LEARNING FEEDFORWARD STATE FEEDBACK INTEGRAL CONTROLLER BASED ON ILC AND ENERGY SHAPING FOR NANOMETER POSITIONING

Xiaoming Lu & Hy. D Tran[1]
University of New Mexico
Albuquerque, NM 87131

Abstract

A primary technology driver in high precision manufacturing is the position measurement and control system that allows manufacturers to control the movement of their equipment at extremely high levels of precision. However, time varying and nonlinear dynamics of the stage, especially at nanometer levels, can cause performance degradation of PID (proportional-integral-derivative) controllers.

The performance of a feedback controller can be improved considerably by combining state feedback integral control with a feedforward controller. In tracking control, the nonlinear, time-delay and time-varying dynamics of system can be decomposed into a stochastic part and a deterministic part. The deterministic dynamics can be learned iteratively from the feedback signal. In point-to-point control, the nonlinear dynamics of system can be described based on energy shaping, which is used to design the profile of motion and the feedforward controller. Experiments show that the test stage will follow a step input with a 10 nm steady state error, and track sinusoid and triangle wave inputs with nm level tracking accuracy (both measurement noise limited).

1. Introduction

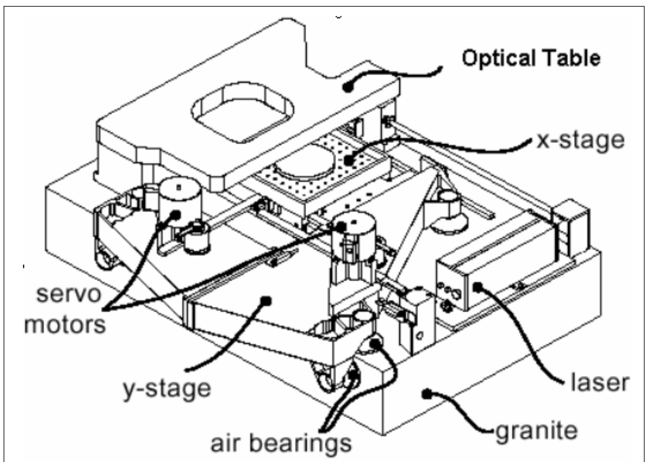

Fig 1 2-dimensional precision stage

Positioning control applications typically fall into two basic categories, tracking and point-to-point. In tracking control, the controlled object must be moved along the desired trajectory. The point to point control problem is concerned with moving an object from one point to another. In either application, feedback uses the positioning error to drive the stage. Reducing transient error requires increasing the feedback gain, which can affect the stability and robustness of the system. Feedforward can be used to improve the transient performance of control systems, by providing most of the control signal during transients, and leaving the feedback controller to compensate for residual errors. Feedforward is therefore generally used in high speed controllers. An air-lubricated capstan drive stage (shown in Fig 1) is used in a precision positioning stage. It

[1] Lu: luxm@unm.edu Tran: tran@me.unm.edu This work supported by ARO DAAD19-99-1-0196

exhibits very low friction and no backlash. However, at the nanometer level, its dynamics still exhibit time varying and nonlinear properties caused by friction, thereby degrading the performance of the off-the-shelf PID controller. We demonstrate improved performance by using state integral feedback combined with an iterative learning feedforward controller.

2. Iterative learning feed-forward tracking controller

As shown in Fig. 2, the learning control system consists of a feedforward controller and a feedback controller. The feedback controller provides the learning signal for the feedforward controller. Furthermore, it determines minimum tracking performance at the beginning of learning. Finally, the feedback controller compensates for random disturbances. Adding an integrator to the state feedback increases the type number of the system, allowing it to track with nm level accuracy. However, we must now trade off between high performance and stability. A high gain integrator will cause instability. With lower gains, the state feedback integral controller does not help to speed up the transient response very much. A feedforward controller improves the control performance by including a feedforward term to the feedback output so that the controller can react to the command signal more quickly. Also, feedforward is outside the feedback loop, and thus does not affect the system's stability. Finally, feedforward can help minimize tracking error during motion by generating most of the DAC output signal from the motion profile instead of the position error.

