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Application of Learning Control to a Robotic Arm for Exercises

운동기구용 로봇의 학습 제어 응용

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ABSTRACT

An application of a simple and effective learning control scheme to a robotic arm for exercise is presented. During exercises, the force applied by a user to an exercise machine varies for different users and for different workouts of the same user. Learning control is used to compensate for the difference between the actual force and the planned one. It is shown through simulation that the learning control method decreases tracking error quickly for both time-invariant and time-varying forcing functions.

요 약

본 논문에서는 단순하고 효율적인 학습제어 로직을 운동기구용 로봇팔 시스템에 적용하였다. 일반적으로 운동시에 운동기구에 적용되는 힘은 사용자마다 다르고 같은 사용자라 하더라도 운동시마다 다를 것이다. 이미 사용자의 신체조건에 따라 입력된 최적의 힘과 실제 가해지는 힘 사이의 오차를 보상하는데 본 논문에서는 학습제어를 적용하여 가해지는 힘의 종류(시변 또는 시불변함수)와 상관없이 빠르게 오차를 제거하고 원하는 운동을 추종함을 시뮬레이션을 통하여 확인할 수 있었다.

1. Introduction

As living standard improves, people pay more attention to health. It leads regular exercise and development of advanced exercise equipment to help people to stay healthy. Research and development in exercise equipment have also greatly motivated by the need for performance enhancement, fitness, and rehabilitation. Today's equipment uses traditional plate-loaded mechanisms in an array of individual machines integrated via a kiosk supervisory station and facility management network software. A few of the equipment represent the current state-of-the-art in robotic exercise technology that is driven by DC motors with controlled torque and speed. A developing trend in wellness exercises is to customize workouts, monitor performance, and communicate with clients over the Internet.

Biomechanics and health research brings advances in proper exercise techniques. Different modes (for example, isotonic, isometric, and isokinetic), motion profiles and load levels of exercises are being used to meet various exercise

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objectives. Future exercise machine will be able to customize exercises based one's physical condition and desired muscles to develop. In order to tailor exercise profile and load level to an individual, an exercise machine may need to use robotic technology to adjust motion trajectories and resistance levels. As safety is paramount, not only limits have to be applied to both resistance level and extremes of trajectory, but the motion control must also be reactive. Such a machine runs repeatedly with predetermined forces and trajectories during preset time period and develops desired muscles ultimately. The actual resistance experienced by a human user depends on relative motions between the limbs of the user and the robotic arm. The discrepancy between user's input force and desired resistance is not well defined and will affect the effectiveness of the exercise.

The exercise machine is extremely large and heavy, and yet to require high precision. This combination of size and accuracy causes such equipment to be very expensive. The possible sources of position or velocity error include machining inaccuracies in which the axis of rotation is not precisely at the geometric center of the roller, similar inaccuracies in the machining of the roller bearings and associated elements, flexibility of the belts used, and in some cases, slippage of the belts, vibration of the tensioning pulley involving elasticity of the belt. They are also subject to inaccuracies from sag produced by gravity.

It is the purpose of this paper to use a simple learning control algorithm to improve the performance of exercise equipment and give the opportunity to make an advanced electromechanical intelligent machine.

A large number of control systems execute repetitive operations, for example, controllers for robots in assembling and manufacturing systems. When controllers are executing the same command repeatedly, majority of the errors are reproduced in the repetitions, except for certain random disturbance effects. In tracking problems these repeating errors can be large. Over the last decade the field of learning control has developed to allow controller designs that learn from previous experience performing a command in order to improve its performance in future repetitions.

It is natural to consider applying learning control ideas targeted at eliminating these repeated errors to an exercise system that perform repetitive motions. This paper has conducted a series of computer simulations in the use of simple D type learning control for high precision tracking in exercise equipment. It studies the ability of these laws to reduce errors in a large angular trajectory combined with external input forces that are quite different from the desired forces. These simulations demonstrate the effectiveness of learning control concepts for improving tracking accuracy by a large margin, and doing so with minimal knowledge about the system dynamics, and doing so very quickly and easily. Starting with not taking the dynamic property of the arm into consideration at all, the tracking errors reach a maximum of about 70° (1.22 radian) when the input force deviated from the desired one by about 70 N. Applying learning control laws for 20 repetitions of the trajectory, the tracking error for the same deviation in input force is reduced to less than 1.3° (0.02 radian).

