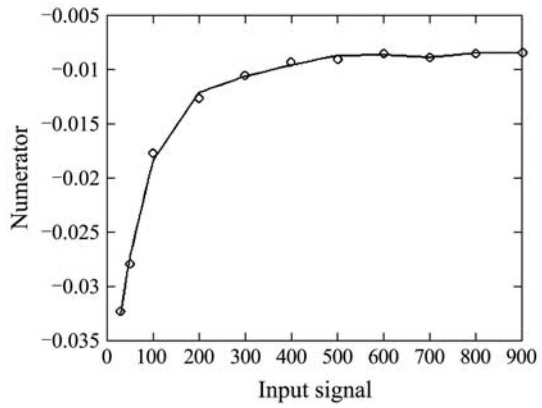


Fig. 6 Numerator parameters b for Eq. (3) fitted to experimental dipper closing data, plotted against the input drive-demand (dots); estimated curve (solid).

5 Simulation and field tests evaluation

In tests, a digital Proportional-Integral-Plus (PIP) [9, 12] control system is developed, with its parameters estimated from the above data-based model using SRIV algorithm. Simulation is carried out in MATLAB/SIMULINK©, and LUCIE is used in field experiments.

Since in the digging process the bucket position is decided by the angle of the boom and dipper according to the kinematic relationship of joints established by [8], the key to the proposed bucket position control depends on the angle control of the boom and dipper.

To test the controller in continuous action, and also to check the path tracking response of the controller, a path tracking experiment is conducted which drives the bucket to move along an oblique straight line. To keep the bucket moving along the set trajectory, a curve command input is applied to control the boom and dipper at the same time. As shown in Fig.7, there are time delays between the actual angles and the desired angles, and the curve of the real position almost coincides with the position curve in computer simulation. This indicates the validity of the system dynamic models utilised to obtain the control parameters for the controller.

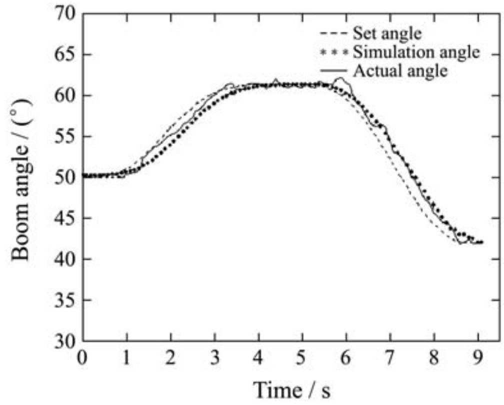
However, it is clear there is vibration when the boom tracks the desired angles as Fig.7(a) shows. From the research, it should be noted that the boom bears the largest inertial load because of its heavy weight, and this will cause the vibration. Usually, the vibration appears in the following situations:

1) the boom changes its direction of motion (e.g. from opening to closing);

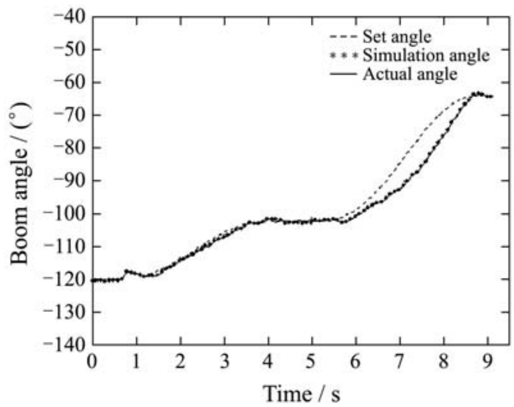
2) any movement from stationary;

3) any big changes of drive-demand even if they are in the same direction.

Another factor that can partially explain the position error is the delayed responses from the hydraulic system. The response time of the hydraulic system lags behind the real time requirements. Although the delay phenomenon has been already considered in the model establishment stage, it is not an exact fit to the real system all the time. For the dipper, most of the responses to the different drive-demands are one-time delays as the dipper TF model described, and proved by the smooth accurate tracking performance shown in Fig.7(b). However, for the heavy boom it is more complicated. The responses of the boom to some drive-demands are not exactly a one-time delay, and in the case of drive-demands to change the motion direction, the response is slower than a one-time would suggest. For simplicity, an integrator with unity time delay was assumed for the boom TF model. This is not necessarily the most appropriate model structure for the control of the boom in some cases. In this regard, the authors are presently considering the model with long time delay.



(a) Boom angle tracking response.



(b) Dipper angle tracking response.

Fig. 7 Arms' angle tracking responses of simulation and field test.

