NONLINEAR CONTROL SYSTEM DESIGN FOR CONSTRUCTION ROBOTS USING STATE DEPENDENT PARAMETER MODELS

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Abstract: This paper considers nonlinear Proportional-Integral-Plus (PIP) control of construction robots, with particular emphasis on two practical demonstrators: a 1/5th scale laboratory representation of an intelligent excavator; and a full scale (commercial) vibro-lance system used for ground improvement on a construction site. In both cases, the hydraulic actuators are modelled using a quasi-linear State Dependent Parameter (SDP) model structure, in which the parameters are functionally dependent on other variables in the system. The approach yields SDP-PIP algorithms with improved performance in comparison to conventional linear control. In the case of the vibro-lance, the new approach has the potential to eliminate verticality errors that have previously lead to probe repair costs of over 8000 GBP on each occasion, whilst also reducing the time taken to complete a complete digging and packing cycle in comparison to a skilled human operator.

Keywords: control system design; state dependent parameters; non-minimal state space; hydraulic actuators; robot arms; system identification

1. INTRODUCTION

The civil and construction industries currently deploy a large number of manually controlled plants for a wide variety of tasks, utilising a range of heavy hydraulic machinery including cranes, excavators and piling rigs. Semi-automatic functions are now starting to be adopted as a means of improving efficiency, quality and safety. Such systems typically provide the operator with a single joystick rather than multiple controls. In addition to improving the ease of operation, the objective is to provide more accurate motion of the hydraulic manipulator.

However, a persistent stumbling block for developers is the achievement of adequate movement under automatic control. The control problem is generally made difficult by a range of factors that include highly varying loads, speeds and geometries. In fact, the behaviour of hydraulically driven manipulators is dominated by the highly nonlinear, lightly damped dynamics of the actuators. The problem is compounded by external uncertainties such as the soil-tool interaction for the case of excavators. Such nonlinear systems present the designer with a difficult challenge, which researchers are addressing using a wide range of approaches: e.g. (Ha *et al.*, 2000; Chang and Lee, 2002; Gu *et al.*, 2004; Budny *et al.*, 2003).

Here, a key objective is to obtain a computer controlled response time that improves on that of a skilled human operator – without this, the economic benefits of automation are limited. For example, previous research using the Lancaster University Computerised Intelligent Excavator (LUCIE) has demonstrated the feasibility of developing a machine that will accurately dig a trench of specified dimensions (Bradley and Seward, 1998). However, control of the excavator was initially based on the ubiquitous Proportional-Integral-Derivative (PID) type algorithm. As a result, the nonlinear dynamics would sometimes yield an oscillatory response, unless a relatively slow control action was specified.

For this reason, recent research using LUCIE has used a state variable feedback-based approach to improve the control and so provide smoother, more accurate movement of the excavator arm (Gu *et al.*, 2004). Here, Non-Minimal State Space (NMSS) models are developed and utilised for *linear* Proportional-Integral-Plus (PIP) control system design. Such PIP controllers can be interpreted as a logical extension of conventional industrial PI/PID algorithms, but with inherent model-based predictive control action (Young *et al.*, 1987; Taylor *et al.*, 2000; Taylor *et al.*, 2004).

To date, however, any inherent nonlinearities in the system have been accounted for in a rather *ad hoc* manner at the design stage, sometimes leading to reduced control performance. In order to improve control in such cases, therefore, the present paper identifies and subsequently exploits State Dependent Parameter (SDP) models. Here, the nonlinear system is modelled using a quasi-linear structure in which the parameters vary as functions of the state variables (Young, 2000). The linear-like, 'affine' structure of the SDP model means that, at each sampling instant, it can be considered as a 'frozen' linear system. This formulation may then be used to design a SDP-PIP control law (McCabe *et al.*, 2000).

The present paper develops two practical demonstrators of this new approach, namely: a 1/5th scale representation of LUCIE, valuable for initial design and testing; and a full-scale commercial hydraulic excavator, with attached vibro-lance, used for ground improvement on a construction site. Whilst earlier research using the 1/5th model was limited to just one joint (Shaban and Taylor, 2004), the present paper describes the complete control system for digging a trench and extends these results to the vibro-lance system.