2. System Model

The exercise arm under study, as shown in Fig. 1, follows a two-degrees-of-freedom RP robot. It has a rotating arm and a translating handle.

Although the robotic arm has two degrees of freedom, only one is used for an exercise. The other joint is locked in a specified position. When the rotary joint is locked, the handle will move linearly along the arm to allow exercises such as chess press. When the prismatic joint is locked, the

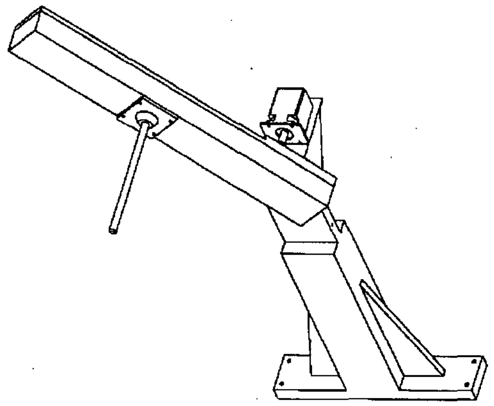

Fig. 1 A robotic arm for exercise

handle is fixed on the arm at the proper distance while the arm rotates to allow exercises such as shoulder flexion. Only the rotational motion is considered in this study.

The overall mass of the arm is 30 kg, and the nominal distance from center of mass to the rotation axis is 0.25 m (this value varies according to the actual location of the handle). In order to accommodate different users, the distance from handle to the rotation axis can change from 0.57 m to 0.71 m. Nominal inertia about the rotating axis is 4.5 kg·m^2 when the handle is at the middle of its adjustment range. The rotating range of the arm used for this study is from -40((-0.70 radian) to 30((0.52 radian), measured with respect to the horizontal line (negative if below the line). The nominal speed of the rotation is 20 to 30 RPM. Thus the duration of each cycle is from 1.0 to 1.5 sec. To provide the desired resistance, the arm is expected to deliver a nominal torque ranging from 100 to 140 N-m.

The dynamics of the above robotic arm is governed by equations of the form

$$I(\theta)\ddot{\theta} + D(\theta,\dot{\theta})\dot{\theta} + G(\theta) = \tau \qquad (1)$$

where θ is the angular position vector, I represents the inertia matrix, D includes centrifugal and Coriolis effects, and G represents the gravity vector. Such equations might be derived using Lagrangian formulation or other methods.

3. Learning Control Law

Starting around 1984[1~3] there has been considerable research activity in the fields of learning control. The original motivation for the work in learning control was to improve the performance of robots on an assembly line performing the same task repeatedly. These control algorithms learn from previous experience performing a specific task in order to improve their performance in future executions of this task. Learning control applies to situations in which the same tracking command is given to a control system many times, and each time the system starts from the same initial conditions.

Learning control could correct for external disturbances that appear every time the command is executed, such as the influence of gravity on the tracking performance of a robot. Dynamics in robotic systems are highly nonlinear and time varying. There are relatively few control methods that rigorously apply to time varying systems. It is fortunate that in many control systems, the time variation characteristics is often duplicated in repetitions. The learning process can treat the time varying system as repetition invariant and make many control methods developed for time invariant systems applicable in the repetition domain. This paper applies a simple learning control method, which is based on integral control concept, to the nonlinear time-varying robotic arm for exercise described in section II. This learning control method gives guaranteed convergence to zero tracking error as the number of repetitions of the task increases.

The learning control algorithms takes the form of[1~8]

$$u_{j+1}(t) = u_j(t) + F(e_j(\cdot),\ \dot{e}_j(\cdot)) \ \ 0<t<T \qquad (2)$$

where u_{j+1} and u_j are the control inputs at the $(j+1)$th and jth iteration, $e_j=\theta_j-\theta_d$ and $\dot{e}_j=\dot{\theta}_j-\dot{\theta}_d$ are the error and error rate between the actual output θ_j and the desired trajectory θ_d at the jth iteration, respectively.

