A&QT-R 2004 (THETA 14)
2004 IEEE-TTTC International Conference on Automation, Quality and Testing, Robotics
May 13 – 15, 2004, Cluj-Napoca, Romania

Robot manipulator controller based on adaptive learning rules

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Abstract: An adaptive PID learning it is proposed controller which combines an adaptive PID feedback control scheme and a feedforward input learning design for the case of a periodic robot motion. The adaptive PID controller will overcome the transient response of the robot dynamics while the feedforward learning controller stands for computing the desired actuator torque needed for the nonlinear dynamics compensation in steady state. All the error signals that could appear in the learning control system are bounded and the robot motion trajectory will converge to the desired one asymptotically. On the other hand, the developed adaptive PID learning controller is compared with the fixed PID learning controller from the stability point of view meaning to assure the gain bound, the performance of tracking and the most important: the convergence rate of learning system.
Keywords: Adaptive control; Robot control; PID, Learning rule.

1 Introduction

The recent trend in learning control methods focuses on the high-gain feedback based learning control schemes which add the feedforward learning terms for nonlinearity compensation to the standard linear PID-type feedback controller. The concept of designing these learning controllers is to use the linear feedback for stabilization and feedforward learning input for nonlinearity compensation and tracking of fast motion. Analyzing the stability of the high-gain-based learning controller leads directly to the lower bound condition on the size of feedback PID gains that states for a magnitude of PID gains set larger to provide the upper bound of tracking error. The drawbacks implied by the high-gain feedback such as actuator saturation, noise unsafety, actuator overdesign are overcame by some learning control schemes that introduce an additional nonlinearity compensation term in the feedforward path of the closed-loop system (Dawson et al., 1991; Kuc&Lee, 1991; Messner et al., 1990).

The approach presented in this paper consists in a learning control scheme capable to overcome the disadvantages of the developed controllers such as the high-gain feedback assumption and computational complexity. There is developed a learning control scheme based on the conventional PID-type feedback controller next to the linear PID feedback stabilization and feedforward learning for nonlinearity compensation and tracking. In other words, the difference resides in using the adaptive PID gains instead of the fixed PID gains. For this there are additional learning rules introduced to continuously update the PID gains for stable learning operation. The convergence of the learning operation is assured by removing the lower bound condition on the size of PID gains imposed on the high-gain feedback learning control methods. The improvement consists in the magnitude of the feedback gain that does not need to meet the lower bound inequality which was derived as a sufficient condition for convergence of the learning system. More than that, the learning control scheme is simplified in comparison to the feedforward compensated scheme presented in Dawson et al., 1991; Kuc&Lee, 1991; Messner et al., 1990. It is also reduced the computational load required for real-time parameter identification.

The conventional linear PID feedback controllers are extensive in current commercial robot system due to their advantageous properties such as robustness, reliability and not the last one and the more important simplicity aspect. Even that these kind of linear PID controllers are not satisfactory for precise control of robot manipulators equipped with direct-drive actuators, the nonlinearities in the coupling and gravity terms are treated locally, for each joint leading to a reasonably good performance

2 The dynamics of the robot arm model

It is considered the case of a rigid robot manipulator system whose dynamics is described by the equation bellow:

$$D(q(t))\ddot{q}(t)+B(q(t),\dot{q}(t))\dot{q}(t)+f(q(t),\dot{q}(t))+d(t)=\tau(t),$$

where $q(t)\in R^n$ denotes the generalized joint variables, $D(q(t))\in R^{n\times n}$ is the inertia matrix, $B(q(t),\dot{q}(t))\dot{q}(t)\in R^n$ is the centripetal plus Coriolis force vector, $f(q(t),\dot{q}(t))\in R^n$ is the gravitational plus frictional force vector, $\tau(t)\in R^n$ is the joint control input vector and *d(t)* is the unknown disturbance vector which is assumed to be bounded.

When the robot manipulator is performing a repetitive task, the desired robot trajectory and the unknown inverse dynamics inputs can be specified using T-periodic functions.

3 The proposed fixed PID learning algorithm

In the specified conditions, the fundamental learning control problem is to find a learning controller that is able to track the desired trajectory. The control scheme mixes two input components: a feedback input module ($\tau_{fb}(t)$) and a feedforward input constituent :

$(\tau_l(t))$: $\tau(\mathrm{t})=\tau_{fb}(\mathrm{t})+\tau_l(\mathrm{t})$ (1)

The feedback control input $\tau_{fb}(t)$ must stabilize the closed loop system and is computed from the conventional PID control scheme. Applying the control input to error system, it is obtained a set of nonhomogenous differential equation:

$$C_d\ddot{e}+(E_d+K_D)\dot{e}+(F_d+K_P)e+K_I\int e=\tilde{\tau}_l\,,\tilde{\tau}_l=\tau_d-\tau_l \qquad (2)$$

Following the approach of (Kuc at al.,1991), the repetitive learning rule can be derived from the learning input τ_l: $\tau_l(t)=\Pr[\tau_l(t-T)]+\beta z(t)$ where *z(t)* is the positive learning gain and Pr[·] denotes the projection operation that limits its argument within a bounded interval.