2. DEMONSTRATORS

With regard to the commercial system, the field tests used a KOMATSU PC-240 LC-7 hydraulic excavator, as illustrated in Fig. 1. The vibro-lance is connected to an excavator arm and hangs freely like a pendulum (Joint 4). The operator first positions the vehicle by manually adjusting the slew (Joint 1) and excavator tracks. The vibrating probe is subsequently lowered into the ground, penetrating downwards by regulating the so called 'boom' (Joint 2) and 'dipper' (Joint 3). Here, the objective is to keep the arm-tip moving in a vertical straight-line path. In this manner, the surrounding soil is compacted up to a distance of about 5m from the probe; for granular soils, the cavity produced is subsequently filled with gravel.

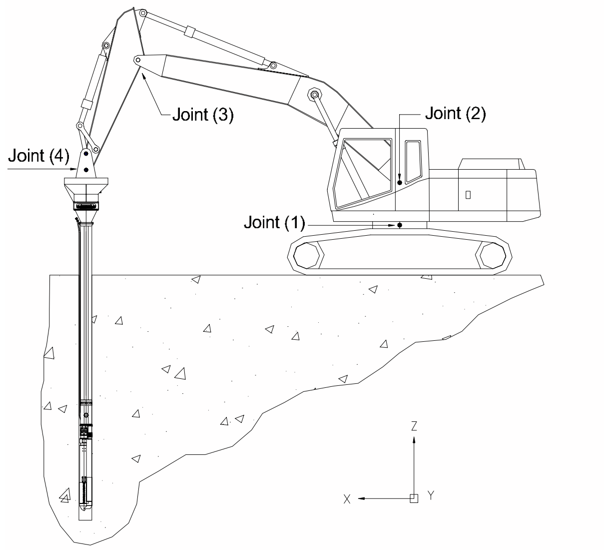

Fig. 1. Two-arm manipulator with vibro-lance.

The laboratory model has a similar arrangement to Fig. 1, except that a bucket is attached at Joint 4. In this case, all 4 joints are under computer control, in order to excavate a trench in the sand-pit. The entire frame is fixed to a workbench. For brevity, the various kinematic equations, together with algorithms for determining the appropriate tool-tip trajectory, are all omitted here. However, in both instances, trajectory planning employs a conventional continuous-path operation, while hardware constraints ensure a straightforward and unique solution to the inverse kinematics: see (Shaban, 2006) for details.

3. IDENTIFICATION

Numerous recent publications describe an approach for the identification of state dependent parameter (SDP) models; see e.g. (Young, 2000). The approach exploits recursive Kalman Filtering and Fixed Interval Smoothing (FIS) methods, within an iterative 'backfitting' algorithm that involves special re-ordering of the time series data. The present paper uses the following SDP model,

$$y_k = \boldsymbol{w}_k^T \boldsymbol{p}_k \tag{1}$$

where,

$$\begin{aligned}
\boldsymbol{w}_k^T &= \left[\, -y_{k-1} \ \cdots \ -y_{k-n} \ u_{k-1} \ \cdots \ u_{k-m} \,\right] \\
\boldsymbol{p}_k &= \left[\, \boldsymbol{p}_{1,k} \ \boldsymbol{p}_{2,k} \,\right]^T \\
\boldsymbol{p}_{1,k} &= \left[\, a_1 \{\boldsymbol{\chi}_k\} \ \cdots \ a_n \{\boldsymbol{\chi}_k\} \,\right] \\
\boldsymbol{p}_{2,k} &= \left[\, b_1 \{\boldsymbol{\chi}_k\} \ \cdots \ b_m \{\boldsymbol{\chi}_k\} \,\right]
\end{aligned}$$

Here y_k and u_k are the output and input variables respectively, while $a_i\{\boldsymbol{\chi}_k\}\,(i=1,2,\ldots,n)$ and $b_j\{\boldsymbol{\chi}_k\}\,(j=1,\ldots,m)$ are state dependent parameters. The latter are assumed to be functions of a non-minimal state vector $\boldsymbol{\chi}_k^T$. For SDP-PIP control system design, it is usually sufficient to limit the model (1) to the case that $\boldsymbol{\chi}_k^T=\boldsymbol{w}_k^T$. Finally, any pure time delay is represented by setting the leading $b_j\{\boldsymbol{\chi}_k\}$ terms to zero.

The first stage of the analysis sometimes involves the identification of conventional, discrete-time linear transfer function models. This helps to define the initial structure of the SDP model above. In this regard, the present research uses the Simplified Refined Instrumental Variable (SRIV) estimation algorithm (Young, 1984). The two main statistical measures utlised to help identify the most appropriate model structure, are the coefficient of determination R_T^2, based on the response error; and Young's Identification Criterion (YIC), which provides a combined measure of model fit and parametric efficiency.