We assume that the form of the nonlinear differential equation (1) is known from the laws of dynamics, but the knowledge of system characteristics such as masses, inertias, lengths, principal axis directions, and load is poor or changeable. It is the task of the learning process to eliminate errors due to poor knowledge of system characteristics and variable load being manipulated. In order to apply learning control algorithm, the dynamic equation of the robotic arm is rewritten as[5]

$$I(\theta_j;p)\ddot{\theta}_j + D(\theta_j,\dot{\theta}_j;p)\dot{\theta}_j + G(\theta_j;p) = \tau_j \qquad (3)$$

Coefficients I, D and G are nonlinear functions of various parameters of the arm and those parameters that appear linearly in the coefficients I, D and G are denoted by p.

The actuator for rotating the arm applies a desired generalized torque τ, which is a combination of a learning control signal (2) with torque error τ_e between input and desired force.[5] This torque expressed in learning control as

$$\tau_j(t) = u_j(t) + \tau_e(t) \qquad (4)$$

Then the learning control algorithms for system (3) can be described as follows:

$$u_{j+1}(t) = u_j(t) + \Phi\dot{e}_j(t) \qquad (5)$$

where Φ is the gain matrix to be chosen.

Let C and B be state output and input matrices with appropriate dimensions and assume that product CB is nonsingular.[1,2] The convergence conditions of the above D type learning control law[1,7] is

$$\| I - \Phi CB \|_\infty < 1 \qquad (6)$$

with initial condition

$$\theta_j(0) = \theta_d(0), \quad (j = 0,1,2\cdots\cdots).$$

$$\text{and} \quad \lim_{j\to\infty} e_j(t) = 0 \qquad (7)$$

4. Simulation Results

Application of the learning control to the robotic arm for exercise is simulated with the same parameter values as described in system model section II. No information on the exercise arm's dynamic property is used in the simulation. This

