Joint stick-slip friction compensation for robotic manipulators by iterative learning

Jing-Sin Liu
Institute of Information Science
Academia Sinica
Nankang, Taipei, Taiwan 115
R.O.C.

Abstract: This paper studies the compensation of internal joint stick-slip friction effects for desired trajectory tracking of robotic manipulators. A PD type iterative learning control, which incorporates a stabilizing feedback control for robot dynamics, is applied to compensate for the friction. Simulations of a two-link robotic manipulator show that our friction compensation scheme is effective for different friction models whose characteristics are not exactly known a priori.

Keyworks: friction compensation, iterative learning, feedforward learning

I. Introduction

Friction represents a complicated combination of all effects opposing the motion of robots. Its effects on the performance of robots undergoing low velocity motions have been studied [5], [7]. Its presence often imposes limits on positioning and tracking performance and the fidelity of position and force control for robot motions [5], [7,8]. Moreover, a significant part of motor torque is spent in overcoming joint friction. In order to improve robot accuracy, it is important to accurately model robot dynamics which incorporates the effects of friction. A better understanding of friction phenomena is thus crucial for this purpose, especially for low-velocity movement [2], [6]. There are considerable recent attentions on friction modelling and compensation. A commonly used model in friction modeling and compensation is a Coulomb and viscous friction model which includes a static friction component at zero velocity. However, this idealized zero-memory nonlinear odd function of velocity model assumes the transition from static to dynamic process is instantaneous. Moreover, this model can't faithfully represent the friction feature at low velocities [2], [6], [8]. Improvements in friction modeling have been made [2,3], [6], [8] in recent years. Evidence drawn from experiments on friction phenomena shows that friction is a dynamic phenomenon. A better description of the friction phenomenon for low velocities is a model incorporating decreasing friction with increasing velocity at low velocities, known as Stribeck effect. To date, the theory of dynamic friction has not yet progressed to the point of providing a definite model. Some models that capture this feature of friction which exhibits smooth transitions between near-zero velocity and normal motion conditions are proposed in [2], [6]. The proposed fully nonlinear model in [2] will be used in this study of friction compensation (see Section 2.1).

The problem of friction compensation has attracted many attentions in applications involving high precision low velocity tracking in recent years. Conventional ways of dealing with the undesirable nonlinear effects of friction are either mechanical design for better lubrication or high gain PD controller for smaller steady-state error. These, however, will increase the design cost and complexity, or cause system instability when the drive train is compliant. In addition, friction compensation is complicated by the lack of accurate friction models and the fact that friction parameters vary with the temperature, age and change of load, etc. To effectively overcome the effects of friction, a wide range of friction compensation techniques have been developed for tracking and positioning control of precision servos and robots. For example, feedforward compensation is often added to a control algorithm to cancel the effect of joint friction. But it works well only when the friction model is exactly known. Overcompensation may result in instability of the system to achieve low values of steady-state error and may limit the closed-loop bandwidth to avoid limit cycling. Adaptive techniques using recursive least squares estimation [1,2] and friction observers [4] to estimate the friction parameters have also been proposed to eliminate the influence of friction. However, the availability of friction models with linear-in-parameters structure is crucial for the success of adaptive friction compensation techniques. Other techniques such as fuzzy control [11] which does not require model, nonlinear control [9] which can improve motion smoothness, and variable structure control [10] are proposed to overcome the friction with varying degrees of success.

This paper addresses the problem of friction compensation to improve robot tracking accuracy by iterative learning control. While friction is a complicated phenomenon, it has been experimentally shown to be highly repeatable [8] and predictable [12] . In applications, robotic manipulators are often required to perform repetitive tasks. This implies the robot dynamics with friction term included can be reasonably assumed to be repeatable. This motivates us to apply Arimoto's iterative learning control method [13] to compensate for friction in robotic manipulators which perform the same task repetitively. For friction compensation, the learning control approach has the advantage of requiring less a priori knowledge about repeatable robot dynamics and friction. Also no observer for friction is needed for the iterative learning approach. In this paper, a PD type iterative learning control scheme, where trial joint displacement and velocity errors are used to update the torque, is presented to compensate for internal joint stick-slip friction in robotic tracking task. The effectiveness of learning control for friction compensation is illustrated by a two-link robotic manipulator simulation.