4. CONTROL DESIGN

The NMSS representation of the system (1) is,

$$\begin{aligned} \boldsymbol{x}_{k+1} &= \boldsymbol{F}_k\boldsymbol{x}_k+\boldsymbol{g}_k u_k+\boldsymbol{d}y_{d,k} \\ y_k &= \boldsymbol{h}\boldsymbol{x}_k \end{aligned} \tag{2}$$

where the non-minimal state vector is defined,

$$\boldsymbol{x}_k=\begin{bmatrix} y_k & \cdots & y_{k-n+1} & u_{k-1} & \cdots & u_{k-m+1} & z_k\end{bmatrix}^T$$

and $z_k=z_{k-1}+[y_{d,k}-y_k]$ is the integral-of-error between the reference or command input $y_{d,k}$ and the sampled output y_k. As usual for NMSS design, inherent type 1 servomechanism performance is introduced by means of this integral-of-error state (Young *et al.*, 1987). Finally, the various state vectors and matrix are defined as follows, with $\boldsymbol{F}_k$ in a separate box over the page,

$$\boldsymbol{g}_k=\begin{bmatrix} b_1\{\boldsymbol{\chi}_k\} & 0 & 0 & \cdots & 0 & -b_1\{\boldsymbol{\chi}_k\}\end{bmatrix}^T$$

$$\boldsymbol{d}=\begin{bmatrix} 0 & 0 & 0 & \cdots & 0 & 1\end{bmatrix}^T$$

$$\boldsymbol{h}=\begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0\end{bmatrix}^T$$

The state variable feedback control algorithm $u_k=-\boldsymbol{l}_k\boldsymbol{x}_k$ is defined by,

$$\boldsymbol{l}_k=\begin{bmatrix} f_{0,k} & \ldots & f_{n-1,k} & g_{1,k} & \ldots & g_{m-1,k} & -k_{I,k}\end{bmatrix}$$

where $\boldsymbol{l}_k$ is the control gain vector obtained at each sampling instant by either pole assignment or optimisation of a Linear Quadratic (LQ) cost function. With regard to the latter approach, earlier research has either used a 'frozen-parameter' system defined as a sample member of the family of NMSS models $\{\boldsymbol{F}_k,\boldsymbol{g}_k,\boldsymbol{d},\boldsymbol{h}\}$ or has solved the discrete-time algebraic Riccatti equation at each sampling instant: see e.g. (McCabe *et al.*, 2000).

A prerequisit of global controllability is that the system $\{\boldsymbol{F}_k,\boldsymbol{g}_k,\boldsymbol{h},\boldsymbol{d}\}$ is piecewise controllable at each sample k. This requirement follows from the fact that if a system is globally controllable, it clearly has to be locally controllable. The NMSS/PIP linear controllability conditions are developed by (Young *et al.*, 1987). However, the derivation of complete controllability and stability results for the nonlinear SDP-PIP system is the subject on-going research by the authors.

5. LABORATORY EXCAVATOR

In order to identify the dominant dynamics of the 1/5th scale LUCIE model, open-loop experiments are conducted for a range of applied voltages and initial conditions, all based on a sampling rate of 0.11 seconds. In this case, the SRIV algorithm, combined with the YIC and R_T^2 identification criteria, suggest that a first order linear model with τ samples time delay, i.e. $y_k=a_1y_{k-1}+b_\tau u_{k-\tau}$, provides an approximate representation of each joint. However, the limitations in this model are clear: the value of b_τ can vary considerably depending on the magnitude of the applied voltage. Indeed, SDP analysis suggests that a more appropriate model for the boom, for which $\tau=2$, takes the form of equation (1) with,

$$\begin{aligned} \boldsymbol{w}_k^T &= \begin{bmatrix} -y_{k-1} & u_{k-1} & u_{k-2}\end{bmatrix} \\ \boldsymbol{p}_k &= \begin{bmatrix} a_1\{\boldsymbol{\chi}_k\} & 0 & b_2\{\boldsymbol{\chi}_k\}\end{bmatrix}^T \end{aligned} \tag{3}$$

where,

$$\begin{aligned} a_1\{\boldsymbol{\chi}_k\} &= 0.238\times10^{-6}u_{k-2}^2-1 \\ b_2\{\boldsymbol{\chi}_k\} &= -5.8459\times10^{-6}u_{k-2}+0.01898 \end{aligned}$$

Note that the arm essentially acts as an integrator, since the normalised voltage has been calibrated so that there is no movement when $u_k=0$. In fact, for the dipper, bucket and slew models, $a_1=-1$ is fixed *a priori*, so that only the numerator parameter b_τ is estimated in practice, taking values of 0.0237, 0.0498 and 0.0179 respectively. With unity time delay, the dipper and bucket joints are relatively straightforward to control using linear (fixed gain) PIP methods. Furthermore, the preliminary slew controller utilised so far is also linear, with $\tau=4$. However, the authors are presently investigating the potential for improved nonlinear control of the slew joint and these results will be reported in future publications.

