Hydraulic System Modeling through Memory-based Learning

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Abstract

Hydraulic machines used in a number of applications are highly non-linear systems. Besides the dynamic coupling between the different links, there are significant actuator non-linearities due to the inherent properties of the hydraulic system. Automation of such machines requires the robotic machine to be atleast as productive as a manually operated machine, which in turn make the case for performing tasks optimally with respect to an objective function (say) composed of a combination of time and fuel usage. Optimal path computation requires fast machine models in order to be practically usable.

This work examines the use of memory-based learning in constructing the model of a 25-ton hydraulic excavator. The learned actuator model is used in conjunction with a linkage dynamic model to construct a complete excavator model which is much faster than a complete analytical model. Test results show that the approach effectively captures the interactions between the different actuators.

I. Introduction

Hydraulic machines are commonly used in the areas of construction, mining and excavation. A typical machine used frequently in excavation - a hydraulic excavator (HEX) - is shown in Fig 1. Today attention is being focused on automating tasks such as mass excavation and continuous mining where a digging machine fills a bucket with material from a pile or a rock face, transports the bucket load to a waiting truck or conveyer belt, and dumps the load in the truckbed/belt. Such tasks are ideal candidates for automation since they are repetitive and there exists room for enhancing productivity.

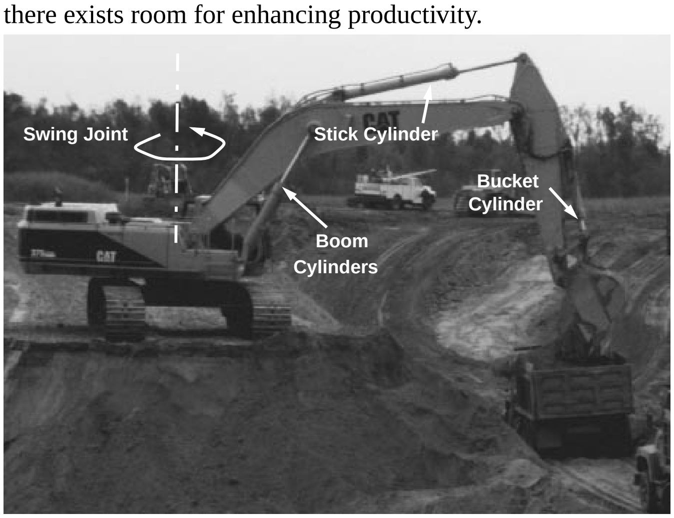

Fig. 1. A typical excavating machine (Hydraulic Excavator)

Automation can be a practical reality only if the robotic machine is more productive than a manually operated one. This requires that tasks be performed optimally to minimize a combination of performance objectives such as time per bucket load and fuel consumption. Optimal motion computation in turn requires a robot model which defines the constraint surface for the path optimization problem. A complete robot model consists of an actuator model and a linkage dynamics model. While the linkage dynamics for an excavator robot can be modeled using the well-known Newton-Euler equations, the actuator model is rather complex and non-linear. The non-linearity is due to the highly non-linear hydraulic system, and also due to the power coupling between the actuators, which are powered by a limited power source (i.e. the engine). An analytical actuator model for an excavator is therefore computationally expensive.

This paper describes the construction of a fast hydraulic system and actuator model for an excavator through memory-based learning. The learned model has been used to construct a complete excavator model which includes the second-order linkage dynamics in addition to the actuator model. This complete model is about an order of magnitude faster than a comparable analytical model.

The following notation will be used through the rest of this document: “Linkage dynamic model” refers to the system of Newton-Euler equations that describe the dynamics of the excavator’s links, while an “actuator model” describes the actuator characteristics. The term “machine model” refers to a complete excavator model which includes both of the above.

Although optimal motion planning can be performed with slower machine models, fast models raise the possibility of performing the optimal path computation as needed, even onboard the robot, rather than pre-computing it off-line. An optimal motion computation may require a few thousand evaluations/simulations, and the speed difference between a slow and a fast model could translate into the optimization taking a few days versus a few hours.

