Some Experiences of the use of Iterative Learning Control for Performance Improvement in Robot Control Systems

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SOME EXPERIENCES OF THE USE OF ITERATIVE LEARNING CONTROL FOR PERFORMANCE IMPROVEMENT IN ROBOT CONTROL SYSTEMS

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Abstract. Some aspects of the use of learning control for improved performance in robot control systems are studied. The learning control signal is used in combination with conventional feed-back and feed-forward control. The effects of disturbances, unmodeled dynamics and friction are studied theoretically and in simulations of a simplified model of a robot arm. Convergence and robustness aspects of the choice of filters in the updating scheme of the learning control signal are studied.

Keywords. Robotics, Iterative Learning Control, Friction, Disturbance signals

1. INTRODUCTION

Learning control has been an active research area for more than a decade, mainly inspired by the pioneering work of Arimoto et al, (Arimoto *et al.* 1984). Due to the repetitive nature of many operations in robotics this has been a main area of interest in research on and applications of learning control, as discussed in, for example, (Craig 1988), (Horowitz 1993) and (Panzieri and Ulivi 1995). An important issue in learning control is the convergence properties of the learning procedure. This issue was addressed already in (Arimoto *et al.* 1984) and further studied in, for example, (Heinzinger *et al.* 1992), (Hideg 1992), (Liang and Looze 1993) and (Amann *et al.* 1995).

In this paper we shall consider iterative learning control as a complement to conventional feed-forward and feed-back control. We shall mainly consider linear systems, but also study the effects of non-linear friction. The aim is to illustrate the fundamental properties of the ILC algorithm applied in this framework, with focus on convergence, robustness and disturbance effects.

2. THE CONTROL PROBLEM

Consider the problem of controlling a SISO linear system

$$Y = G(U + D) \quad (1)$$

where U , Y and D represent input, output and load disturbance respectively, and G is the transfer function. Capital letters indicate that we work with transformed signals, and the discussion covers both continuous time

and discrete time signals unless otherwise stated. The system is controlled by combined feed-forward and feed-back using

$$U = F_f Y_D + F(Y_D - (Y + N)) \quad (2)$$

where Y_D and N denote the reference signal and a measurement disturbance respectively. Furthermore F_f and F denote the transfer functions of the feed-forward and the feed-back regulators. We shall consider the control signal generated by the feed-back regulator as error signal, i.e.

$$E = F(Y_D - Y) \quad (3)$$

In robot applications F is often a PD-regulator, which means that the error signal will be a combination of the position error and the velocity error. We then get

$$E = G_C((G^{-1} - F_f)Y_D - D + FN) \quad (4)$$

where G_C is the transfer function of the closed loop system, i.e.

$$G_C = \frac{FG}{1 + FG} \quad (5)$$

3. ITERATIVE LEARNING CONTROL

The use of feed-forward and feed-back control will in many cases give very good properties of robot control systems, but in order to further improve the performance we shall consider the use of learning control. We therefore add a correction signal ΔU_k to the input torque according to Figure 1. The input signal will thus be given by

$$U_k = F_f Y_D + F(Y_D - (Y_k + N_k)) + \Delta U_k \quad (6)$$

Fig. 1. A control system with feed-forward, feed-back and an ILC correction signal

where the index k denotes the iteration number.

Considering only linear operations the updating of the correction signal can, in the frequency domain, be expressed as

$$\Delta U_{k+1} = \sum_{j=0}^k \bar{H}_j E_j \quad (7)$$

where $\bar{H}_j$, $j = 0, \dots, k$ are linear filters. For convenience we shall here however consider recursive update equations on the form

$$\Delta U_{k+1} = H_1 \Delta U_k + H_2 E_k \quad (8)$$

where H_1 and H_2 are linear filters. The choice of the filters H_1 and H_2 is a main task when designing a learning control algorithm, since the filters determine the convergence and robustness properties. One method for choosing appropriate filters in the update equation is presented in (de Roover 1996) where methods from design of robust controllers are applied. The filters are designed to give a convergent ILC algorithm despite uncertainties in the process model. In (Gorinevsky *et al.* 1995) the problem is considered from a different viewpoint and the choice of the ILC input signal is formulated as an optimization problem, resulting in a time domain updating equation for the input signal.