Earlier research for control of the *boom* joint in isolation, shows that SDP-PIP methods yield improved performance and robustness in comparison to linear PIP control (Shaban and Taylor, 2004).

$$
\boldsymbol{F}_k = \begin{bmatrix}
-a_1\{\boldsymbol{\chi}_k\} & -a_2\{\boldsymbol{\chi}_k\} & \cdots & -a_{n-1}\{\boldsymbol{\chi}_k\} & -a_n\{\boldsymbol{\chi}_k\} & b_2\{\boldsymbol{\chi}_k\} & \cdots & b_{m-1}\{\boldsymbol{\chi}_k\} & b_m\{\boldsymbol{\chi}_k\} & 0 \\
1 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & 0 \\
0 & 0 & \cdots & 1 & 0 & 0 & \cdots & 0 & 0 & 0 \\
0 & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\
0 & 0 & \cdots & 0 & 0 & 1 & \cdots & 0 & 0 & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\
0 & 0 & \cdots & 0 & 0 & 0 & \cdots & 1 & 0 & 0 \\
a_1\{\boldsymbol{\chi}_k\} & a_2\{\boldsymbol{\chi}_k\} & \cdots & a_{n-1}\{\boldsymbol{\chi}_k\} & a_n\{\boldsymbol{\chi}_k\} & -b_2\{\boldsymbol{\chi}_k\} & \cdots & -b_{m-1}\{\boldsymbol{\chi}_k\} & -b_m\{\boldsymbol{\chi}_k\} & 1
\end{bmatrix}
$$

Since there is little interaction between the various joints, multiple-loop controllers are developed. In other words, the control system for automatically regulating the entire digging cycle, is based on separately identified controllers for each joint angle. These are combined with higher level algorithms for determinating the appropriate bucket trajectory in 3D space and for solving the inverse kinematic equations (Shaban, 2006).

In this regard, Fig. 2–4 show typical implemention results for one digging cycle in the sandpit, showing the time response for each joint, control input signals and a 3D co-ordinate plot of the end-effector. These graphs show the bucket being first lowered into and subsequently being dragged through the soil, followed by extraction, displacement and release of the sand, before the bucket is finally returned to the start point. In this manner, a trench is gradually excavated.

The experience gained using this laboratory excavator was subsequently exploited for the development of the full scale vibro-lance system below.

6. GROUND COMPACTION

In the first instance, open-loop experiments are conducted on the KOMATSU PC-240 LC-7 hydraulic excavator shown in Fig. 1, here based on a sampling rate of 0.44 seconds. Experimentation suggests that the latter value provides a good compromise between a fast response and a desirable low order model. In this case, the linear model $y_k = a_1 y_{k-1} + b_2 u_{k-2}$ provides a reasonable explanation of the data for a wide range of operating conditions. In fact, this model has been successfully used in the design of a preliminary *linear* PIP control system (Shaban, 2006). For nonlinear design, the SDP model takes the form of equation (3) with $a_1\{\boldsymbol{\chi}_k\} = a_1 = -1$ and,

$$b_2\{\boldsymbol{\chi}_k\} = -7.63 \times 10^{-6} u_{k-2} + 0.0066 \qquad (4)$$

for the boom, while for the dipper,

$$b_2\{\boldsymbol{\chi}_k\} = -1.078 \times 10^{-6} |u_{k-2}| + 0.015 \qquad (5)$$