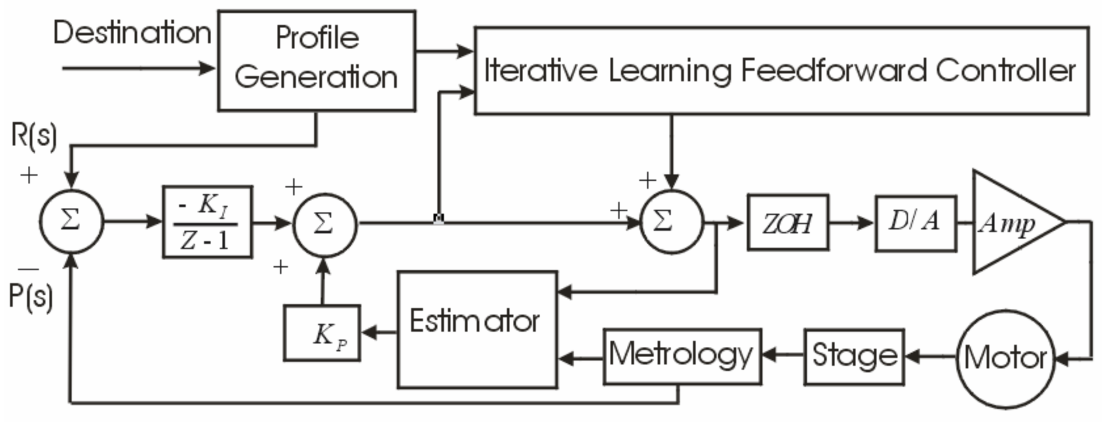

Fig 2 The structure of state feedback integral feedforward controller

For linear system, the feedforward gains can be designed based a model of the plant. In order to correctly compensate for the deterministic time varying and nonlinear properties in the system dynamics, the learning feedforward controller is implemented as a function approximator. During control, the input-output relation of the function approximator is adapted such that it learns the inverse plant and the compensation of the reproducible disturbances. A learning signal can be obtained from the output of the feedback controller by utilizing the fact that the system is operated repeatedly for the same task. In each iteration, the system dynamics $p_i(t)$ can be decomposed into a stochastic (non repeatable) part ${p^{NR}}_i(t)$ and a deterministic (repeatable) part ${p^R}_i(t)$

$$p_i(t) = p_i^R(t) + p_i^{NR}(t) \tag{1}$$

The deterministic part is a repeatable phenomenon, recurring in the same way when a specific motion is repeated. To minimize disturbances caused by the stochastic part of the plant during learning, $p^R{}_i(t)$ is learned gradually. In every iteration, stochastic noise is removed by a digital filter.

For practical digital control systems, it is reasonable to assume the following:

(1) The plant to be controlled is internally stable.

(2) The desired control input $u_d(t_k)$ exists uniquely for a given desired output trajectory $y_d(t_k)$.

(3) The control input $u_i(k)$ can be decomposed into a stochastic (non repeatable) part $u_i^{NR}(t_k)$ and a deterministic (repeatable) part $u_i^R(t_k)$.

$$u_i(t_k) = u_i^R(t_k) + u_i^{NR}(t_k) \tag{2}$$

where $u_i^{NR}(k)$ is a random variable with zero mean, and bounded by

$$h_M * u_i^{NR} \le \varepsilon^* \tag{3}$$

In Equation (3), $\varepsilon *$ is usually very small. The * operator denotes discrete convolution. Therefore $h*$ is a mapping operation between input and output. The learning and updating law is hence given by

$$u_{i+1}(t_k) = u_i^{ff}(t_k) + \gamma h_M * u_i^{fb}(t_k) \tag{4}$$

where γ represents learning rate, and satisfies

$$0 < \gamma < 1 \tag{5}$$

The overall control is simply

$$u_{i+1}(t_k) = u_{i+1}^{ff}(t_k) + u_{i+1}^{fb}(t_k) \tag{6}$$

It can be proved [5] that $u_i^{ff}(t_k)$ will converge to $u_i^R(t_k)$, that is

$$\lim_{i\to\infty} u_i^{ff}(t_k) = u_i^R(t_k) \tag{7}$$

3. Learning feedforward controller in point to point based on energy shaping

The point to point control problem (PTP) is concerned with moving the control object from one point to another fast and accurately. The difficulties of PTP lie in:

(1) The trajectory changes abruptly. It is impossible to make the system follow up the set-point changes exactly, as this would incur non-causality or an impulse control signal at the instant of set-point changes. Furthermore, the rate and amplitude of input voltage is

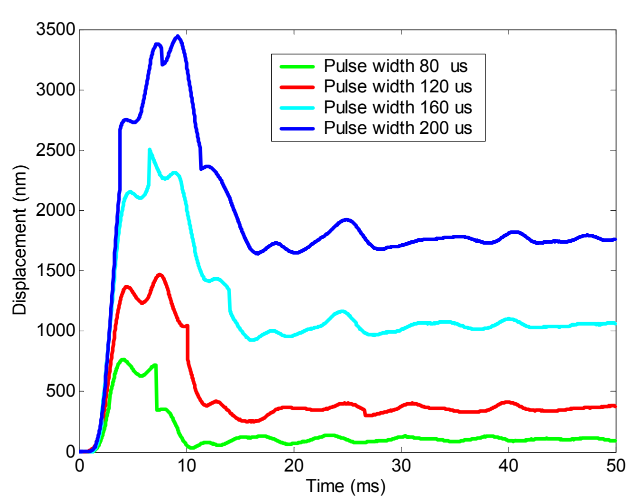

Fig 3 Moving distance of the stage is a non-linear function of pulse width

limited by the dynamic properties of D/A, amplifier and motor, including saturation nonlinearities.

(2) Open loop tests revealed that the capstan friction drive is non-linear, including time-delay dynamics and time varying dynamics with uncertainty. The non-linear, time-delay and time-varying dynamics of the system model can be described based on energy shaping. Energy is one of the fundamental concepts in science and engineering practice, where it is common to view dynamical systems as energy-transformation devices. The plant of the capstan friction drive can be modeled as a lumped-parameter system interconnected to the external environment through some power variable $u \in R^m$ (e.g., input currents or voltages of system). Of course, the system satisfies the energy balance equation

$$H\left[x(t)\right] - H\left[x(0)\right] = \int_0^t u(s)u^T(s)ds - d(t) \tag{8}$$

where d(t) is a nonnegative function that captures the dissipation effects (e.g. due to frictions and resistances in the amplifier and motor), $x \in R^n$ is the state vector (displacement x and velocity $\frac{dx}{dt}$), H(x) is the total energy function, which include elastic potential energy during presliding, gravitational potential energy as the result of plant vertical position (i.e., height) and kinetic energy while the stage is moving. In point to point (PTP), the input electronic energy is transformed into the thermal energy caused by friction and resistance. When the stage is moved from one point to another point (from one equilibrium to another equilibrium of dynamic system), the elastic potential energy and kinetic energy of the system reach minima in initial position and target position, considering that the stage vibrates around equilibrium point. Also, friction can be modeled as a stiff spring behavior with damper in presliding regime, making it possible that every position in the working range of stage can be the candidate of equilibrium. So the total displacement in the presence of energy dissipation effects is a non-linear function of input electronic energy.

Given the limited control authority, maximum energy should be inputted into the plant in the minimum possible time in order to minimize the time to destination, resulting in a pulse input. Also, maximum amplitude voltage will guarantee breakaway of static friction in minimum time. After breakaway, the plant will be governed by macro-dynamics model. Obviously, the total displacement in the presence of energy dissipation effect is then a non-linear function of pulse width t_p for fixed maximum amplitude

$$d = f(T_w, A_m) \tag{9}$$

The function $d = f(T_w, A_m)$ can be determined experimentally, and results are shown in Fig 3.