II. Robot dynamics with joint stick-slip friction

2.1 Friction model

Stick-slip friction is a natural resistance to relative motion between two contacting bodies. It is present in the transmission elements in robotic manipulators such as harmonic drive gears, pulleys etc. Investigations into friction models have received considerable attentions in robotics applications which require high precision and smooth movement [3],[5],[6],[8]. Attempts at modeling the friction are complicated by the fact that friction changes as the robot ages, as well as variations with changes in temperature, lubricant condition, and similar factors which can't be readily measured or controlled. So far, there is no consensus about the mathematical friction model that best characterizes the reality. The commonly used model is a Coulomb and viscous friction model which includes a static friction component at zero velocity as well as a dynamic friction component at nonzero velocity. On the other hand, recent experiments involoving the motion of a PUMA 560 robot at low velocities suggest a more complete model incorporating exponentially decreasing friction with increasing velocity at low velocities, known as Stribeck effect [6,8]. This downward exponential bend (or negative velocity dependence) phenomenon at low velocities, as shown in characteristic friction force vs. velocity curve depicted in Fig.1, appears immediately after the applied torque exceeds the maximum static torque (or breakaway torque). In particular, a five-parameter stick-slip friction model which captures the exponential friction characterization at low velocities is proposed in [2], as follows:

$$F_f(v) = [\alpha_0 + \alpha_1 e^{-\beta_1|v|} + \alpha_2(1 - e^{-\beta_2|v|})]sgn(v) \quad (1)$$

where v is the velocity, the five constants $\alpha_0, \alpha_1, \alpha_2, \beta_1, \beta_2 > 0$. For this model, if no velocity reversals, the friction is a continuous function of velocity. In model (1), $(\alpha_0 + \alpha_1)$ represents the initial stiction value, $(\alpha_0+\alpha_2)$ is the constant dynamic value for large velocities, while β_1 and β_2 determine respectively the decay rate of friction force in the stiction region and the increasing rate of friction force in the viscous region to achieve its final value. Asymmetries can be included in (1) by letting the $\alpha_i s$ be different for different velocity directions. The $\beta_i s$ can be kept constant. For the sake of simplicity, we only consider the frictional behavior which is symmetric with respect to velocity.

2.2 Dynamics of robot manipulators with friction

The dynamics of an n-link rigid manipulator including the stick-slip friciton acting at the joints is of the form

$$M(q)\ddot{q} + n(q, \dot{q}) = \tau \quad (2)$$

$$N(q, \dot{q}) = C(q, \dot{q})\dot{q} + G(q) + \tau_f(\dot{q}) \quad (3)$$

where $q \in R^n, \tau \in R^n$ are the vectors of joint coordinates and generalized actuator forques, respectively; $M(q)$ is the symmetric positive-definite moment of inertia matrix; $C(q, \dot{q})\dot{q}$ is the vector of centrifugal and Coriolis forces; $G(q)$ the gravitational forces; $\tau_f(\dot{q})$ is the vector of joint stick-slip friction forces described by

$$\tau_f(\dot{q}) = [F_f(\dot{q}^1) \cdots F_f(\dot{q}^n)]^T \quad (4)$$

where $F_f(\dot{q}^k)$ denotes the internal aggregate stick-slip friction force of kth joint. Two models of joint friction will be used in the following simulation study. One is the traditional Coulomb and viscous friction model, the other is the friction model defined in (1).