Fig. 5 shows a typical SDP model response for the dipper joint. Note that, because of nonlinearities in the system dynamics, transfer function models yield a very poor fit to the data in Fig. 5, which is based on a wide range of input magnitudes. By contrast, it is clear that the SDP model provides a reasonable description of the data ($R_T^2 = 0.81$), sufficient for control system design purposes. Solution of the discrete-time algebraic Riccatti equation for a sample member of the family of NMSS models $\{\boldsymbol{F}_k, \boldsymbol{g}_k, \boldsymbol{d}, \boldsymbol{h}\}$, yields the following SDP-PIP gain vector (Shaban, 2006),

$$\boldsymbol{l}_k^T = \begin{bmatrix} 22.8143 \\ -1.741 \times 10^{-4} u_{k-2} + 0.1506 \\ 1.4655 \end{bmatrix} \qquad (6)$$

for the boom, while for the dipper,

$$\boldsymbol{l}_k^T = \begin{bmatrix} 25.8 \\ -2.78 \times 10^{-4} |u_{k-2}| + 0.387 \\ -3.1456 \end{bmatrix} \qquad (7)$$

Typical closed-loop results for lowering the probe in air are illustrated in Fig. 6. Here, it is clear that the SDP-PIP approach yields more accurate control than the preliminary fixed gain PIP algorithm, particularly in the initial positioning of the arm. In general, SDP-PIP control offers smoother, more accurate movement of the excavator tool and hence potentially allows for faster response times.

7. CONCLUSIONS

This paper has developed State Dependent Parameter, Proportional-Integral-Plus (SDP-PIP) control systems for two practical demonstrators, including: a 1/5th scale laboratory representation of an intelligent excavator; and a commercial vibro-lance system used for ground improvement on a construction site.

In both cases, the device was modelled using the quasi-linear SDP model structure, in which the parameters are functionally dependent on other variables in the system. This formulation is subsequently used to design a PIP control law using linear system design strategies, such as suboptimal Linear Quadratic (LQ) design. The approach yields SDP-PIP control systems in which the state feedback gains are themselves state dependent.

In the case of the laboratory model, the new approach yields improved control of the boom joint in comparison to earlier linear designs based on either PIP or conventional PID methods (Shaban and Taylor, 2004). In this paper, the approach has been integrated into a complete system for automatic trench digging in the sand-pit. This laboratory demonstrator provides a readily accessible 'hands-on' example, valuable for both teaching and for further research into nonlinear control.

With regard to the full scale system illustrated in Fig. 1, a vibrating probe is lowered into the ground and penetrates downwards by means of the two arm excavator, compacting the surrounding soil. In contrast to the laboratory model, the vibro-lance is a *semi-automated* device, i.e. there is human-machine interaction. Here, the operator adjusts movement of the probe by means of a joystick, while the control task is to maintain the *verticality* of the probe, as it is first lowered into the soil and subsequently raised from it. Inverse kinematics are utilised on-line to convert the task into a desired trajectory, whilst SDP-PIP controllers maintain the specified joint angles.

Automatic control of Joints 2 and 3 provides a number of practical benefits, such as a reduced dependence on operator skills and a lower work load, both of which might be expected to contribute to improvements in quality, productivity and an increase in tool life. In fact, the long term bending moment leads to probe damage when the average deviation from the vertical exceeds ≈ 30cm.

On-site implementation experiments for lowering the probe into soil using a preliminary *linear* PIP controller are very promising, as reported by (Shaban, 2006). Here, the error between the measured tool-tip trajectory and the horizontal set point is typically less than 10cm for over 90% of the time. To the authors knowledge, this level of performance is not normally achieved by a skilled human operator. However, relatively large transient deviations of up to 37cm do occasionally occur using linear methods. Although these are often associated with difficult obstructions in the soil, they provide the motivation for the present research using nonlinear methods.

In this regard, SDP-PIP methods yield improved performance with the potential to eliminate the verticality errors that have previously lead to probe repair costs of over 8000 GBP on each occasion. Furthermore, preliminary results suggest that the automatic system completes an entire cycle *at least* as fast as a skilled human operator.

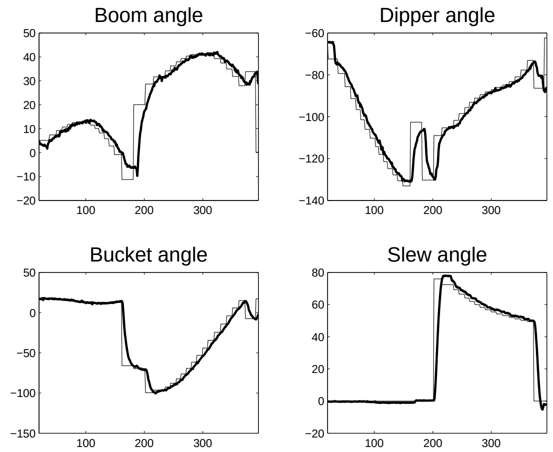

Fig. 2. Implementation results for the laboratory excavator in sand, showing the four joint angles (degrees) and respective set-points, all plotted against sample number.