6 Conclusion

Nonlinearities in electro-hydraulic servo-systems have a deep impact on the system stability and control performance. The contribution of this paper is the development of the data-based models utilised to describe the nonlinear dynamics of the excavator arm. These models are basedon the experimentally acquired data, and the SRIV algorithm is employed to estimate the parameters for the control models. With this method, given sufficient data, the nonlinearities such as nonlinear pressure/flow gains, variations in fluid volume, friction in the hydraulic actuator, etc, can be all taken into account in the model. These dynamic TF models have been extensively used in experiments. Both simulation and experimental results conducted on the robotic excavator confirm the validity of the proposed dynamic models and the technique employed. Compared with traditional methods based on using physical laws such as the mass balance equation for oil volumes, equations of motion for moving parts, equations of turbulent flow through small restrictions, etc, this paper provides a fast and reliable way that can benefit not only the hydraulic excavator presented here, but also any other highly nonlinear dynamic system and that would offer the opportunity to improve machine utilisation and throughput in the industry.

References

[1] P. C. Young. *Recursive Estimation and Time Series Analysis (Communication and Control Engineering Series)*[M]. Berlin: Springer-Verlag, 1984.

[2] P. C. Young. Simplified refined instrumental variable (SRIV) estimation and true digital control (TDC): a tutorial introduction[C] // *Proceedings of the First European Control Conference*. Grenoble, 1991.

[3] P. C. Young. The instrumental variable method: a practical approach to identification and system parameter estimation[M] // *Identification and System Parameter Estimation*. Oxford: Pergamon, 1985: 1 – 15.

[4] M. J. Lees, C. J. Taylor, P. C. Young, A. Chotai. Modelling and PIP control design for Open Top Chambers[J]. *Control Engineering Practice*, 1998, 6(10): 1209 – 1216.

[5] L. Price, P. C. Young, D. Berckmans, K. Janssens, C. J. Taylor. Data-based mechanistic modelling (DBM) and control of mass and energy transfer in agricultural buildings[M] // *Annual Reviews in Control*, 1999, 23: 71 – 82.

[6] C. J. Taylor, P. C. Young, A. Chotai, A. R. Mcleod, A. R. Glasock. Modelling and Proportional-Integral-Plus control design for fFree air carbon dioxide enrichment systems[J]. *Journal of Agricultural Engineering Research*, 1999, 75(4): 365 – 374.

[7] D. W. Seward, S. Quayle. LUCIE-Lancaster university computerised intelligent excavator[J]. *Circle Cellar: Computer Application Journal*, 1997, 79: 67 – 73.

[8] D.A. Bradley, D. W. Seward. The development, control and operation of an autonomous robotic excavator[J]. *Journal of Intelligent and Robotic Systems*, 1998, 21(1): 73 – 97.

[9] J. Gu, C. J. Taylor, D. W. Seward. Proportional-integral-plus control of an intelligent excavator[J]. *Journal of Computer-Aided Civil and Infrastructure Engineering*, 2004, 19(1): 16 – 27.

[10] P. C. Young, A. Chotai, W. Tych. Identification, estimation and control of continuous-time systems described by delta operator models[M]// N. K. Sinha, G. P. Rao, eds. *Identification of Continuous Time Systems*. Dordrecht: Kluwer Academic Publishers, 1991: 363 – 418.

[11] P. C. Young, A. J.Jakeman. Refined instrumental variable methods of recursive time-series analysis, part 3: extension[J]. *International Journal of Control*, 1980, 31(4): 741 – 764.

[12] C. J. Taylor. Generalized proportional-integral-plus (PIP) control[D]. Lancaster: Lancaster University, 1996.

[13] E. Merritt.*Hydraulic Control Systems*[M]. New York: John Wiley, 1976.

[14] J. Craig. Introduction to Robotics: Mechanics and Control[M]. California, USA: Addison-Wesley, 1986.

[15] P. K. Vaha, M. J. Skibiniewski. Dynamic model of an excavator[J]. *Journal of Aerospace Engineering*, 1993, 6 (2): 148 – 158.

[16] P. D. Lawrence, S. E. Salcudean, N. Sepehri, D. Chan, S. Bachmanm, N. Parker, M. Zhu, R. Frenette. Coordinated and force-feedback

control of hydraulic excavators[C]//*Proceedings 4th International Sympsium on Experiment Robotics*. Stanford, CA, 1995: 114 – 121.

[17] S. Sarata,, K. Sato, S. Yuta. Motion control system for autonomous wheel loader operation[C]//*Proceeding of the International Sympsium on Mine Mechanization and Automation*. Golden, Colorado, USA, 1995: 155 – 165.

[18] R. Dixon, A. Chotai, P. C. Young, J. N. Scott. The automation of piling rig positioning utilising multivariable Proportional-Integral-Plus (PIP) Control[C] //*Proceedings 12th International Conference on Systems Engineering*. Coventry UK: Coventry University, 1997: 9 – 11.

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