III. Friction compensation by iterative learning

If the robot is to be operated at low velocities or with velocity reversals, then effective friction compensation is very important to achieve precision. The complexity and negative slope at low velocities of the nonlinear friction model given in (1) excludes the immediate application of adaptive control strategies where a linear-in-parameters model is often needed. For the robot dynamics (2)-(3), a purely feedforward control action is not effective since the dynamic parameters of the robot and the characteristics of friction are usually difficult to obtain accurately. In general, the selection of adequate methods to compensate for the friction depends on the friction model. In this section, we will present an iterative learning control scheme to generate a feedforward torque function to overcome the joint frictional effects for the case of repeated trials of a path during a robotic tracking task. The iterative learning control has the advantage of requiring less a priori knowledge about the robot dynamics and thus the characteristics of friction. Moreover, it can improve the tracking performance by learning through practice. These two features of iterative learning control make it suitable for robotic manipulators because current robots are used in applications in which they repeat the same trajectory over and over. Previous applications of iterative learning control to position and force control of robotic manipulators [13] do not take into account the discontinuity nature of friction explicitly. In this section, we address the problem of applying the iterative learning control to repeatable robot dynamics with emphasis on compensation of effects due to the static-kinetic friction discontinuity at zero velocity or the Stribeck effect at low velocities.

In spite of having a complicated physical nature, friction has been shown to be highly repeatable [8]. Thus, it is reasonably to assume that the response of the robotic manipulators, which repeat their motion over and over in cycles, is repeatable. Iterative learning control takes advantage of the repeatable property of robot dynamics and thus is naturally suited to the problem of friction compensation. We aim to apply the iterative learning control to a robotic tracking problem. Suppose the joints of robotic manipulator are required to track a given desired trajectory $q_d(t)$ in a finite time interval $[0, T]$. The basic idea of iterative learning control is to apply a simple algorithm over and over to the robot for tracking of a given trajectory profile. As is well known, iterative learning control algorithm is structured in such a way that tracking errors of previous motion trials are used to reduce the errors which will occur during the next trial, until the eventual convergence to a given desired trajectory is achieved. For the construction of a friction compensator, we present the following iterative learning control law for torque update

$$\tau_{i+1} = \tau_i + L(\dot{e}_i + \Lambda e_i) + u_f(e_{i+1}, \dot{e}_{i+1}, t) \qquad (5)$$

where $e_i(t) = q_d(t) - q_i(t)$ is the joint tracking error in ith trial, $L > 0$ is a constant learning gain, Λ is a positive-definite matrix. In (5), $u_f(\cdot, \cdot, t)$ is a stabilizing feedback control for robotic manipulators. A natural approach is to design the feedback part u_f under the assumptions of perfect friction compensation. The controller (5) is a combination of a PD type iterative learning control part and a feedback control part. The learning control part uses the torque of previous trial plus terms proportional to the joint displacement and joint velocity tracking errors of previous trials as the torque update information. The block diagram of the proposed iterative learning controller (5) for friction compensation is shown in Fig. 2. Essentially, the learning controller (5) takes into account the robot dynamics due to the use of feedback information in updating the feedforward torque. The learning control algorithm (5), if converges, constructs a sequence of feedforward torque histories which effectively cancel the friction effects.

IV. Simulation of a two-link rigid robot with joint frictions

The effectiveness of the PD type learning control algorithm (5) described in foregoing section is now illustrated by simulations. A planar robotic manipulator with two rotary joints is used in simulation (see Fig.3). The gravity lies in the plane of the robot. We assume that all mass is located at a point at the distal end of each link. Its dynamics with internal joint stick-slip friction included is given by

$$[l_2^2 m_2 + 2 l_1 l_2 m_2 c_2 + l_1^2(m_1 + m_2)]\ddot{\theta}_1 +$$
$$(l_2^2 m_2 + l_1 l_2 m_2 c_2)\ddot{\theta}_2 - l_1 l_2 m_2 s_2 \dot{\theta}_2^2 +$$
$$l_2 m_2 g c_{12} + (m_1 + m_2) l_1 g c_1 + F_{f_1}(\dot{\theta}_1) = \tau_1$$
$$(l_2^2 m_2 + l_1 l_2 m_2 c_2)\ddot{\theta}_1 + l_2^2 m_2 \ddot{\theta}_2 +$$
$$l_1 l_2 m_2 s_2 \dot{\theta}_2 + l_2 m_2 g c_{12} + F_{f_2}(\dot{\theta}_2) = \tau_2$$

