LEARNING-BASED HYBRID CONTROL OF CLOSED-KINEMATIC CHAIN ROBOTIC END-EFFECTORS

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Abstract: *This paper proposes a control scheme that combines the concepts of hybrid control and learning control for controlling force and position of a six-degree-of-freedom robotic end-effector with closed-kinematic chain mechanism, which performs repeatable tasks. The control scheme consists of two control systems: the hybrid control system and the learning control system. The hybrid control system is composed of two feedback loops, a position loop and a force loop, which produce inputs to the end-effector actuators, based on errors in position and contact forces of selected degrees of freedom. The learning control system consisting of two PD-type learning controllers arranged also in a hybrid structure provides addtional inputs to the actuators to improve the end-effector performance after each trial. The paper shows that with proper learning controller gains the actual position and contact force can approach the desired values as the number of trials increases. Experimental studies performed on a two-degree-of-freedom end-effector show that the control scheme provides path tracking with satisfactory precision while maintaining contact forces with minimal errors after several trials.*

1. INTRODUCTION

To perform repeatable tasks, robot manipulator can be taught off-line by a so-called *teaching and playback scheme* or can learn on-line from its experience via a *self learning control scheme* without human supervision. Learning control theory has attracted attention of control researchers since many years [5] and recently has been developed for control of robot manipulators [1]-[4]. The first learning control scheme was proposed by Uchiyama [18] for controlling mechanical arms. Motivated by the idea that robots can learn autonomously from measurement data of previous operations to improve their performance, Arimoto and his research group [2] proposed a so-called *Betterment Process* whose operation is based on a simple iteration rule. The iteration rule autonomously generates a present actuator input better than the previous one by using stored data of errors in previous operation. Application of the proposed learning control scheme has been studied mostly for the problem of controlling robot position* [1] and some attention was paid to force* control [7]. Hara and others [6] considered the synthesis of repetitive control systems for a subclass of control systems whose outputs are controlled to follow periodic reference commands. Togai and Yamano [17] studied the synthesis of a discrete learning control scheme that relaxes the rank condition in Arimoto learning control scheme. Craig [4] studied an adaptive scheme for robot manipulators for the case of repeated trials of a path. In [3], a learning algorithm based on explicit modeling of robot manipulators was developed.

*) *In this paper, "position" implies both position and orientation and "force" implies both force and torque.*

In this paper, combining the concepts of learning control and hybrid position/force control [15], we propose a control scheme to control position and contact force of a six-degree-of-freedom robot end-effector recently built at the Goddard Space Flight Center (NASA) to study potential applications of robotic assembly in space [14]. The proposed control scheme mainly consists of a feedback hybrid control system and a learning control system whose structure is also hybrid. Using linearization around a selected desired pattern, we will show that the controller gains of the hybrid control system and the learning control system can be designed such that the end-effector can autonomously improve its performance by repeating the assembly task. The developed control scheme is then tested on a 2-degree-of-freedom robot end-effector. Experimental results will be given and the performance of the proposed control scheme will be discussed.

2. THE CKCM ROBOTIC END-EFFECTOR

The structure of the CKCM robotic end-effector is depicted in Figure 1. The end-effector is attached to the last link of a robot manipulator. In a typical assembly process, the manipulator provides gross motion and the end-effector fine and precise motion. Closed-kinematic chain mechanism was chosen to design the end-effector because it has several advantages compared to open-kinematic chain mechanism, such as smaller positioning errors due to the lack of cantileverlike configuration and higher force/torque and greater payload handling capability. The end-effector has six degrees of freedom provided by six in-parallel actuators and mainly consists of a base platform and a payload platform coupled together through the actuators using pin joints and ball joints at both ends of the actuator rods. Position feedback is achieved by 6 linear voltage differential transformers (LVDT) mounted along the actuator lenghts. Force sensing is provided by mounting a six-degree-of-freedom wrist sensor between the last link of the manipulator and the base platform.

For the above type of end-effectors, the inverse kinematic problem possesses closed-form solutions. However its forward kinematic problem must be solved by using an iterative method such as Newton-Raphson algorithm. A complete development of forward kinematics, inverse kinematics, Jacobian matrix and dynamics can be found in [12].