The motion of stage can be divided into four states: move forward, idle, move back, and steady state. The trajectory in the “move forward” states can be used to design the profile of motion (trajectory) in order to smooth out the set-point references in PTP control, and convert point to point problem into a tracking problem. The position of steady state is also a non-linear function of pulse width, which is used to determine one of the feedforward controller signals $A_m T_w$. The deterministic dynamics of the positioning system can be further learned by an iterative feedforward controller. The deviation of trajectory in the motion caused by non-deterministic dynamics or disturbances are then compensated by the state feedback integral controller.

The overall control is then

$$u_{i+1}(t_k) = \begin{cases} A_m & t_k \le T_w \\ u^{ff}_{i+1}(t_k) + u^{fb}_{i+1}(t_k) & t_k > T_w \end{cases} \tag{10}$$

4. Experiment and results

The optical nanolithography stage testbed (shown in Fig 1) used for the experiments The plant is an air-bearing, capstan drive lithography stepper. The moving stage is supported by air bearings on the granite surface table. An XY grid-based planar encoder system is used to measure 2-dimensional planar displacements of the stage, which avoids the turbulence effects which are commonly encountered with laser interferometers or the Abbe errors associated with separate linear scales. The XY grid measurement resolution is 0.3nm. The update rate of metrology is 375 kHz, which is adequate for high performance servomechanism.

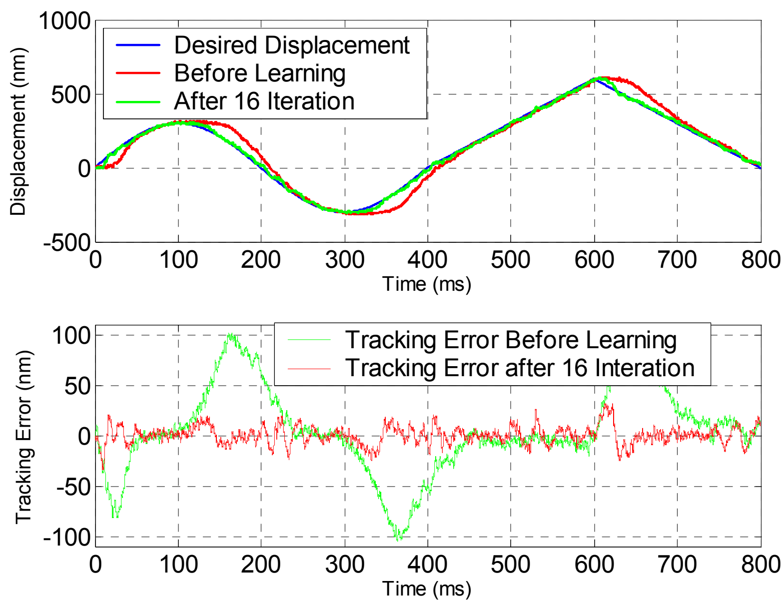

Fig 5 Tracking error before and after 14 iterations

An iterative learning feedforward controller is implemented digitally with a TI TMS320C67 floating point digital signal processor, on an Innovative-DSP M67 card. The sampling period is 10μs. The 16 bit D/A output from the DSP board is amplified and then drives the capstan DC motor.