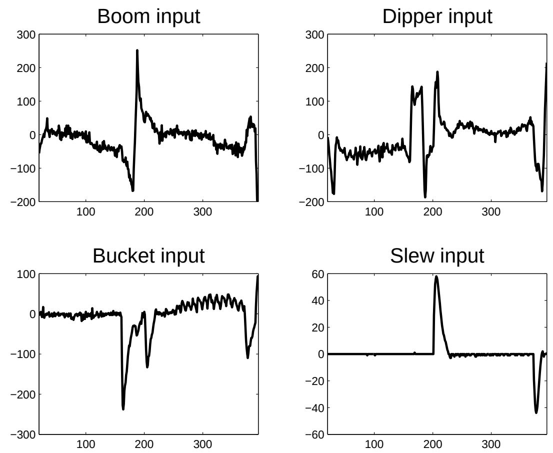

Fig. 3. Scaled input voltages for the experiment in Fig. 2. Positive inputs imply raising the arm or bucket, while negative voltages reverse the direction of movement.

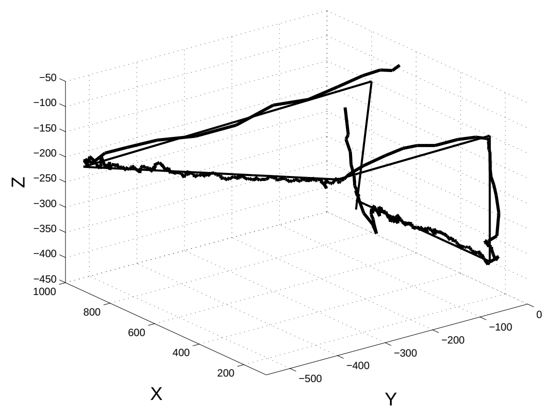

Fig. 4. Resolved position of the end-effector for the experiment in Fig. 2, represented by the planar horizontal and vertical displacements (X and Z), together with the slew (Y), with the set-point shown as straight lines (mm).

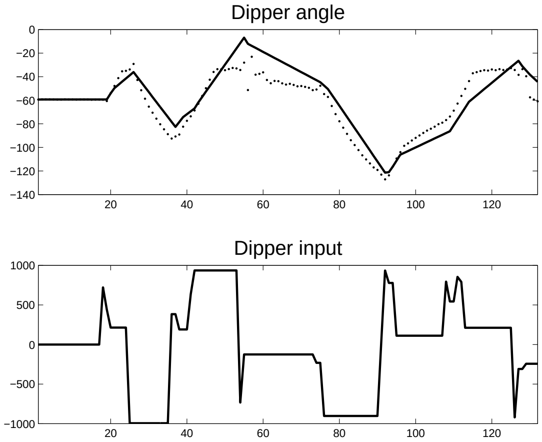

Fig. 5. Open-loop experiment for the vibro-lance being moved in air. Top subplot: SDP model response and experimental data (dots) for the dipper angle. Bottom subplot: scaled voltage.

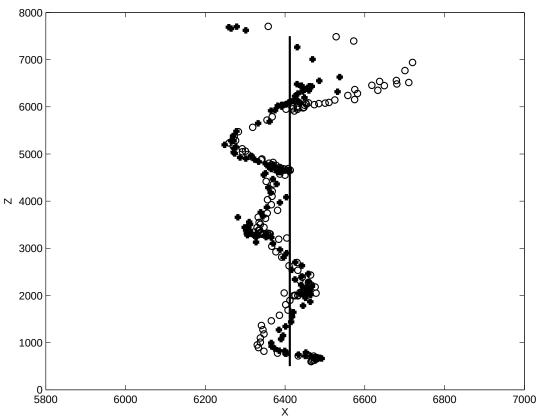

Fig. 6. Implementation experiment for the vibro-lance being lowered in air, showing the resolved position of the end effector, represented by the horizontal and vertical displacements (mm). Nonlinear SDP-PIP control (thick crosses) is compared with linear PIP (circles) and horizontal set point (solid).

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www.lancs.ac.uk/staff/taylorcj/nonlinear

The statistical tools and associated estimation algorithms have been assembled as the CAPTAIN toolbox within the Matlab® software environment:

www.es.lancs.ac.uk/cres/captain

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