3. THE LEARNING-BASED HYBRID CONTROL SCHEME

Figure 2 illustrates the structure of the learning-based hybrid control scheme proposed for controlling position and force of the CKCM end-effector presented in Section 2. The control scheme consists mainly of two systems: the *hybrid control system* is aimed at the improvement of the

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end-effector dynamics in terms of stability and tracking capability of desired pattern and the *learning control scheme* at the control of the transient and steady-state errors of the end-effector responses using repeated trials. The hybrid control scheme [15] is composed of two loops: the upper for position and the lower for force. In the position loop, the actual Cartesian positions are computed by using the forward kinematic transformation and the actual joint positions measured by six LVDT's. In the force loop, the actual Cartesian contact forces are obtained by transforming the force sensor signals into the base coordinate system by employing an appropriate coordinate transformation. Depending on a particular task to be performed during a robotic part assembly, the user may specify which degrees of freedom are to be position-controlled and which are to be force-controlled. The selection is done by using a *Selection Matrix* S, which is a (6x6) diagonal matrix whose main diagonal elements specify which degrees of freedom are to be position-controlled (s_{ii} = 0) and which are to be force-controlled (s_{ii} = 1) for i = 1,2,..., 6 by discarding the unwanted components of the positions and forces. In the position loop, the joint position errors corresponding to the Cartesian position errors for degrees of freedom selected to be position-controlled are obtained by the inverse Jacobian matrix. Similarly, the joint force errors corresponding to the Cartesian force errors are computed by the transpose Jacobian matrix in the force loop. The selected error-driven control signals are then transformed into the corresponding joint variable errors and joint force errors via the inverse Jacobian matrix and its transpose, respectively. Using linearization about a desired pattern of position and force, the gains of the fixed PD position controller and the PD force controller are designed such that the end-effector tracks a Cartesian position trajectory with minimum steady-state errors and settling time while keeping a relatively constant pattern of desired contact forces on the environment. This hybrid control scheme has been proved to provide satisfactory performance by both simulation and experimental results for fixed PD control in [11] and for adaptive control in [13]. However a deviation still exists between the desired and actual patterns of force and position because of dynamic interferences and frictional disturbances resulted from the reaction force. Therefore, for robotic assembly tasks that are repeatable, we propose to add to the above system a learning control system that can "learn" from the errors of the force and position pattern during a trial and provide additional signals which improve the end-effector performance during the next trial. The design of the learning control system is based also on the hybrid structure. It consists of two PD-type learning controllers, one learns from the joint position errors corresponding to those in degrees of freedom selected to be position-controlled and the other learns from the joint force errors corresponding to those in degrees of freedom selected to be force-controlled. After each trial, the signal provided by the learning control system is improved by using the data of previous signal and the errors of joint positions and joint forces during the previous trial. The improvement process is described in the following learning scheme [Figure 3]:

$$u_{k+1} = u_k + \Phi[\alpha_p \dot{\bar{q}}_e(t) + \beta_p \bar{q}_e(t) + \alpha_f \dot{\bar{\tau}}_e(t) + \beta_f \bar{\tau}_e(t)] \quad (1)$$

where Φ is a positive definite matrix, α_f and β_f are non-negative constant scalars and

$$\bar{q}_e(t) = J^{-1}(I-\bar{S})[x_d(t) - x(t)] \quad (2).$$

$$\bar{\tau}_e(t) = J^T\bar{S}[F_d(t) - F_c(t)] \quad (3)$$

where J is the Jacobian matrix, $x_d(t)$ and $x(t)$ denote the desired and actual Cartesian positions, respectively, $F_d(t)$ and $F_c(t)$ denote the desired and actual contact forces, respectively. The Selection Matrix $\bar{S}$ of the learning control system is defined similar to the Selection Matrix S of the hybrid control system. The Selection Matrix $\bar{S}$ is introduced here instead of using the same matrix S for we can independently select which degrees of freedom are to be force- or position-controlled in the learning process.

During the kth trial, the information of u_{k+1} is stored in the lower part of a memory (LSI RAM) as a set of densely sampled digital data. After the kth trial, the stored data will be loaded to the upper part of the memory and will be sent to the actuators during the (k+1)th trial. The lower part of the memory is now ready to store new data. During the kth trial the end-effector input is composed of an auxiliary signal τ_d and signals coming from the position loop, the force loop the learning control system, namely:

$$\tau_k = \tau_d + \tau_{p,k} + \tau_{f,k} + u_k. \quad (4)$$

The auxiliary signal τ_d is added to the end-effector input in order to compensate the end-effector dynamics as seen later in the linearization process discussed in Section 4.

We observe that the hybrid control acts here as a feedback controller that improves the end-effector dynamics and the learning control system provides additional input to improve the transient and steady-state responses of the end-effector using repeated trials. The controller gains of the hybrid control scheme should be designed such that the closed-loop feedback system is asymptotically stable with minimized steady-state errors. The design of the learning control scheme should be performed the transient errors converge to zero as the number of trials increases.