4. CONVERGENCE PROPERTIES

We shall now investigate how the error signal behaves when the update equation (8) is applied. Let us first introduce the signal E_0 defined by

$$E_0 = G_C((G^{-1} - F_f)Y_D) \quad (9)$$

which is the (disturbance free) error signal obtained in the first iteration when no correction signal is added, i.e. $\Delta U_0 \equiv 0$. This gives

$$E_{k+1} = E_0 - G_C H_1 \Delta U_k - G_C H_2 E_k - G_C D_{k+1} + F G_C N_{k+1} \quad (10)$$

and by adding and subtracting relevant terms on the right hand side we get

$$\begin{aligned} E_{k+1} = & (1 - H_1)E_0 + H_1(E_0 - G_C \Delta U_k - G_C D_k \\ & + F G_C N_k) - G_C H_2 E_k + H_1 G_C D_k \\ & - G_C D_{k+1} - H_1 F G_C N_k + F G_C N_{k+1} \end{aligned} \quad (11)$$

which implies the following error update equation

$$\begin{aligned} E_{k+1} = & (1 - H_1)E_0 + (H_1 - G_C H_2)E_k \\ & + G_C(H_1 D_k - D_{k+1}) + F G_C(N_{k+1} - H_1 N_k) \end{aligned} \quad (12)$$

A corresponding equation is presented in (Panzieri and Ulivi 1995) for the open loop case and for load disturbances only.

The convergence properties are determined by the homogeneous part of the difference equation (13) and referring to (Craig 1988) the convergence condition, in the continuous-time case, is that

$$|H_1(i\omega) - H_2(i\omega)G_C(i\omega)| < 1 \quad \forall \omega \quad (13)$$

Provided that the learning procedure converges the error signal becomes

$$\bar{E} = \frac{1 - H_1}{1 - H_1 + G_C H_2} E_0 \quad (14)$$

We see that by using $H_1 \neq 1$ we are not able to eliminate the error completely, but as will be seen later other advantages are obtained by this choice. In e.g. (Owens 1993) the case $H_1 = \mu$, where $\mu < 1$ is a scalar, is studied. An alternative parameterization of the filters in the learning law was presented in (Mita and Kato 1985), where

$$H_1 = \frac{1}{1 + V} \quad H_2 = \frac{1}{1 + V} H \quad (15)$$

and where V and H are filters. In (Mita and Kato 1985) this configuration is used with H scalar. The condition for convergence now becomes

$$|1 - H(i\omega)G_C(i\omega)| < |1 + V(i\omega)| \quad (16)$$

and it is obvious that the stability region can be extended by a suitable choice of the filter V , resulting in a so called stabilizing circle. By letting V be frequency dependant the stability region can be extended in a frequency dependant way.

5. DISTURBANCE EFFECTS

A number of observations can be made using equation (13). Let us first consider the case $H_1 = 1$, which implies the update equation

$$\begin{aligned} E_{k+1} = & (1 - G_C H_2)E_k + G_C(D_k - D_{k+1}) \\ & + F G_C(N_{k+1} - N_k) \end{aligned} \quad (17)$$

The disturbances contribute to the error equation by their differences between the iterations. If a disturbance is of repetitive nature in the sense that the disturbance signals $d_k(t) = d_{k+1}(t)$ and $n_k(t) = n_{k+1}(t)$ for all k the contribution to the error difference equation is zero. This assumption is more likely for the load disturbance where for example load disturbances due to gravitational forces can be expected to be rather similar during different iterations. Measurement disturbances, on the other hand, are more likely to be of random character which means that $n_{k+1}(t) \neq n_k(t)$ in general, and there will hence always be a driving term on the right hand side of equation (18) that prevents $E_k(s)$ from tending to zero.

Let us also consider the situation with $H_1 \neq 1$, neglect measurement disturbances and assume that $d_k(t) = d(t) \forall k$. This corresponds to the error difference equation

$$E_{k+1} = (1 - H_1)E_0 + (H_1 - G_C H_2)E_k - G_C D(1 - H_1) \quad (18)$$

The load disturbance will act as a driving term similar to the initial error E_0 .