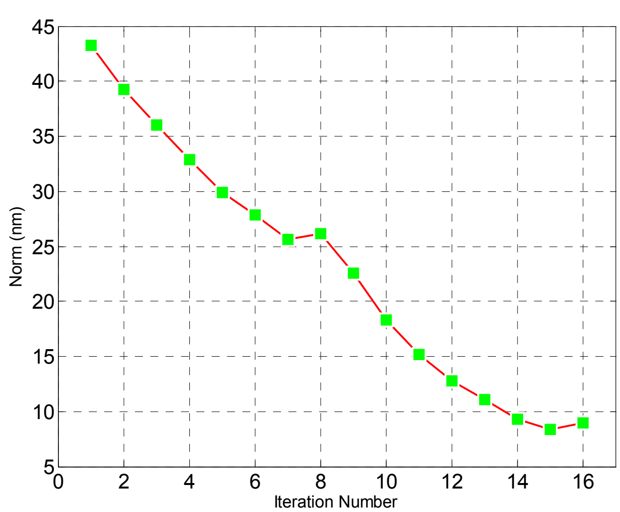

Fig 4 The 2-norm of tracking error in subsequent iteration

Fig 4 shows the tracking error before and after 14 iterations. There are two remarkable things about the tracking error after convergence. First, most important, the tracking error is reduced by a factor of 10, compared to the error before the learning iteration. Also, possible non-linear effects, like friction in capstan drive and time delay, appear reproducible, and consequently can be learned. Obviously, the iteration has converged after approximately 14 iterations. The L_2 convergence is clearly visible in Fig 5 where the 2-norm of the tracking error in subsequent iterations are plotted. This once more stresses the practical usefulness of a learning feedforward controller. Although the theoretical convergence results are asymptotic in nature, in practical situations convergence is obtained in a finite time.

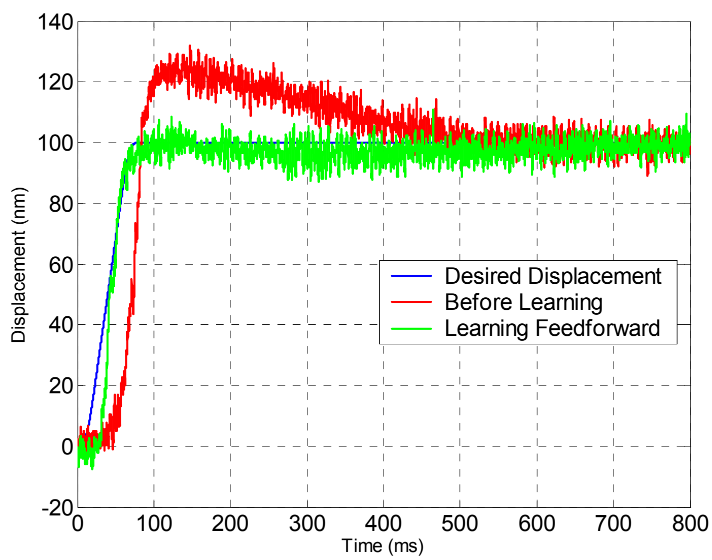

Fig 6 Positioning error of learning feedforward controller based energy shaping

Fig 6 shows the positioning error of leaning feedforward controller based on energy shaping in point to point control. After learning, the stage follows the desired profile, and reaches final position with nm accuracy. Obviously, overshoot and settling times are minimized by using the learning feedforward controller, which adapts for dynamic behavior caused by the time varying and nonlinear properties inherent in the positioning systems.

References

[1] Junhong Mao, Hiroyuki Tachikawa, Akira Shimokohbe, Precision positioning of a DC-motor-driven aerostatic slide system, Precision Engineering, Vol 27,No1, January 2003, p32-41

[2] Rao G S, Ro P I. Submicrometer control of a traction drive using state feedback and estimation, Precision Engineering; 17: p125-130. (1995)

[3] C.L.Chao,J.Neou. Model reference adaptive control of air-lubricated capstan drive for precision positioning. Precision Engineering; 24: p285-290.(2000)

[4] Moore, K.L, Dahleh, M., and Bhattacharrya,S.P., "Iterative learning control: a survey and new results", Journal of Robotics, p563-594, (1992)

[5] Y.Chen, T.H Lee, J.X Xu, and S. Yamamoto, "Noncausal filtering based on design of iterative learning control ", Proc. 1st Int Workshop Iterative Learning Control, p63-70 (1998).