4. DESIGN OF THE CONTROLLER GAINS

In this section we present the design of the controller gains of the hybrid control system and the learning control system. The design mainly consists of three steps: 1) Linearizing the end-effector dynamics about a desired operating pattern, 2) Selecting controller gains for the hybrid control system such that the linearized closed-loop control system is asymptotically stable and 3) Selecting the controller gains of the learning control system such that the error between the desired and actual pattern during the k-th trial converges to zero as k increases to infinitive.

The dynamics of the end-effector in an n-dimensional joint space is expressed in terms of the joint position q(t) as [13]

$$M(q)\ddot{q}(t) + N(q,\dot{q}) + G(q) + J^TF_c(t) = \tau(t) \quad (5)$$

where M(q), the end-effector mass matrix is an (nxn) positive definite matrix, $N(q,\dot{q})$ represents the (nx1) centrifugal and Coriolis force vector, G(q) is the (nx1) gravitational force vector, and $\tau(t)$ is the (nx1) joint force vector. The term $J^TF_c(t)$ represents joint forces corresponding to the Cartesian force $F_c(t)$ exerted by the end-effector on the environment (which is equal to the reaction force) and can be rewritten as

$$J^TF_c(t) = J^TKx(t) = J^TKT(q) = R(q) \quad (6)$$

where K is the (nxn) diagonal generalized stiffness matrix representing the stiffness of the force sensor and part of the environment, which is in contact with the end-effector. The diagonal elements of K corresponding to those degrees of freedom being position-controlled are set to zero.

Linearizing (5) around the given desired joint position trajectory $q_d(t)$ corresponding to the given desired Cartesian position trajectory $x_d(t)$, by using Taylor Series expansion and neglecting higher order terms, we obtain

$$M(t)\ddot{\omega}(t) + N(t)\dot{\omega}(t) + G(t)\omega(t) + \tau_d(t) = \tau \quad (7)$$

where $M(t) = M(q_d)$ (8)

$$N(t) = \partial/\partial\dot{q}[N(q,\dot{q})]|_{q_d,\dot{q}_d} \quad (9)$$

$$G(t) = \partial/\partial q[M(q)\ddot{q}_d + N(q,\dot{q}) + R(q) + G(q)]|_{q_d} \quad (10)$$

$$\tau_d(t) = M(q_d)\ddot{q}_d + N(q_d,\dot{q}_d) + G(q_d) + R(q_d) \quad (11)$$

and $\omega(t) = q(t) - q_d(t)$. (12)

The end-effector input $\tau(t)$ can be expressed as

$$\tau(t) = -A_1(t)\omega(t) - A_2(t)\dot{\omega}(t) + u(t) + \tau_d(t) \quad (13)$$

where

$$A_1(t) = K_{pp}A_3(t) + K_{pd}\dot{A}_3(t) + K_{fp}A_4(t) + K_{fd}\dot{A}_4(t) \quad (14)$$

$$A_2(t) = K_{pd}A_3(t) + K_{fd}A_4(t) \quad (15)$$

$$A_3(t) = J^{-1}(I-S)J|_{q_d}; \quad A_4(t) = J^TSKJ|_{q_d} \quad (16)$$

where K_{pp} and K_{pd} are the gains of the PD-controller in the postion loop and K_{fp} and K_{fd} are the PD-controller gains in the force loop.

Substituting (13) into (7) yields

$$M(t)\ddot{\omega}(t)+[N(t)+A_2(t)]\dot{\omega}(t)+[G(t)+A_1(t)]\omega(t) = u(t) \quad (17)$$

which represents a linear time-varying multivariable system. The controller gains K_{pp}, K_{pd}, K_{fp} and K_{fd} can be systematically designed such that system (17) is asymptotically stable by using for example, the eigenvalues assignment method proposed in [9].

We proceed to rewrite (1) as

$$u_{k+1}(t) = u_k(t) - \Phi\bar{A}_1(t)\omega_k(t) - \Phi\bar{A}_2(t)\dot{\omega}_k(t) \quad (18)$$

where $M(t)\ddot{\omega}_k(t) + [N(t) + \Phi A_2(t)]\dot{\omega}_k(t) +$

$$+ [G(t) + \Phi A_1(t)]\omega_k(t) = u_k(t) \quad (19)$$

where

$$\bar{A}_1(t) = [\beta_p\bar{A}_3(t) + \alpha_p\dot{\bar{A}}_3(t) + \beta_f\bar{A}_4(t) + \alpha_f\dot{\bar{A}}_4(t)] \quad (20)$$

$$\bar{A}_2(t) = [\alpha_p\bar{A}_3(t) + \alpha_f\bar{A}_4(t)] \quad (21)$$

$$\bar{A}_3(t) = J^{-1}(I-\bar{S})J; \quad \bar{A}_4(t) = J^T\bar{S}KJ. \quad (22)$$