where $s_1 = sin\theta_1, c_1 = cos\theta_1, c_{12} = cos(\theta_1 + \theta_2)$ *etc.*, the parameters are $m_1 = 6, m_2 = 4, l_1 = l_2 = 0.4, g = 9.8$. Suppose the joints of rigid robot are required to track a desired sinusoidal position trajectory given by $q_d(t) = [-cos2\pi t \;\; cos2\pi t]^T$ within one period, the time interval [0, 1]. The trajectory requires the joint axes to move from one point and to return in a symmetric manner. The desired trajectory passes through the critical region of interest, i.e. the region of zero velocity crossing, where friction behavior is highly nonlinear and difficult to control. The iterative learning control incorporating with a traditional PD error feedback

$$\begin{aligned} u_{i+1} &= u_i + 6(\dot{e}_i + \frac{7}{3}e_i) + \ddot{q}_d + K_p e_{i+1} \\ &\quad + K_v \dot{e}_{i+1}, \ i \geq 0 \\ u_0 &\equiv 0 \end{aligned}$$

where $u = [\tau_1, \tau_2]^T$, is used to enhance the tracking performance of the two-link robot, where the gain matrices are $K_p = 2K_v = diag(160, 80)$.

The simulation results for tracking of the planar robot using iterative learning control are shown in Fig.4 and 5. The learning process starts from the same initial condition which is set as $q_i(0) = q_d(0), \dot{q}_i(0) = \dot{q}_d(0), \forall i \geq 1$. In addition to the smooth rigid body terms, friction is also simulated at each joint. Two friction models are studied in the following to show that effectiveness of the iterative learning control in friction compensation does not depend critically on the a priori knowledge of friction. One is the Coulomb and viscous friction model, the other is the fully nonlinear model given in (1). Tracking performance is measured by the sum of magnitude of trial tracking errors over the finite time interval [0, 1]. In simulations, the first trial represents friction compensation results using the conventional PD feedback control scheme alone.
Case 1: $F_{fi}(\dot{\theta}_i) = \dot{\theta}_i + 2sgn(\dot{\theta}_i), i = 1, 2$. Simulation results for this case are shown in Fig.4. Fig.4(a) shows how the tracking error is gradually reduced with the number of trials. Here the error value is calculated as the total sum of trial error magnitude over an entire cycle. The results demonstrate that after a sufficiently large number of trials (see Fig.4(b), 4(c) for a sample of learning sequences), the PD type learning controller performs quite well. Through learning process, it can gradually compensate for the frictional effects to achieve satisfactory desired joint trajectory tracking. Thus, the application of learning control to joint friction compensation does not require precise knowledge of Coulomb and viscous friction coefficients.
Case 2: $F_{fi}(\dot{\theta}_i)$ is the nonlinear model described by the model (1) with parameters $\alpha_0 = 2.5, \alpha_1 = 2, \alpha_2 = 2, \beta_1 = 1.5, \beta_2 = 1.5$, for each joint. In this case, resembling the results shown in Fig.4, simulations shown in Fig.5 reveal that the joints will converge to their desired trajectories with very small residual errors after a large number of trials. Thus, the proposed iterative learning controller is still effective even the friction exhibits a behavior different from that of Coulomb and viscous friction model.
In both cases, the learning control works iteratively in updating the torque so that tracking errors incurred over previous trials are reduced. Significant improvement in tracking performance is observed when the iterative learning control is applied to the two-link robotic manipulator. The friction compensated joint behaviors are nearly the same in both cases, and differ most significantly only around the region of zero velocity crossing (around $t = 0.5$). The joint behaviors around the zero velocity crossing are smooth. In addition, the responses are all stable in both cases.