Fast machine models are also needed for collision avoidance through predictive simulation of motion commands before they are executed. The expected trajectory through space can be scanned for collisions and the robot stopped in time in the event of a predicted collision. (The use of predictive models is necessary when the masses are large and/or the velocities are high since the dynamics of the system can make the response quite different from a linear extrapolation of the velocity [5])

The use of machine learning techniques to learn robot dynamics is not new. Neural networks that learn the dynamic equations of a robot manipulator ([2][3]) have been used in

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model-based controllers. In [4] a neural network was used to learn the error between an analytical dynamic model and actual machine behavior during operation of the controller. This learned error function was used to improve controller performance. Although all the above cited researchers describe how neural networks improved controller performance, they do not describe how well the neural network learned the dynamic model. This is probably because their goal was to improve controller performance and not learn the dynamic model. In [8] McDonell et al. describe the construction of an analytical pneumatic cylinder model, which was used to improve the control by modelling the non-linearities inherent in pneumatic actuators. However, their pneumatic robot does not encounter any flow limitations (and hence actuator interactions of the type seen in a typical hydraulic machine) due the presence of a large enough reservoir of high-pressure air.

In [9] Singh et al. use a simple approach to handle the flow distribution between multiple hydraulic cylinders on a hydraulic machine. They assume that the circuit with a valve closest to the pump gets all the flow it requires, and the remaining flow is distributed among the rest. This approach is valid when the interacting cylinders have very different force loads, but not when the cylinders have similar force loads.

The rest of the paper is organized as follows. Sec II gives a brief description of the structure of the equations involved in a complete analytical model, to introduce the reader to the nature of such a problem. The following section (Sec III) describes the memory-based learning approach used to learn the actuator model. The results of the learning exercise are described in Sec IV followed by some conclusions in Sec V.

II. Problem background

The testbed used for the work described in this paper is a Caterpillar 325 HEX, similar to the one in Fig 1. This machine has two tracks which give it the ability to turn-in-place. The excavation activities are performed using four joints driven by hydraulic actuators. These are:

- Swing: The waist joint
- Boom: The shoulder joint
- Stick: The elbow joint
- Bucket: The wrist joint.

Although described as shoulder, elbow, and wrist joints the boom, stick, and bucket only have one degree-of-freedom. All three joints move in the plane of the excavator's arm. The three joints are actuated by linear hydraulic cylinders labelled in Fig 1. The swing joint and the tracks are actuated by separate hydraulic motors (rotary actuators) not visible in the figure. The tracks are usually not actuated when excavating; they are periodically used to reposition the excavator.

Fig 2 shows a simple schematic[1] of the hydraulic system of a CAT 325 HEX. The hydraulic system is driven by two hydraulic pumps which take low-pressure hydraulic oil from a tank (at atmospheric pressure) and output high-pressure oil. The power required to achieve the pressure rise is obtained from a single engine (not shown) which drives the pumps.

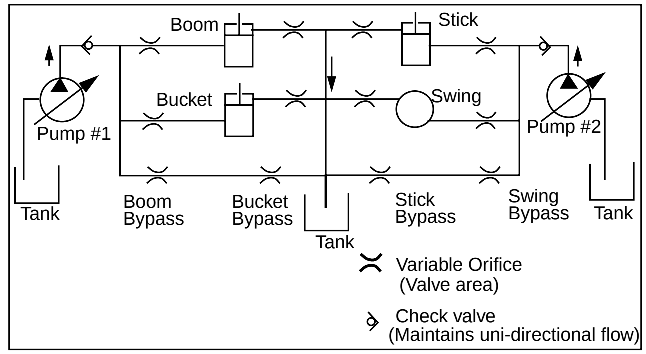

Fig. 2. Schematic of hydraulic system of a typical hydraulic excavator

The high-pressure oil flows to the hydraulic cylinders, which in turn actuate the different joints. Each of the two pumps supplies two implement circuits, i.e. one pump supplies the boom and bucket cylinders while the other supplies the stick cylinder and swing motor. (For the rest of the discussion the tracks will not be mentioned since they are not used during excavation. When they are used, one pump is dedicated to each track motor).

The flow from the pumps to the cylinders is controlled through variable orifices shown in Fig 2. If an orifice is completely closed no flow is supplied to that cylinder and no motion results. The hydraulic system shown above is an open-center system. In an open-center system the pumps do not reduce their output to zero. When no actuator flow is being demanded, the pumps still output a non-zero flow - between 10 and 20% of maximum flow for the testbed in Fig 1. This "idle" flow goes to the tank through the bypass (or "center") passages shown in the figure. When the actuators are being commanded to move, the bypass passages slowly close and are fully closed when maximum velocity is being demanded.