Since $\omega(t)$ represents the deviation between the actual joint position q(t) and the desired joint position $q_d(t)$, the desired error $\omega_d(t)$ should be set to $\omega_d(t)=0$. Therefore (18) can be expressed as

$$u_{k+1}(t) = u_k(t) + \Phi[\bar{A}_1(t)(\omega_d-\omega_k) + \bar{A}_2(t)(\dot{\omega}_d-\dot{\omega}_k)]. \quad (23)$$

Equations (23) and (19) represent the general learning scheme of the hybrid learning control system.

Before presenting the main results of this paper, we first state the following lemma:

Lemma 1: Consider a class of n-dimensional linear time-varying systems described by

$$R(t)\ddot{z}(t) + Q(t)\dot{z}(t) + P(t)z(t) = v(t) \quad (24)$$

where z(t) and v(t) are the (nx1) controlled variable and the (nx1) input vectors, respectively. R(t), Q(t) and P(t) are time-varying square matrices that are continuously differentiable on [0,T]. In addition, R(t) is positive definite for all $t \in [0,T]$. A learning scheme is defined by

$$v_{k+1}(t) = v_k(t) + \Gamma[\alpha(\dot{z}_d-\dot{z}_k) + \beta(z_d-z_k)] \quad (25)$$

$$R(t)\ddot{z}_k(t) + Q(t)\dot{z}_k(t) + P(t)z_k(t) = v_k(t) \quad (26)$$

$$\dot{z}_k(0) = \dot{z}_d(0); \; z_k(0) = z_d(0) \quad (27)$$

where α and β are constant scalars, $z_d(t)$ denotes the desired pattern for z(t) and Γ is a positive definite square matrix. If $v_1(t)$ is continuous, $z_d(t)$ is continuously differentiable on [0,T], and the constant scalars α and β are set such that $0 < \alpha \le 1$ and $0 \le \beta < 1$, then $z_k(t)$ converges to $z_d(t)$ uniformly on [0,T] as $k \to \infty$.

The proof of Lemma 1 can be found in [7]. Now the main result of this paper is given below

Main Theorem: Consider the end-effector described by (5) and adequately modelled by (7). If the desired Cartesian position $x_d(t)$ and desired Cartesian contact force $F_d(t)$ are continuously differentiable on [0,T], and $\dot{x}_k(0) = \dot{x}_d(0)$, $x_k(0) = x_d(0)$, then the learning control scheme described by (23) and (19) can be designed such that $x_k(t)$ converges to $x_d(t)$ uniformly on [0,T] as $k \to \infty$.

Proof: The iterative learning scheme expressed by (23) and (19) is intended for the general hybrid learning control system. To prove the above theorem, we consider the special case of pure position learning scheme, which is realized by setting $\bar{S} = 0$. In this case, using (20)-(23), we obtain

$$u_{k+1}(t) = u_k(t) + \Phi[\beta_p(\omega_d-\omega_k) + \alpha_p(\dot{\omega}_d-\dot{\omega}_k)]. \quad (28)$$

We note that M(t), $N(t) + \Phi A_2(t) = N(t) + \alpha_p\Phi$, $G(t) + \Phi A_1(t) = G(t) + \beta_p\Phi$ are continuously differentiable matrices on [0,T] because $x_d(t)$ and $F_d(t)$ are continuously differentiable on [0,T]. In addition,

$$\dot{\omega}_k(0) = \dot{q}_k(0) - \dot{q}_d(0) = 0 = \dot{\omega}_d(0) \quad (29)$$

and $\omega_k(0) = q_k(0) - q_d(0) = 0 = \omega_d(0)$ (30)

since $\dot{x}_k(0) = \dot{x}_d(0)$ and $x_k(0) = x_d(0)$ as given from the hypothesis of the main theorem. Besides, M(t) is positive definite on [0,T] since M(q) is positive definite [see Eq. (5)]. We also observe that (28) and (23) assume the same form where in (28) $\Gamma = \Phi$, which positive definite and $u_1(t)$ is continuous on [0,T] because the closed-loop system (17) is asymptotically stable. Now using Lemma 1, selecting α_p and β_p such that $0 < \alpha_p \le 1$ and $0 \le \beta_p < 1$ will make $\omega_k(t)$ converge to $\omega_d(t) = 0$ uniformly on [0,T] as $k \to \infty$, meaning that $x_k(t)$ converges to $x_d(t)$ uniformly on [0,T] as $k \to \infty$. We just proved the main theorem.

