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:

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.

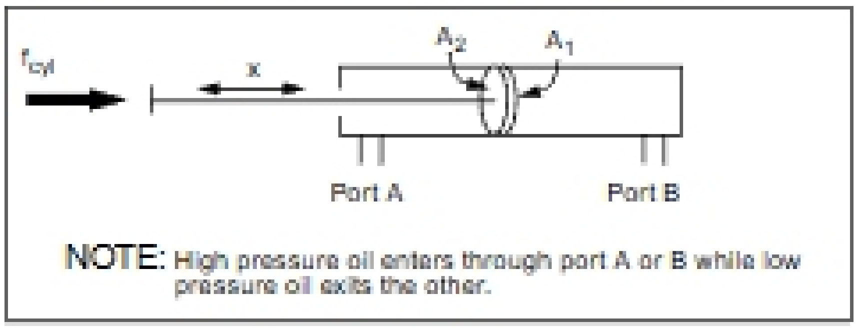

Fig. 3. Schematic of bi-directional hydraulic cylinder

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_i 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.

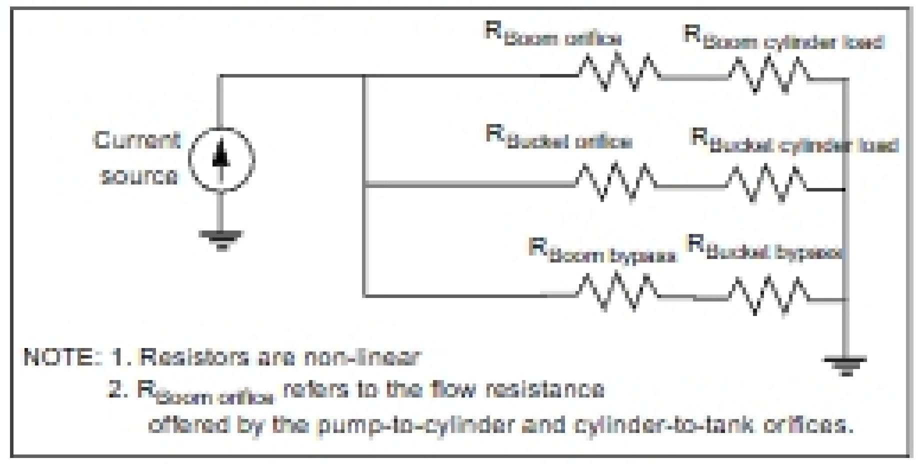

Fig. 4. Electrical equivalent of hydraulic system

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