A complete analytical model of the hydraulic system includes orifice flow equations, fluid compressibility equations for all the oil volumes, as well as the force balance equations for all the cylinders. The orifice flow equation governing flow and pressure drop across an orifice (for turbulent flow) is:

$$Q = C_d A \sqrt{\Delta P} \qquad (1)$$

where Q is the flow rate through an orifice, C_d is the orifice discharge coefficient (a constant), A is the orifice area, and ΔP is the pressure drop across the orifice. The concepts of flow and pressure drop are analogous to current and voltage drop in electrical circuits. Thus, an orifice can be viewed as a non-linear resistor.

Fluid compressibility can modeled using the following equation:

$$\dot{P} = -\frac{\beta Q}{V} \qquad (2)$$

[1]This schematic only corresponds to one particular direction of motion of the cylinders. A different set of valves come into play when the cylinders move in the opposite direction.

where P is the pressure in a control volume, β is the bulk modulus of the oil, V is the volume of oil in the control volume, and Q is the flow rate through the control volume.

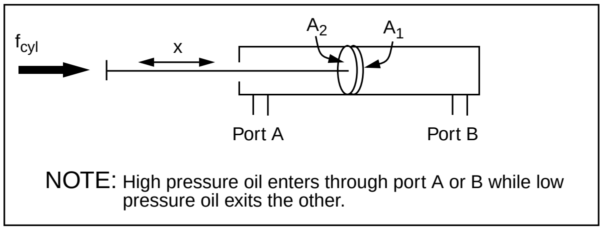

Fig. 3. Schematic of bi-directional hydraulic cylinder

The force balance equation for a cylinder - boom, stick or bucket, is:

$$m\ddot{x} = P_1A_1 - P_2A_2 - f_{cyl} - f_{friction} \qquad (3)$$

where m is the mass of the cylinder rod, P_i is the pressure with the subscripts indicating the two cylinder chambers, A_i is the surface area on the two sides of the cylinder piston, f_{cyl} is the force on the cylinder due to the linkages, and $f_{friction}$ is the friction force on the piston. The force load is due to linkage dynamics and tip forces. However, in the work described in this paper, no forces (e.g. digging forces) are applied at the bucket tip - only free space motion is considered.

The cylinder extension x is mapped to the joint position θ via a non-linear function: $x_{cyl} = C(\theta)$

The linkage force f_{cyl} appears in the excavator linkage dynamic equations:

$$M(\Theta)\ddot{\Theta} + V(\Theta, \dot{\Theta}) + G(\Theta) = \tau \qquad (4)$$

where each joint torque τ_ι is related to the corresponding cylinder force via the transform:

$$\tau_i = f_{cyl_i} \cdot \frac{\partial}{\partial\theta_i} C_i(\theta_i) \qquad (5)$$

Thus, the complete solution of the response of even the simplified hydraulic system in Fig 2 involves the simultaneous solution of multiple orifice equations (Eqn 1), multiple compressibility equations for all the oil volumes (Eqn 2), and force balance equations for each cylinder (Eqn 3, Eqn 4, Eqn 5). A steady state solution would not include the fluid dynamics in Eqn 2. The excavator hydraulic system also has non-linear components such as the check-valves (shown in Fig 2) which prevent oil flow from the cylinder to the pump.

A complete analytical model of the excavator which includes linkage and actuator dynamics is a coupled eighth-order non-linear system of 515 equations, which is partially described in [1]. A detailed model of the complete excavator hydraulic system has been constructed using a proprietary numerical solver, and its performance has been verified against results obtained from the CAT 325 testbed. This detailed model takes approx. 100 secs to simulate 1 sec. of a typical excavation cycle when running on a SUN Sparc20 workstation.

III. Model construction

The purpose of the learned HEX model is to aid in optimal motion computation which requires many robot motion simulations when searching for the optimal. It is not very essential to capture all the transients in the robot response since the time period of the oscillatory transients (for all the joints of the HEX) is much smaller than the time-window of interest. As a result most of the oscillatory error due to the steady-state approximation gets integrated out. (For instance, the lowest resonant frequency of the boom joint is 1.5 Hz.) This principle governs the actuator model construction.