V. Conclusion

Friction imposes limits on positioning and tracking accuracy in robotic manipulators. In this study the friction is treated as a periodic disturbance. An iterative learning control approach is applied to overcome the joint stick-slip friction for robotic manipulators performing low velocity position tracking. The iterative learning controller generates a sequence of feedforward torque functions which gradually compensate for the joint friction through repeated trials of a given desired trajectory. Compared to most existing friction compensation techniques, the iterative learning control does not need accurate knowledge of friction, which is often accessed by an observer in many compensation methods for effective compensation. Two joint stick-slip friction models, with or without taking into account the Stribeck effect, have been used in this study. In both cases, simulations of a two-link robot show that after sufficient number of trials, iterative learning control is effective in compensating for friction effects whose characteristics are not exactly known a priori.

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Figure Captions

Fig.1 The stick-slip friction curve

Fig.2 Block diagram of iterative learning controller

Fig.3 Schematic of a two-link robotic manipulator

Fig.4 Friction compensation by iterative learning for Coulomb and viscous friction
(a)tracking performance (b)a sample of trial errors (c)a sample of trial input

Fig.5 Friction compensation by iterative learning for friction model described by eq.(1)
(a)tracking performance (b)a sample of trial errors (c)a sample of trial input

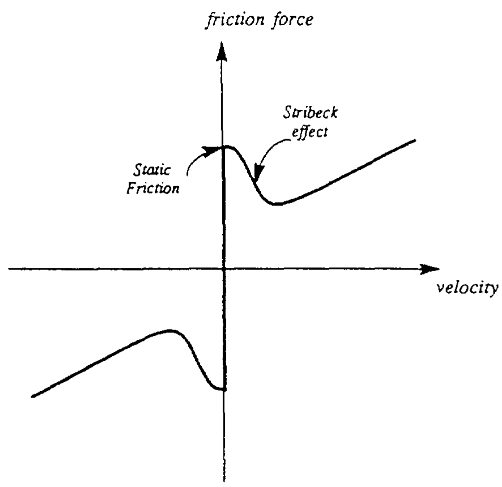
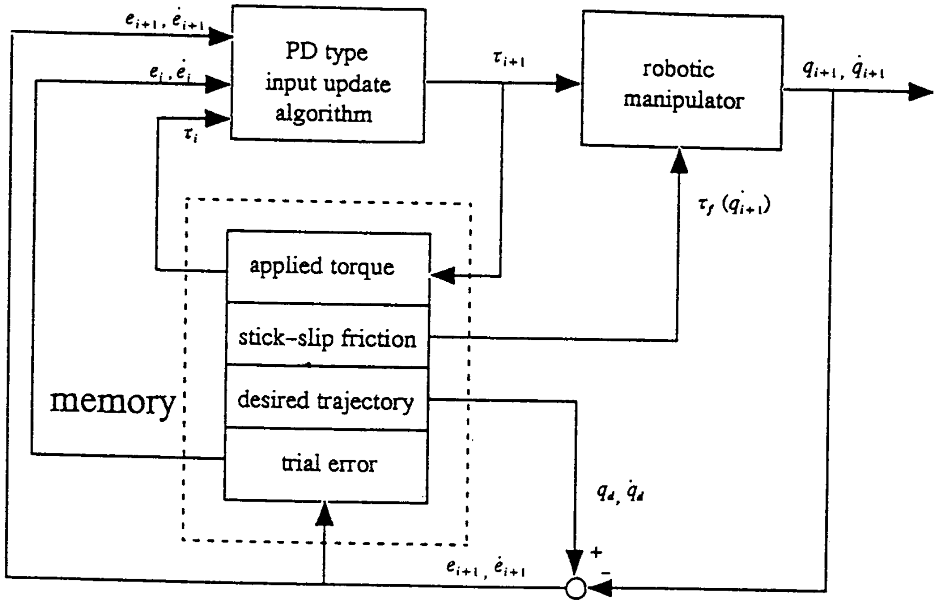


Fig. 1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algorithm
robotic
manipulator
applied torque
stick-slip friction
desired trajectory
trial error
memory