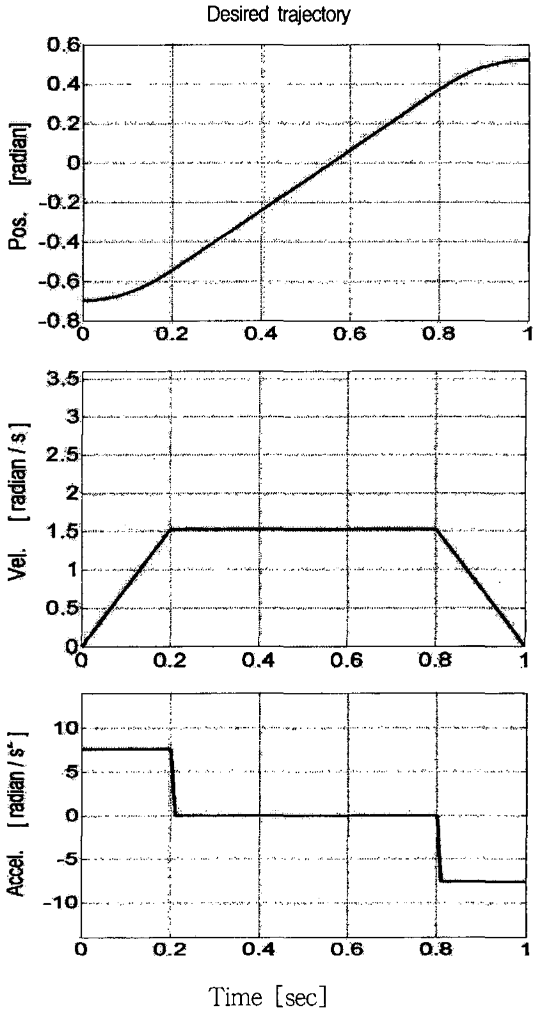

Fig. 2 Desired trajectory profile

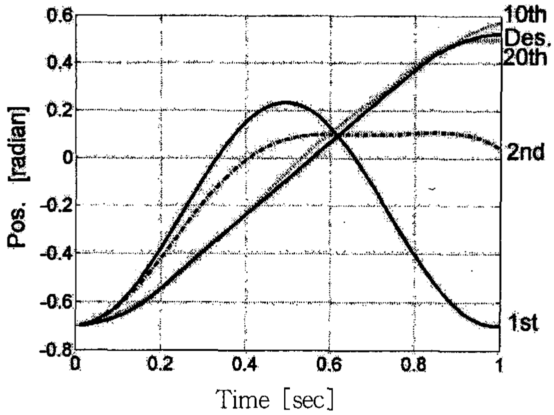

Fig. 3 Trajectory tracking histories for case 1

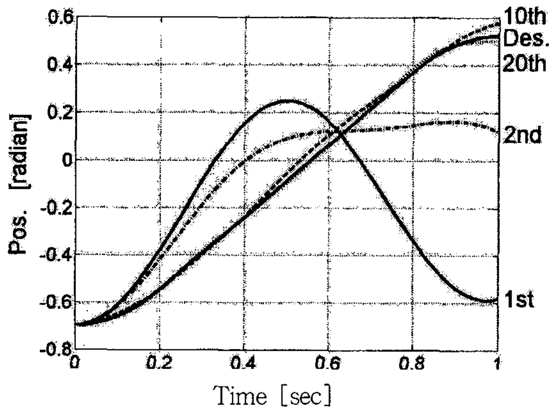

Fig. 4 Trajectory tracking histories for case 2

may be viewed as an extreme approach, since certain known information can be used for control purpose. We want to see the effectiveness of the learning control in this situation.

The desired trajectory is defined as a linear function with parabolic blends, as shown in Fig. 2. The angular position of the arm increases smoothly from -40° (-0.70 radian) to 30° (0.52 radian) in 1 sec.[8,9]

The sample time used in the simulation is chosen as 10 milliseconds. The gain for the learning process is selected as $\Phi = 15I$ (with only one joint, it is actually a scalar).

These simulations investigate three different cases in the application of the learning control to the arm. They are:

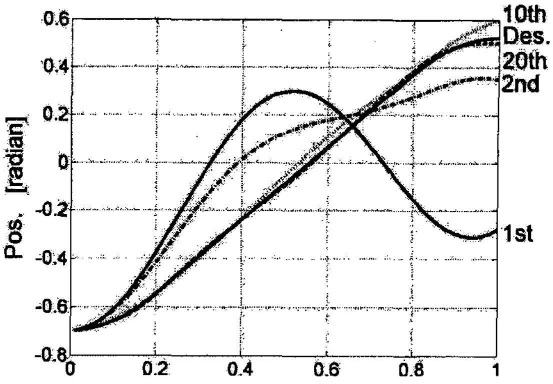

Fig. 5 Trajectory tracking histories for case 3

Case 1: Desired force and actual input force are both constant. The simulation results plotted in Fig. 3 show one of the examples where the desired force f_{des} = 184.62 N and the actual force f_{act} = 250.0 N.

Case 2: Desired force and actual input force are both time-varying. The simulation results plotted in Fig. 4 show one of the examples where the desired force f_{des} = 184.62*cos(φ) N and the actual force f_{act} = 250.0*cos(φ) N, with φ = t rad.

Case 3: Desired force is constant while actual input force is time-varying. The simulation results plotted in Fig. 5 show one of the examples where the desired force f_{des} = 184.62 N and the actual force f_{act} = 250.0*cos(φ) N, with φ = t rad.

In Figs. 3, 4 and 5, the tracking histories of the first, second, tenth and twentieth repetitions are plotted against the desire trajectory. The first trial is the trajectory produced without any knowledge of the exercise arm's dynamic property. Repetitions 2 through 20 add the learning control signal to improve the tracking error when the wrong input force is applied. The results show that the arm's ability in following the desired trajectory improved with each repetition no matter whether the input force applied is constant or time-varying.