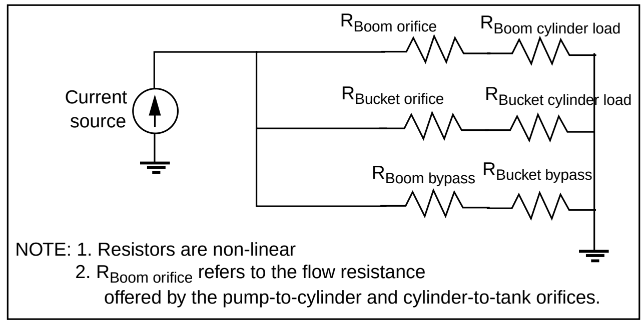

Fig. 4. Electrical equivalent of hydraulic system

The complete excavator model is partitioned into the actuator model and the linkage dynamics. Eqn 4 is used to capture the linkage dynamics, while memory-based learning is used to construct the actuator model as described below.

To understand the construction of the actuator model it would be useful to first understand the basic concept behind the physical operation of the hydraulic system shown in Fig 2. The boom-bucket part of the hydraulic circuit in Fig 2 can be viewed as a parallel combination of resistors as shown in Fig 4.

The flow of hydraulic oil into any cylinder determines the velocity of that cylinder. The flow (current) from the pump (current source) is distributed between the three parallel paths. The flow (current) going down each branch is determined by the ratio of the resistances of the different branches. For a given set of orifice areas - boom, bucket and bypass - and for a given set of boom and bucket cylinder loads, the distribution of flow between the different paths can be determined for a steady-state condition. This in turn allows the determination of the steady-state cylinder velocities.

We therefore approximate the actuator velocity response by the *steady-state* actuator response for a given set of orifice areas and cylinder force loads. The force loads themselves are not restricted to be steady-state forces - they are computed using the dynamic model (Eqn 4) of the excavator. This approximation is made since learning the complete actuator dynamics requires the specification of a set of state variables in addition to the orifice areas and cylinder forces, which greatly increases the dimensionality of the space. The approximation is justified since the machine model being developed is not focused on simulating transients.

The different orifice areas (Fig 2) are controlled by the position of a control spool. For example, the position of the boom control spool determines the boom pump-to-cylinder, cylinder-to-tank, and bypass areas. Thus a single spool position can represent all the orifice area variables for a joint.

A multivariate locally weighted regression technique is used to learn the mapping from the space of inputs - the spool positions and cylinder loads - to the space of outputs (the cylinder velocities). For instance, the boom actuator steady-state velocity is determined from knowledge of the boom and bucket spool positions, and the boom and bucket cylinder loads.

The memory-based learning is performed using a software tool - *Vizier* - developed by Schneider et. al. ([6][7]) at Carnegie Mellon University. *Vizier* allows the use of locally weighted linear regression to learn data sets and make predictions. The best parameters for the regression are determined by a black-box utility available within *Vizier* which performs a number of leave-one-out type predictions on the learning data set before arriving at the best set of parameters.

Vizier is used to construct four Memory-Based Learning tables (or MBL tables) - one for each of the four joints of the excavator, i.e. the boom, stick, bucket, and swing. The input dimensions of the boom table (and bucket table) are boom and bucket spool positions, and boom and bucket cylinder force loads. The input dimensions of the stick table are swing and stick spool positions, swing inertia, and stick cylinder force load. The single output dimension for each of the three joints is the joint velocity.

The swing is more complicated to model since the inertial acceleration term in the dynamic equation is quite significant. This makes it impractical to use the steady-state assumption used for the other three joints. The other three joints - boom, stick, and bucket - are in a vertical plane and have a large gravity load term in the dynamic equation, which is absent for the swing. The acceleration phases of those joints are rather short (during a typical move) while the swing joint response is dominated by acceleration and deceleration phases.The swing table therefore uses the following input dimensions - swing and stick spool positions, stick cylinder force, swing inertia and swing velocity. The output dimension is swing acceleration. Note that the swing inertia is dependent on the position of boom, stick, and bucket joints.

Data Collection: Collecting training data is an important part of any machine learning exercise. Training data for learning the actuator model was collected using a slow but complete analytical machine model[2]. The slow model was driven through a number of motion sequences to adequately cover the operating space for each MBL table. For instance, the boom and bucket joints were actuated in various combinations to obtain adequate coverage of the boom-bucket space, whose dimensions are the boom and bucket spool positions, and boom and bucket force loads. While the spool positions are directly controllable the cylinder forces are not. The motions were therefore repeated for a fully loaded bucket, half-empty bucket, and completely empty bucket to cover the cylinder load dimensions. All motions were performed slowly to minimize transient effects.