REMARK: In the above proof, we considered the special case of designing the learning control system based on the pure position control. In general, the above proof can be extended to the hybrid case where concentration on certain degrees of freedom can be specified through the Selection Matrix $\bar{S}$. It is expected that the hybrid learning control scheme performs better than the pure position learning control scheme as we will see when implementing the hybrid learning control scheme in the next section.

5. STUDY OF THE SPECIAL CASE

In this section we present the implementation of the proposed learning-based hybrid control scheme for controlling a two-degree-of-freedom robot end-effector resembling a part of the complete CKCM end-effector discussed in Section 2. Experimental study will be performed on the above robot end-effector.

5.1 THE TWO-DEGREE-OF-FREEDOM END-EFFECTOR

Figure 3 illustrates the robotic end-effector built at CUA for the study of postion/force control. Two links of the end-effector are made up by 2 ball-screw actuators, driven by 2 DC motors and hung below a fixed platform by means of pin joints. The other ends of the links are joined together also by pin joints on which a 2-degree-of-freedom force sensor is mounted to provide contact force feedback. Position feedback is achieved by 2 LVDT's mounted along the link lenghts. A reaction table with variable stiffness is placed under the end-effector. The reaction table is made by plexiglass so that horizontal friction is minimized and is held to a solid board by 4 springs at four corners.

The Cartesian positions x and y, of the end-effector end-point, expressed with respect to a reference coordinate system attached to the fixed platform, are related to the link lenghts l_1 and l_2 by

$$x = (l_1^2-l_2^2+d^2)/(2d) \quad (31)$$

$$y = -[4d^2l_1^2-(l_1^2-l_2^2+d^2)^2]^{1/2}/(2d) \quad (32)$$

where d is the distance between the pin joints hanging the actuators. Using the Lagrangian formulation the dynamical equations of this end-effector are given by

$$M(q)\ddot{q}(t) + N(q,\dot{q})\dot{q}(t) + G(q) + J^T(q)F_c = \tau(t) \quad (33)$$

where the joint position vector q is defined by $q = [l_1 \ l_2]^T$ and

$$M = \begin{bmatrix} m_1 & 0 \\ 0 & m_1 \end{bmatrix}; \quad (34)$$

$$N = \begin{bmatrix} 0 & m_1 l_m(l_2-l_1)/(3u) \\ m_1 l_m(l_1-l_2)/(3u) & 0 \end{bmatrix} \quad (35)$$

$$G = [G_1 \ G_2]^T \quad (36)$$

where G_1, G_2, u_1, u_2 and u are given by:

$$G_1 = \{-m_1 g[2u_1 l_1^2(l_1 l_m+l_2 l_m+2l_2 l_2)-l_2 l_m u^2] -mgl_m[2l_1^2u_1(l_1+l_2)-l_2u^2]\}/(4dl_1^2l_2u) \quad (37)$$

$$G_2 = \{-m_1 g[2u_2 l_2^2(l_1 l_m+l_2 l_m+2l_1 l_2)-l_1 l_m u^2] -mgl_m[2l_2^2u_2(l_1+l_2)-l_1u^2]\}/(4dl_1l_2^2u) \quad (38)$$

$$u_1 = l_2^2-l_1^2+d^2; \ u_2 = l_1^2-l_2^2+d^2; \ u = [4d^2l_1^2-u_2]^{1/2} \quad (39)$$

where m_1 is the mass of the moving part of the link, m is the total mass of the link, and l_m represents the fixed lenght of the actuators. In this experimentation study, we are interested in controlling the horizontal position x of the end-effector and the vertical contact force F_y the end-effector applies on the reaction table. Thus for this particular case, the contact force vector is given by $F_c = [0 \ \ F_{cy}]^T$ and the end-effector Jacobian is given by

$$J = \begin{bmatrix} l_1/d & -l_2/d \\ (l_1d^2+l_1l_2^2-l_1^3)/(ud) & l_2d^2+l_2l_1^2-l_2^3)/(ud) \end{bmatrix}. \quad (40)$$

5.2 EXPERIMENTAL STUDY

In this experimental study, the end-effector as shown in Figure 3 is controlled to follow a desired horizontal trajectory specified by

$$x_d = x_0 + 3(3\,e^{-1.25t} - 4\,e^{-0.909t} + 1)$$

while keeping a desired vertical contact force F_{dy} = 3lbf. In each trial, the end-effector tip will start at the same position which is the home position indicated by $\{x_0$ = 13.564 in., y_0 = -33.2 in.$\}$. The starting point is about .15 in. vertically above the reaction table whose vertical postion is -33.35 in.. The end-effector parameters and controller gains used in this experiment are given below:

End-Effector Parameters:

d = 29 in., l_m = 11 in., m_1 = 0.59 kg, m = 4.5 kg.