Maximum error of angular position $\theta(t)$ is defined as

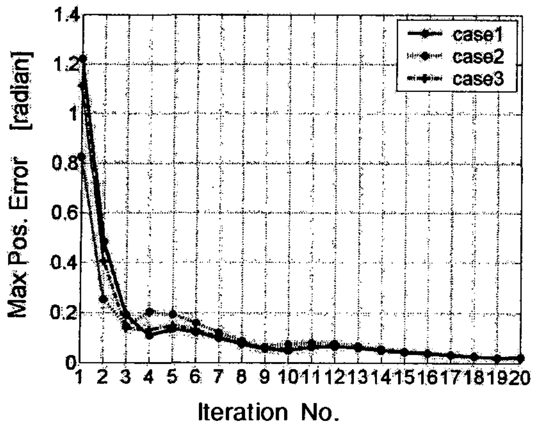

Fig. 6 Maximum error with three cases

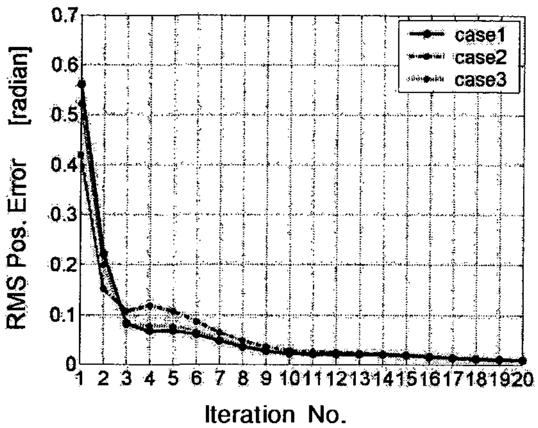

Fig. 7 RMS error with three cases

$$\max_{0<t\le T}|e(t)| = \max_{0<j\le N}|e_j(t)| \tag{8}$$

Fig. 6 shows the maximum error for the three cases. The error history shows the maximum angular position errors reaches approximately 70° (1.22 radian), 47° (0.82 radian), and 64° (1.12 radian) respectively when the desired trajectory is given as a command to the system with the learning control turned off.

Root mean square (RMS) error of angular position $\theta(t)$ is defined as

$$\sqrt{\frac{1}{T}\int_0^T e^2(t)dt} = \sqrt{\frac{1}{N}\sum_{j=0}^{N} e_j^2} \tag{9}$$

Fig. 7 shows the RMS error for the three cases. Figs. 6 and 7 show the monotonic decay of the errors as functions of time and repetition and the convergence of the variable $e(t)$ as the repetitions progress. The value of $e(t)$ decays very quickly initially to a relatively small error level and then decays slowly thereafter. The maximum errors are between 1.2° (0.021 radian) and 1.3° (0.023 radian) after 20 repetitions. The RMS errors are between 0.51° (0.0089 radian) and 0.53° (0.0093 radian) after 20 repetitions. The remaining errors are small enough to be considered as white noise level.

This indicates that the implemented learning control scheme guarantees convergence to zero tracking error for both time-varying and time-invariant systems and does compensate for the discrepancy between the actual and the desired input forces. Thus, the learning controller eliminates all deterministic error in following the desired trajectory. The number of repetitions needed to learn, however, must be small in practical applications. Therefore, the learning control should be combined with model-based control so that any known information on the robotic arm's dynamic property can be used to speed up the learning process.

5. Conclusions

In this paper simulations are performed on a robotic arm for exercise to study the effectiveness of the learning control methods in this type of applications. A simple learning controller of *D* type with integral control is implemented in simulation without the knowledge of the dynamic characteristics of the robotic arm.

The simulation results show reduction in the tracking error of the robot arm for exercise down to the reproducibility level of the system. This decrease in the tracking error of over two orders of magnitude is accomplished after 10 to 20 repetitions. The simulations reported here indicate that learning control has the potential to significantly decreases the error in exercise machine.

Future experiments will develop methods to know the phase of all error frequency components to be learned, and then determine the actual capability of the method for producing high precision velocity control. Future research will also address the use of methods to increase the bandwidth used in the low-pass filter.

Acknowledgement

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