The spool positions have a range of ± 11 mm. Data was sampled at a resolution of 1mm along the spool position axes. The cylinder forces were determined by the excavator's configuration. The boom and bucket tables had 5500 points each while the stick and swing had 6400 points each.

Complete Model Construction: The complete excavator model is constructed by partitioning the actuator dynamics and linkage dynamics into two separate problems. Instead of solving them simultaneously they are solved in a serial fashion. First, the linkage dynamic model (Eqn 4) is used to compute the forces for a given excavator state. This force is assumed to remain constant over the time period that the actuator response is simulated using the learned actuator model. The results of the actuator simulation are used to compute a new state, which is used in the linkage dynamic model for force computation as the cycle continues. The steps are spelled out explicitly below.

- Step #1: The dynamic model of the excavator is used to compute the force loads on the different hydraulic cylinders.
- Step #2: The force loads computed in Step #1 are used with the input spool commands to predict the resulting cylinder velocities using the corresponding MBL tables. The swing table uses the current swing velocity to compute the swing acceleration.
- Step #3: The computed velocities (or accelerations) are integrated to obtain an updated excavator state. (Repeat steps 1 through 3)

IV. Results

The above approach was used to construct a complete model of a CAT 325 HEX. The performance of the model was evaluated by comparing it to the performance of the excavator testbed. The results from three tests are shown in Fig 5 through Fig 11. During the first test (Fig 5, Fig 6), the boom and bucket cylinders were actuated to demonstrate the interaction between them, while the second test (Fig 7, Fig 8) demonstrated interaction between the swing and stick joints. In the third test (Fig 9-Fig 11) an operator in the cab of the HEX performed operations similar to that during a normal loading cycle. The HEX was operated manually through joysticks, which control the position of the hydraulic control spools through proportional pilot valves. No soil interaction was involved during any of the tests and therefore no digging forces at the bucket tip were applied. This was done since the excavator testbed is not setup to measure digging forces during interaction with the soil. (The structure of the model however does allow the model to simulate machine motions in response to external tip forces, once the forces are known, since they would simply add to the f_{cyl} term in Eqn 3, Eqn 5)

In the figures below, the actuator commands refer to the displacement of the hydraulic spools (measured indirectly). The

[2] The testbed was not used to collect training data due to our inability to measure spool positions directly on it. Also, the initial attempt at training used a large amount of training data which was much easier to collect from a simulation model (which had been verified to match the testbed).

different orifice areas are controlled by moving the spools. By controlling the orifice areas the operator controls the flow to the hydraulic cylinders, and hence the velocity of the cylinders. Thus, the commands can be viewed as open-loop velocity commands to the machine.

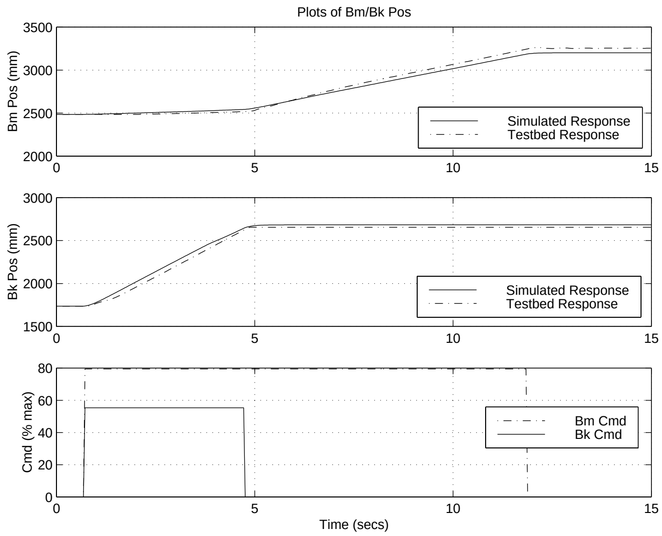

Fig. 5. Boom response (Test #1)