Hybrid Control System (PD-controller for position, P-controller for force):

$$K_{pp} = \begin{bmatrix} 22V/in. & 0 \\ 0 & 22V/in. \end{bmatrix}; \ K_{pd} = \begin{bmatrix} .7Vsec/in. & 0 \\ 0 & .7Vsec/in. \end{bmatrix}$$

$$K_{fp} = \begin{bmatrix} 0.8\ V/in. & 0 \\ 0 & 0.8V/in. \end{bmatrix}; \quad S = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$$

Learning Control System (PD-controllers for both position and force):

$$\alpha_p = \alpha_f = 1/20; \ \beta_p = \beta_f = 19/20$$

$$\Phi = \begin{bmatrix} 220 & 0 \\ 0 & 2 \end{bmatrix}; \ \bar{S} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}.$$

Figures 5 and 6 illustrate the position errors and force errors of the experiment, respectively. In the first trial, when the end-effector started to move out of the home position, the force errors were very big because the end-effector was not in contact with the reaction table yet. Trying to compensate the force error, the end-effector moved down in the direction of the reaction table as quickly as possible and consequently disturbed the position. This created relatively big position errors at the beginning. After touching the table, the end-effector followed the desired position trajectory with some steady-state errors in force (about ±0.6lbf) and in position (about 0.1in.). The errors in force and position were produced because the hybrid control could not compensate the unforeseen table surface friction and changing stiffness of the table. By repeating the same task, the end-effector was able to learn from the errors of the previous operation through the learning control system and improved the performance as the number of trials increased. As seen in Figures 5 and 6, the end-effector performance at the 10th trial has been improved drastically with almost zero error in position and ±.1lbf in contact force.

6. CONCLUSION

In this paper, we proposed a learning-based hybrid control scheme for controlling position/force of a CKCM end-effector. The proposed control scheme consists of a hybrid control system serving as a feedback controller and a learning control system that can "learn" to improve the performance of theend-effector. Employing the method of linearization around a desired force and position pattern, we showed that the controller gains of the hybrid control system can be selected to asymptotically stabilize the end-effector. After that, using the results in [7], we proved that the controller gains of the learning control system can be designed such that the end-effector responses approach the desired pattern uniformly as the number of trials increases. Experimental investigation performed on a real-life end-effector showed that the proposed control scheme provided excellent convergence of the errors in force and postion. In order to further improve the end-effector performance, it is suggested that future research be extended to studying the implementation of the proposed learning control scheme in a robotic system whose feedback control system is hybrid and adaptive [13], [16].