4 Adaptive PID learning control

The fixed PID gains should satisfy the lower bound condition to guarantee the stability of the homogenous part of error dynamics equation. This condition can be removed if the adaptive PID gains are used instead of constant ones.

The basic idea is to update the PID gains using adaptive gain learning rule s as well as the learning control inputs by adding the feedforward input learning rules. So, the adaptive controller will be able to keep the error bound of learning system within a reasonable region without using the lower bound gain conditions that guarantee the stability.

First, the error system is rearranged as:

$$C_d\dot{z}+\left(E_d+K_D^0\right)z+K_I^0\int z+K_P^0e=\tilde{\tau}_l+\tilde{K}_Dz+\tilde{K}_I\frac{1}{\alpha}\int z+\tilde{K}_{PID}e \qquad (3)$$

where $\{K_D^0,K_I^0,K_P^0\}$are gain matrices with nominal values, $\tilde{K}_D=K_D^*-K_D$, $\tilde{K}_I=K_I^*-K_I$, $\tilde{K}_{PID}=K_{PID}^*-K_{PID}$, $K_{PID}=K_P-\frac{1}{\alpha}K_I-\alpha K_D$, and $\{K_D^*,K_I^*,K_P^*\}$ are the desired gain matrices. $K_D^*\equiv\alpha C_d+K_D^0,K_I^*\equiv\alpha K_I^0,K_{PID}^*\equiv K_P^0-\alpha^2C_d+\alpha E_d-F_d$. Hence, the desired proportional gain can be calculated as:

$$K_P^*\equiv\alpha K_D^*+\frac{1}{\alpha}K_I^*+K_{PID}^*=K_P^0+K_I^0+\alpha K_D^0+\alpha E_d-F_d \qquad (4)$$

It is also introduced an additional learning rules for PID gains estimation.

It can be proved that the adaptive PID learning system (Figure 1) with the presented learning rules converge.

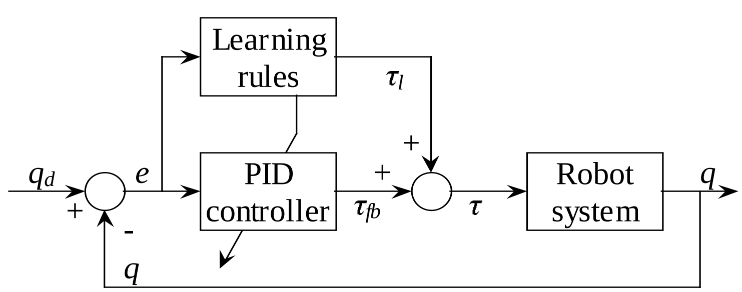

Figure 1Schematic diagram of the adaptive PID learning controller

The algorithm consists in three main steps:

(S1): Choose the nominal gain matrices of $\{K_D^0, K_I^0, K_P^0\}$ positive and symmetric, where the fixed gains are bounded.

(S2): Select the initial gain matrices so that $\{K_D^0, K_I^0, K_P^0\} \geq \{K_D^*, K_I^*, K_P^*\}$.

(S3): Set the projection bounds ($\{\underline{k}_{ij}, \bar{k}_{ij}\}$) of PID learning rules to satisfy the inequality $k_{ii} > \sum_{\substack{j=1 \\ j \neq i}}^{n} k_{ij}^m$, where $k_{ii}'s$ are diagonal elements of PID gain matrices and $k_{ij}^m - \max\{|\underline{k}_{ij}|, |\bar{k}_{ij}|\}$.

5 Experimental results

A robot manipulator design will be used to apply the fixed and adaptive PID learning control scheme, which are ulterior compared with each other. Quite good amount of the experimental data as well as simulation results were obtained by applying the learning controller to a SCARA robot manipulator. In table 1 are presented the experimental results in which the rms position errors of adaptive PID learning system decrease as the learning proceeds and reduce to about 1% of the initial errors after 50 periods.

Throughout the simulation and experiments, the adaptive PID learning controllers show better performance than the fixed ones in tracking and the rate of error convergence even when they do not necessitate the lower bound conditions on the size of feedback gains for stability of learning operation. It was also observed that the learning rules using the current errors work better than the learning rules with the update error of previous trial due to usage of more recent information in updating the learning inputs and PID gains.

Computer simulations demonstrate the feasibility and effectiveness of the proposed adaptive PID learning controller for on-line learning of periodic robot motion.

Table 1
RMS position and velocity errors using learning rules

Trials	Possition error		Velocity error	
	Link 1	Link 2	Link 1	Link 2
1	0.0685	0.0425	0.1687	0.0623
5	0.0091	0.0031	0.0254	0.0124
25	0.0024	0.0004	0.0142	0.0054
50	0.0007	0.0001	0.0112	0.0031

6 Conclusions

The purpose of the presented control scheme based on adaptive PID learning rule is mainly to put in evidence the advantages of applying it on an uncertain robot arm performing periodic tasks.

There are major differences compared to the adaptive learnig rule described in Kuc et al. (1991) that consist in adapting not only the control parameteres but also the system parameters.

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