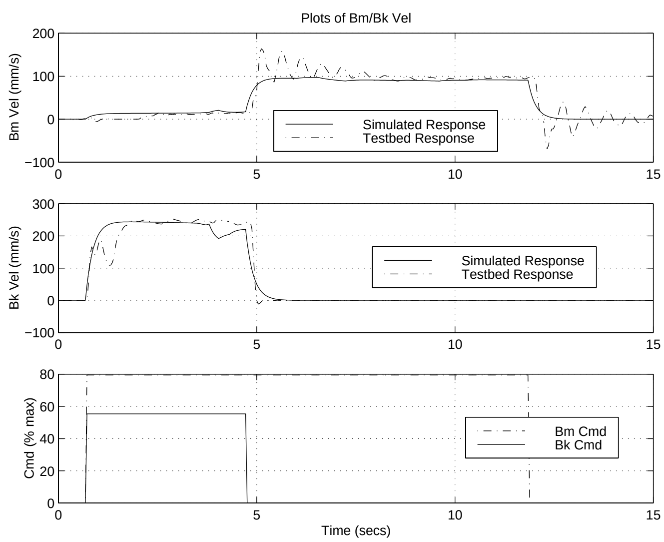

Fig. 6. Bucket response (Test #1)

Inter-actuator coupling is clearly demonstrated in the first two tests. In the first test the boom and bucket joints are both commanded to move but due to the actuator interaction the heavier boom joint does not get very much flow until the bucket has stopped moving. This inter-actuator coupling is primarily because the excavator reaches a power limit, resulting in insufficient actuator flow. The next set of figures show results from the second test where the swing and stick joints were commanded to move simultaneously causing the swing joint to slow down. The swing velocity can be seen to increase dramatically once the stick stops moving.

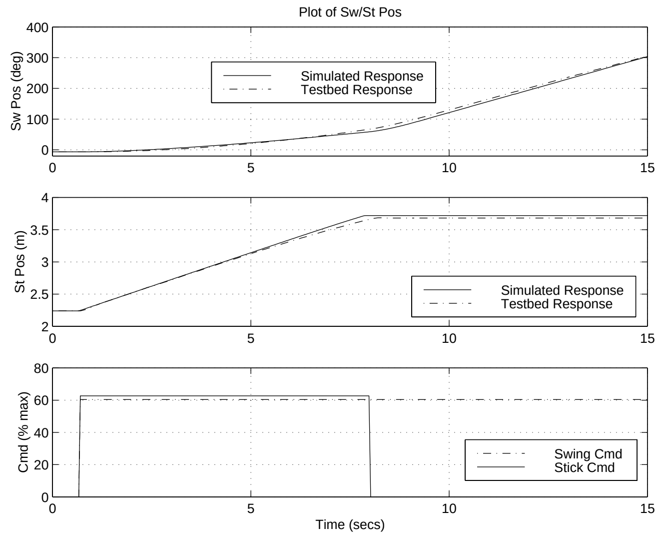

Fig. 7. Swing response (Test #2)

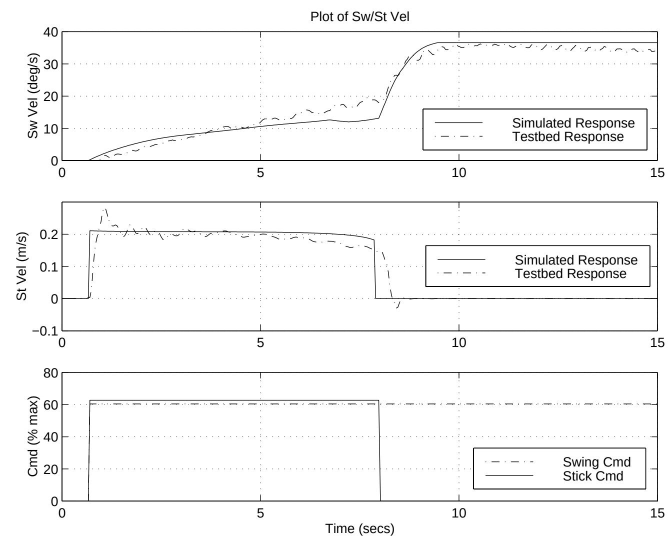

Fig. 8. Stick response (Test #2)

Fig 10 and Fig 11 show the error in the prediction of the position of the bucket tip. Fig 10 shows the contribution due to each of the four joints of the excavator. As expected, small errors in the swing and boom joints contribute to large errors at the bucket tip. These plots were created by using the Jacobian of the excavator to map joint angular errors to cartesian tip position errors.

Fig 11 shows the total error in the prediction of the bucket tip position. This is plotted along with the distance from the base of the boom joint to the bucket tip to give the reader an idea of the scale of the tip position error.