Fig. 2

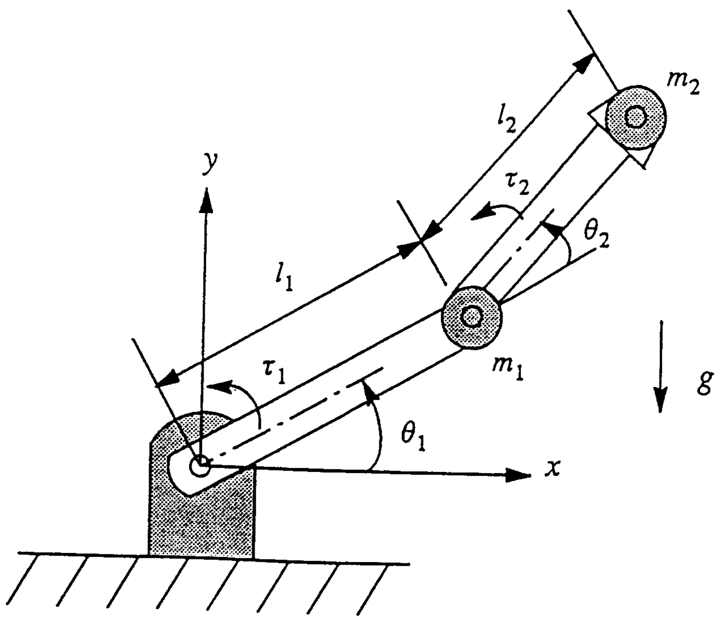
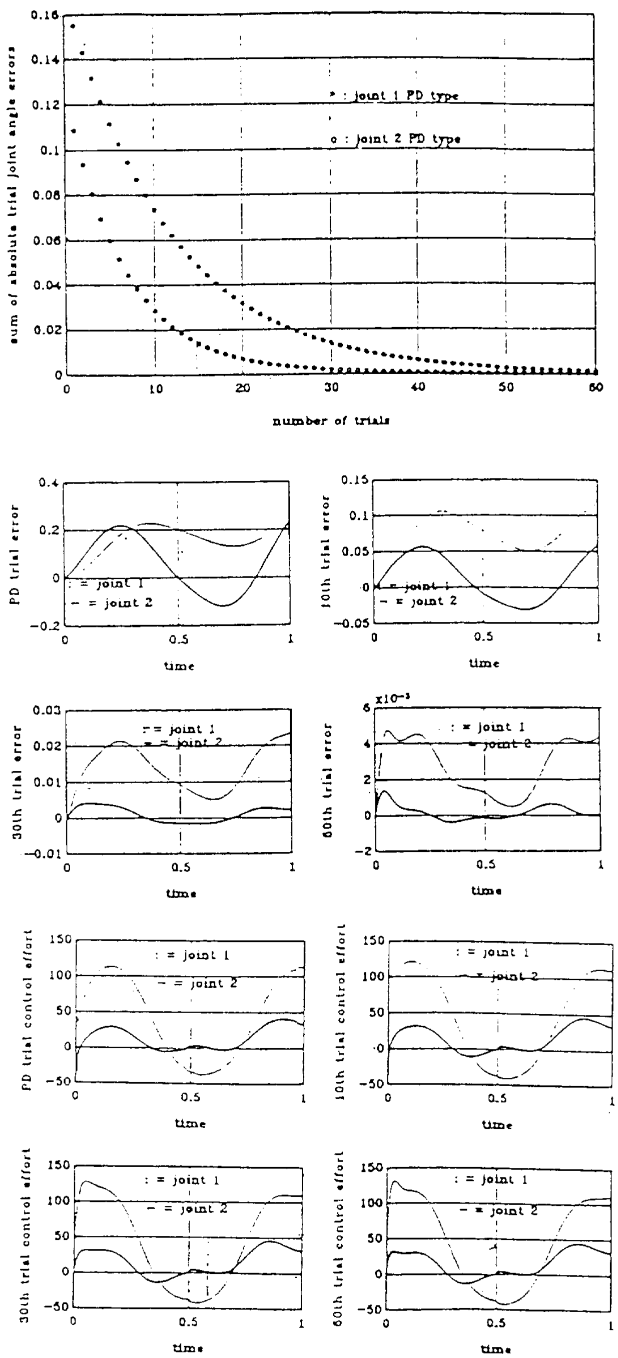