6. SIMULATION EXAMPLE

6.1 System description

We shall consider a simplified description of a single robot joint modeled as a double integrator, i.e.

$$G(s) = \frac{1}{Js^2} \quad (19)$$

Since the system is computer controlled we shall use the discrete time representation given by the transfer function

$$G(z) = \frac{T^2(z+1)}{2J(z-1)^2} \quad (20)$$

where $J = 0.0094$ is the moment of inertia. The system is controlled by a discrete time PD-regulator given by

$$F(z) = K_P + \frac{K_D}{T} \frac{(z-1)}{z} \quad (21)$$

where $K_P = 12.7$ and $K_D = 0.4$. The feed-forward filter is chosen as a double differentiation represented by

$$F_f = \frac{2J^*(z-1)^2}{T^2 z^2} \quad (22)$$

where J^* is the estimated moment of inertia. The correction signal will be updated according to equation (8) where $H_1(z)$ and $H_2(z)$ are filters that both may be non-causal. The model is simulated using 1 kHz sampling frequency. For evaluation of the algorithm we shall apply the reference trajectory shown in Figure 2. This

is a comparatively smooth trajectory and in real robot applications trajectories with more sharp acceleration profiles can be expected.

6.2 Unmodeled dynamics

The first goal is to investigate how the learning control approach can deal with unmodeled dynamics. We shall consider the case when there is an 30 % error in J^* , i.e. the control system is based on an incorrect value of the moment of inertia. For $H_1(z) = 1$ the ideal choice of H_2 would be to choose it as the inverse of $G_C(z)$, which, theoretically, would result in convergence to zero in one step. This is however an unrealistic choice since it requires exact knowledge of the system and results in a filter with very high gain for high frequencies. Instead we consider

$$H_2(z) = \hat{G}_C^{-1}(z)(1 - H_B(z)) \quad (23)$$

where $\hat{G}_C(z)$ denotes the closed loop transfer function we obtain by using the model of the open loop system and $H_B(z)$ is a Butterworth high pass filter (here of second order) for which the gain tends to one for high frequencies. Choosing $H_2(z)$ according to this design rule, with cut-off frequency of the high pass filter equal to 0.4 times the Nyquist frequency, gives the Nyquist curve depicted in Figure 3. Figure 3 also shows $G_C(z)$ for comparison. The whole Nyquist curve is now inside the learning circle while it for large frequencies tends to the origin. The learning control algorithm is then tested in simulations. Figure 4 shows the FFT of the error signal $e_k(t)$ for different iterations.

6.3 Friction

Since all robots contains some amount of friction it is of interest to evaluate the performance of the learning control algorithm under such conditions. The dynamics of the robot is then described by

$$J\ddot{y}(t) = u(t) - f \operatorname{sign}(\dot{y}(t)) \quad \dot{y}(t) \neq 0 \quad (24)$$

and

$$J\ddot{y}(t) = 0 \quad |u(t)| \leq f, \quad \dot{y}(t) = 0 \quad (25)$$

where the coefficient f is chosen such that the friction force corresponds to 30% of the maximum torque, in this case 0.12. The linear analysis carried out above is not applicable when we have introduced nonlinear elements into the problem but we can still evaluate the learning control algorithm using simulations. If we carry out the same simulations as in the previous case we get the result shown in Figure 5.

Even though the filter $H_2(z)$ designed above was robust enough to handle that it was designed based on an incorrect value of the moment of inertia it is of interest to further improve the stability margins of the learning control algorithm. This can be done by using the filter $V(z)$ discussed above. In the simulations we have chosen $V(e^{i\omega})$ as a first order high pass filter with cut-off frequency 0.7 times the Nyquist frequency. The high frequency gain of the filter is 0.1, which means that the stability region is extended in the high frequency regions. The result of this choice is shown in Figure 3, where the obtained stabilizing circle is shown. In Figure 6 the simulations results are shown. The convergence properties are comparable with what was obtained without the use of $V(e^{i\omega})$ and the error converges to approximately the same level. We have hence achieved the improved robustness without any significant increase in the error level.

7. CONCLUSIONS

The potential of learning control as a way of improving the performance of robot control systems has been investigated. Convergence and robustness aspects of the choice of design filters have been discussed. The proposed update method of the learning control signal works well also in the presence of nonlinear friction.

8. ACKNOWLEDGMENTS

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Fig. 2. Reference signal

Fig. 3. Nyquist curves for $G_C H_2$ for the choices $H_2 = 1$ and $H_2 = \hat{G}_C^{-1}(1 - H_B)$. Learning circle and stabilizing circle.

Fig. 4. Error signal spectrum for iterations 0, 5 and 10. Linear system. $H_2 = \hat{G}_C^{-1}(1 - H_B)$.

Fig. 5. Error signal spectrum for iterations 0, 5 and 10. System with friction. $H_2 = \hat{G}_C^{-1}(1 - H_B)$.

Fig. 6. Error signal spectrum for iterations 0, 5 and 10. System with friction. $H = \hat{G}_C^{-1}(1 - H_B)$. V high pass filter