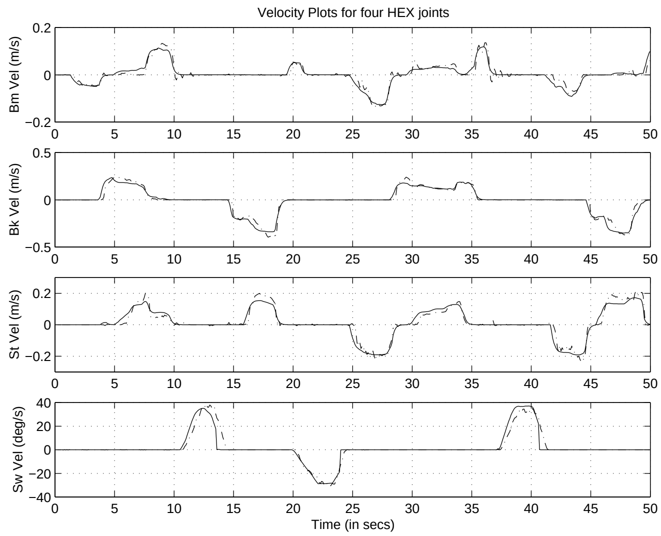

Fig. 9. HEX joint velocities (Test #3)

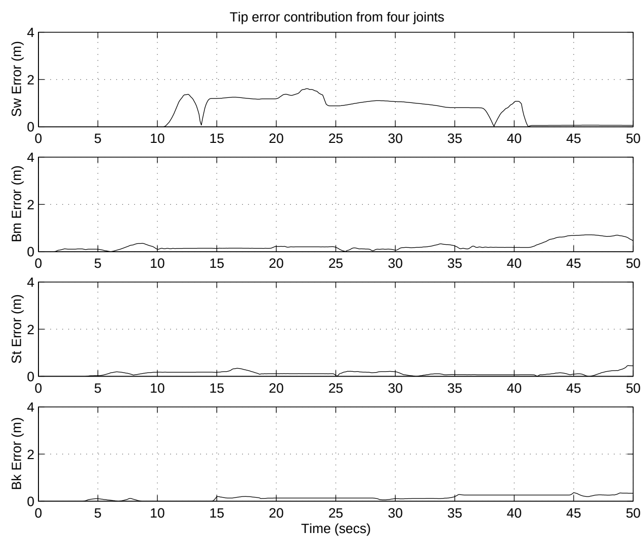

Fig. 10. Tip error contribution due to each of the four joints (Test #3)

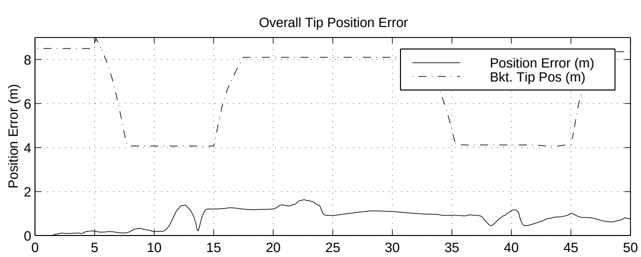

Fig. 11. Overall bucket tip position prediction error (Test #3)

The current implementation of the learned model uses a locally-weighted regression scheme in conjunction with a table-lookup to learn the data. The model runs at a run-time:real-time ratio of 15:1, i.e. simulating 15 seconds of motion requires 1 sec. of computation time on a SUN Sparc 20 workstation.

V. Conclusions

The results show that the learned model does a very reasonable job of predicting the response of a hydraulic excavator during a typical excavating cycle. The mean bucket tip position prediction error is around 1.0m for most of the 50 secs of motion in test #3 (1.5m = width of the excavator's bucket).

This model is focused at capturing the interactions between the different actuators of the excavator and it manages to accomplish this goal fairly well.

In summary, a model of a hydraulic excavator has been constructed by decomposing the complete 8th order non-linear system of equations into two separate models - the 2nd order linkage dynamic model and the actuator model. The two were independently solved with the results of one problem being fed to the other at every time step, instead of solving the complete system simultaneously. The non-linear actuator model was learned using a memory-based learning technique.

The complete excavator model created using this approach is much faster than a complete analytical model. This model cannot simulate actuator transients since the learned actuator model is a steady state model. We believe, though, that it can be used in optimal path planning for robotic hydraulic excavators since the effect of actuator transients does not significantly affect the overall loading cycle operation. The model can also be used for collision avoidance by predicting collisions, and preventing them by not executing commands that cause collisions.

VI. References

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