Fig. 3

(a)

(b)

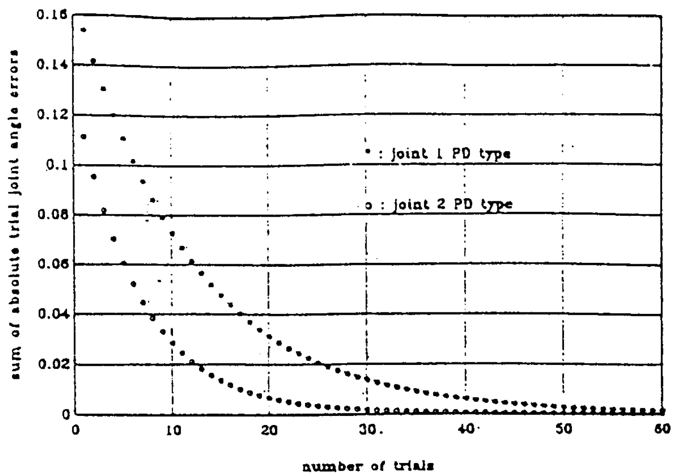
(c)



sum of absolute trial joint angle errors
* : joint 1 PD type
o : joint 2 PD type
number of trials
PD trial error
10th trial error
30th trial error
60th trial error
: = joint 1
- = joint 2
time
PD trial control effort
10th trial control effort
30th trial control effort
60th trial control effort

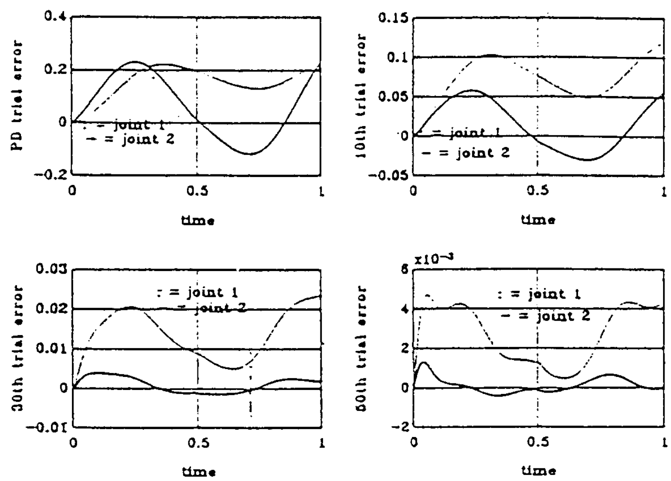
Fig. 4

(a)



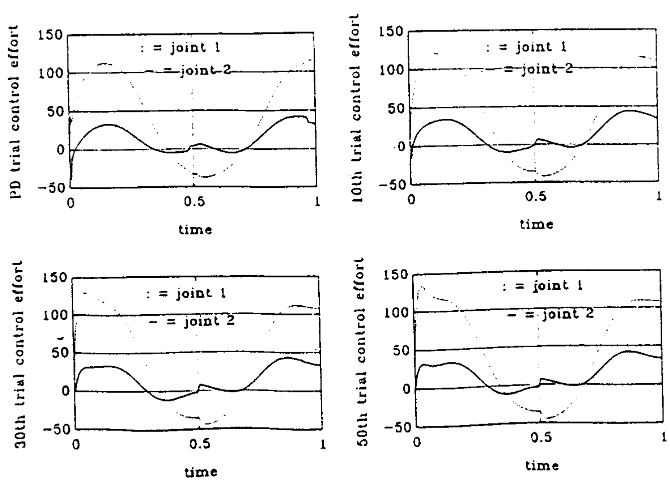
sum of absolute trial joint angle errors
• : joint 1 PD type
o : joint 2 PD type
number of trials

(b)



PD trial error
10th trial error
30th trial error
50th trial error
: = joint 1
– = joint 2
x10⁻³
time

(c)



PD trial control effort
10th trial control effort
30th trial control effort
50th trial control effort
: = joint 1
– = joint 2
time