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REFERENCES

1. Arimoto, S., et al., **"Can Robot Learn by Themselves?"**, *Robotic Research, 3rd Int. Symposium*, H. Hanafusa and H, Inoue, Eds, MIT Press, Massachusetts, 1985.
2. Arimoto, S. et al., **"Bettering Operation of Dynamic Systems by Learning: A New Control Theory for Servomechanism or Mechatronics Systems"**, *Proc. 23rd Conf. Decision and Control*, pp. 1064-1069, December 1984.
3. Atkeson, C. G., and McIntyre, J., **"Robot Trajectory Learning Through Practice"**, *Proc. IEEE Conf. Robotics and Automation*, pp. 1737-1742, San Francisco, 1986.
4. Craig, J.J., **"Adaptive Control of Manipulators Through Repeated Trials"**, *Proc. American Control Conf.*, pp 1566-1573, June 1984.
5. Fu, K.S., **"Learning Control Systems-Review and Outlook"**, *IEEE Trans. Automatic Control*, AC-15, pp. 210-221, April 1970.
6. Hara, S., Omata, T., and Nakano, M., **"Synthesis of Repetitive Control Systems and Its Applications"**, *Proc. 24th Conf. on Decision and Control*, pp. 1387-1392, Dec. 1985.
7. Kawamura, S., Miyazaki, F., and Arimoto, S., **"Applications of Learning Method for Dynamic Control of Robot Manipulators"**, *Proc. 24th Conf. on Decision and Control*, pp. 1381-1386, Dec. 1985.
8. Mita, T. and Kato, E., **"Iterative Control and Its Application to Motion Control of Robot Arm: A Direct Approach to Servo Problems"**, *Proc. 24th Conf. Decision and Control*, pp. 1393-1398, Dec 1985.
9. Nguyen, C.C., **"Arbitrary Eigenvalue Assignments for Linear Time-Varying Multivariable Control Systems,"** *International Journal of Control*, Vol. 45, No. 3, pp. 1051-1057, 1987.
10. Nguyen, C.C., Pooran, F.J., and Premack, T., **"Control of Robot Manipulator Compliance,"** in *Recent Trends in Robotics: Modeling, Control and Education*, edited by M. Jamshidi, J.Y.S. Luh, and M. Shahinpoor, North Holland, New York, pp. 237-242, 1986.
11. Nguyen, C. C., Pooran, F. J. and Premack, T., **"Modified Hybrid Control of Robot Manipulators for High Precision Assembly Operations,"** *Proc. ISMM Conference on Computer Applications in Design, Simulation and Analysis*, Honolulu, Hawaii, pp. 191-195, Feb. 1988.
12. Nguyen, C. C., and Pooran, F. J., **"Kinematics and Dynamics of a Six-Degree-of-Freedom Robot Manipulator with Closed-Kinematic Chain Mechanism,"** *Proc. Second Int. Symp. Robotics and Manufact. Research, Education and Applications*, New Mexico, November 1988.
13. Nguyen, C.C. and Pooran, F.J., **"Adaptive Control of Robot Manipulators with Closed-Kinematic Chain Mechanism,"** *Proc. Second International Symposium on Robotics and Manufacturing Research, Education and Applications*, New Mexico, November 1988.
14. Premack, T., et.al., **"Design and Implementation of a Compliant Robot with Force Feedback and Strategy Planning Sofware,"** *NASA Technical Memorandum* 86111, 1984.
15. Raibert, M. H., and Craig, J.J., **"Hybrid Position/Force Control of Manipulators,"** *ASME, Journal of Dynamic Systems, Measurement and Control*, 102, pp. 126-133, June 1981.
16. Seraji, H., **"Adaptive Force and Position Control of Manipulators,"** *Journal of Robotics Systems*, 4(4), pp. 551-578, 1987.
17. Togai, M., and Yamano, O., **"Analysis and Design of an Optimal Learning Control Scheme for Industrial Robots: A Discrete System Approach"**, *Proc. 24th Conf. on Decision and Control*, pp. 1399-1404, Dec. 1985.
18. Uchiyama, M., **"Formation of High Speed Motion Pattern of Mechanical Arm by Trial"**, *Transactions, Society of Instrument and Control Engineers*, Vol. 19, # 5, pp. 706-712, 1978.

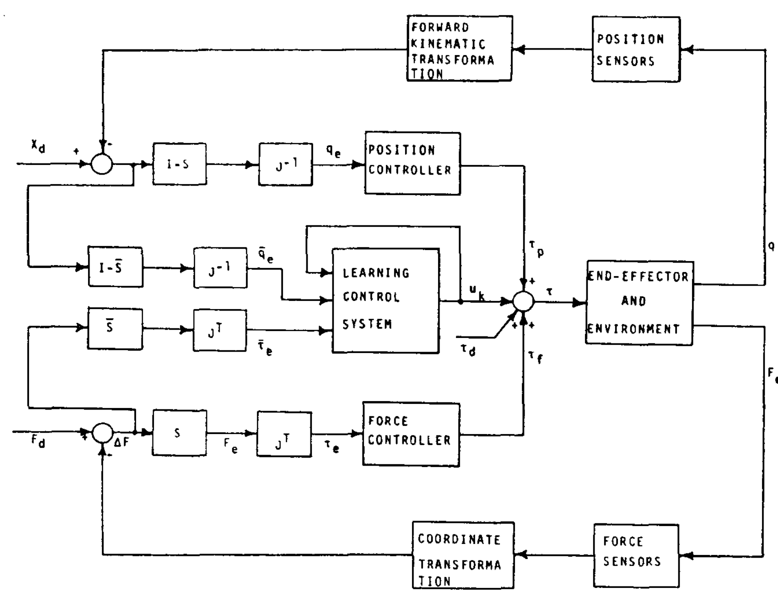

Fig. 2: The Learning-Based Hybrid Control System

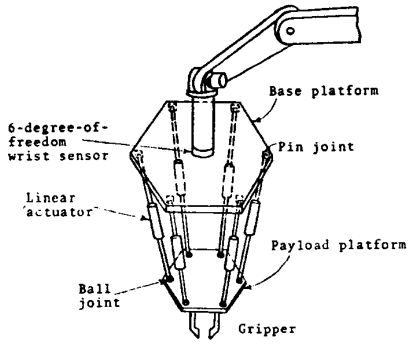

Fig. 1: The CKCM Robotic End-Effector

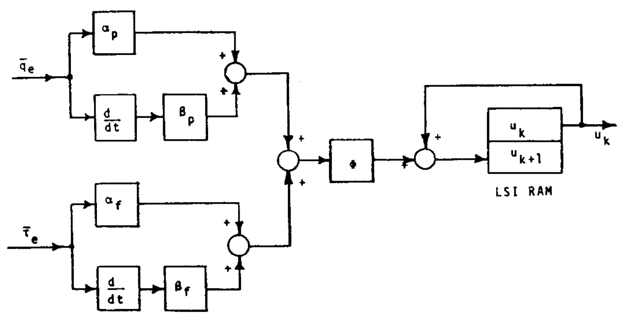

Fig. 3: The Learning Controller

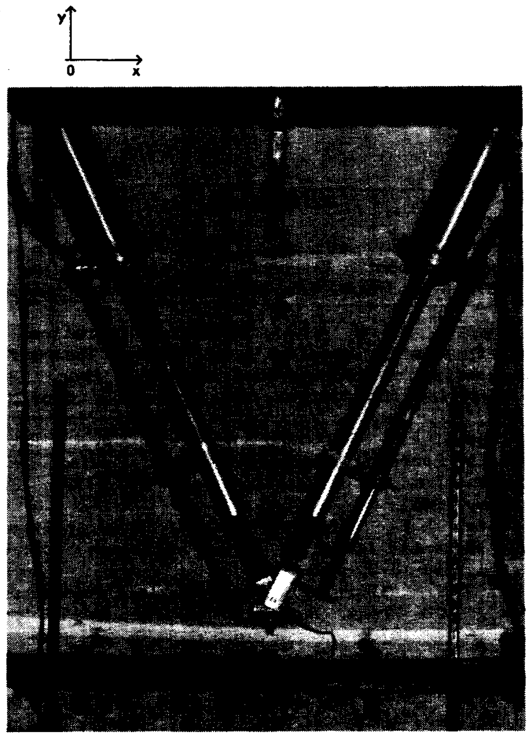

Fig. 4: The 2-DOF CKCM End-Effector

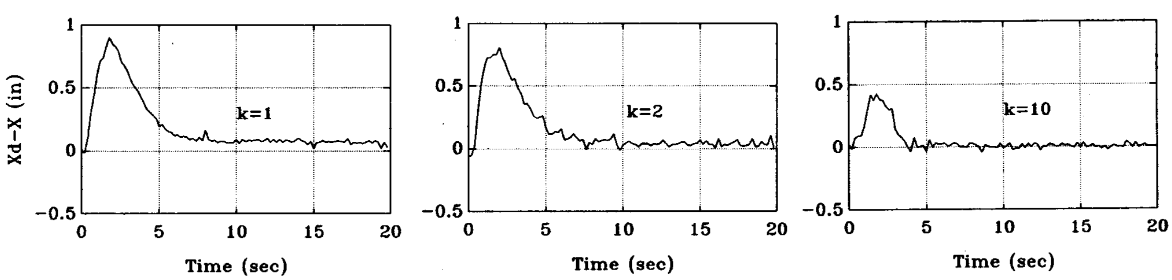

Fig. 5: Experimental Results of Position Errors

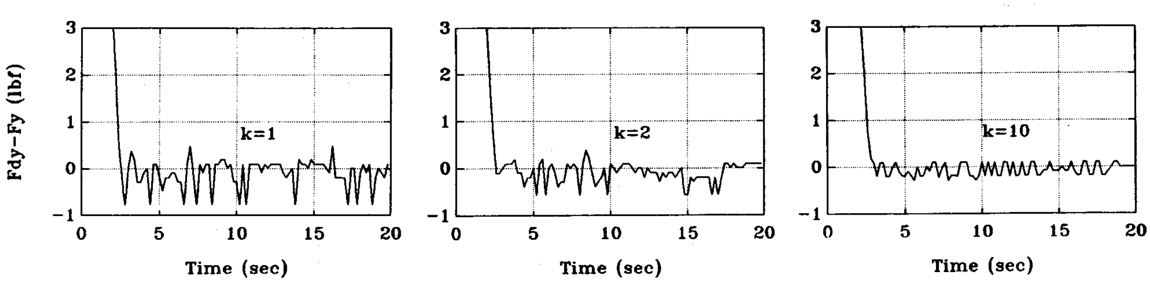

Fig. 6: Experimental Results of Force Errors