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# INTELLIGENT ADAPTIVE ACTIVE FORCE CONTROL OF A ROBOTIC ARM WITH EMBEDDED ITERATIVE LEARNING ALGORITHMS

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**Abstract**. The robust and accurate control of a robotic arm or manipulator are of prime importance especially if the system is subjected to varying forms of loading and operating conditions. The paper highlights a novel and robust method to control a robotic arm using an iterative learning technique embedded in an active force control strategy. Two main iterative learning algorithms are utilized in the study – the first is used to automatically tune the controller gains while the second to estimate the inertia matrix of the manipulator. These parameters are adaptively computed on-line while the robot is executing a trajectory tracking task and subject to some forms of external disturbances. No priori knowledge of both the controller gains and the estimated inertia matrix are ever assumed in the study. In this way, an adaptive and robust control scheme is derived. The effectiveness of the method is verified and can be seen from the results of the work presented in this paper.

*Keywords*: Adaptive, active force control, iterative learning, inertia matrix, controller gain

**Abstrak**. Kawalan jitu dan lasak bagi satu sistem lengan robot atau pengolah adalah amat penting terutama sekali jika sistem mengalami pelbagai bentuk bebanan dan keadaan pengendalian. Kertas kerja ini memaparkan satu kaedah baru dan lasak untuk mengawal lengan robot menggunakan teknik pembelajaran secara berlelaran yang dimuatkan dalam strategi kawalan daya aktif. Sebanyak dua algoritma pembelajaran utama digunakan dalam kajian – yang pertama digunakan untuk menala gandaan pengawal secara automatik manakala yang satu lagi pula untuk menganggarkan matriks inersia pengolah. Kedua-dua parameter ini dihasilkan secara adaptif dan dalam talian ketika robot sedang menjalankan tugas menjejak trajektori dalam persekitaran tindakan daya gangguan. Dalam kajian ini, pengetahuan awal tentang kedua-dua nilai gandaan pengawal dan anggaran matriks inersia tidak wujud. Dengan demikian, suatu skema kawalan yang jitu dan lasak terhasil. Keberkesanan kaedah yang dicadangkan dapat ditentusahkan melalui hasil kajian yang diperoleh dan dibentangkan dalam kertas kerja ini.

*Kata kunci*: Adaptif, kawalan daya aktif, pembelajaran berlelaran, matriks inersia, gandaan pengawal

## LIST OF NOTATION:

| | |
|---|---|
| $\theta$ | vector of positions in joint space |
| $\ddot{\theta}_{ref}$, $\ddot{x}_{ref}$ | reference acceleration vectors in joint and *Cartesian* spaces |

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| | |
|---|---|
| $\boldsymbol{G}$ | vector of gravitational torque |
| $\boldsymbol{h}$ | vector of the *Coriolis* and centrifugal torques |
| **H** | (*N* dimensional manipulator and actuator inertia matrix |
| $\boldsymbol{I_a}$ | compensated current vector |
| $\boldsymbol{I_c}$ | current command vector |
| **IN** | estimated inertia matrix |
| $\boldsymbol{I_t}$ | armature current for the torque motor |
| $K_p$, $K_d$ | PD controller gains |
| $K_t$ | motor torque constant |
| $\boldsymbol{T_d}^*$ | estimated disturbance torque |
| $\boldsymbol{T_d}$ | vector of the disturbance torque |
| $\boldsymbol{TE_k}$ | current root of sum-squared positional track error, $TE_k = \sqrt{\Sigma}((x_{bar} - x_k)^2$ |
| $\boldsymbol{T_q}$ | vector of actuated torque |
| $\boldsymbol{V_{cut}}$ | endpoint tangential velocity |
| $\boldsymbol{x}$, $\boldsymbol{x_{bar}}$ | vectors of actual and desired positions respectively in *Cartesian* space |
| $\boldsymbol{x}$ | vector of the end-effector positions in *Cartesian* space |
| $y_k$ | current value of the estimated parameter |
| $y_{k+1}$ | next step value of the estimated parameter |
| $\phi$, $\Gamma$ and $\Psi$ | learning parameters (constants) |

## 1.0 INTRODUCTION

Robot force control is concerned with the physical interaction of the robot's end effector with the external environment in the forms of applied forces/torques, changes in the mass payloads and constrained elements. A number of control methods have been proposed to achieve stable, accurate and robust performance ranging from the classical proportional-derivative (PD) control [1] to the more recent intelligent control technique. The PD control is simple, efficient and provides stable performance when the operational speed is low and there are very little or no disturbances. The performance however is severely affected with the increase in speed and presence of disturbances. Adaptive control method [2, 3] improves the stability and robustness of the system via its adaptive feature, which enable it to operate in a wider range of parametric uncertainties and disturbances. Nevertheless, this technique is more commonly confined to theoretical and simulation study as it involves rigorous mathematical manipulation and assumptions. Active force control (AFC) of a robot arm has been demonstrated to be superior compared to the conventional methods in dealing with compensating a variety of disturbances [4, 5]. There is a growing trend in robotic control to include adaptive and intelligent mechanism such as neural network, knowledge-based expert system, fuzzy logic and iterative learning algorithm.

In this paper, an iterative learning technique acting as an adaptive mechanism is used together with the AFC strategy to control a rigid two-link horizontal planar robotic arm. The scheme is in fact an extension to the works described in [6, 7] where the effectiveness and practicality of the scheme applied to a two-link planar arm has been clearly demonstrated in the study. It is the objective of the proposed study to demonstrate the additional adaptive feature of the control scheme employing two iterative learning algorithms. The first is used to automatically and adaptively tune the controller gains while the second one to compute the estimated inertia matrix of the robot arm both without any prior knowledge of the controller and inertial parameters.

The paper is structured as follows. The first part presents a description of the problem statement and the fundamentals of both the AFC and iterative learning control technique. The integration of the iterative learning algorithms and AFC applied to a manipulator is then demonstrated in the form of a simulation study. Consequently, an analysis and discussion of the results obtained are presented. Finally, a conclusion is derived and the direction for future works outlined.

## 2.0 PROBLEM STATEMENT

AFC is a force control strategy originated by Hewit [4, 8] and is primarily designed to ensure that a system remains stable and robust even in the presence of known or unknown disturbances. In AFC, the system mainly uses the estimated or measured values of a number of identified parameters to effect its compensation action. In this way, we can reduce the mathematical complexity of the robotic system, which is known to be highly coupled and non-linear.

The main drawback of AFC is the acquisition of the estimated inertia matrix that is required by the AFC feed-forward loop. Previous methods greatly rely on either perfect modeling of the inertia matrix, crude approximation or the reference of a look-up table. Obviously, these methods require the prior knowledge of the estimated inertia matrix. Although the methods are quite effective to implement, they lack in systematic approach and flexibility to compute the inertia matrix. Thus, a search for better ways to generate efficiently suitable estimated inertia matrix is sought. If a suitable method of estimating the inertia matrix can be found, then the practical value of implementing AFC scheme is considerably enhanced. Obviously, intelligent methods are viable options and should be exploited to achieve the objective as already discussed in [6, 7]. Another common problem that is associated with a classical control system is the tuning of the controller gains in order to achieve good and stable performance. While there are some other adaptive techniques used to solve this difficulty, the more common approach is through heuristic means. Here, another novel technique is proposed that is simple, effective and readily embedded into the main active force control strategy to control the robot arm.

The basic idea of the proposed scheme is to generate both the PD controller gains ($K_p$ and $K_d$) and the estimated inertia matrix (**IN**) of the arm in the AFC controller continuously, automatically and on-line using suitable learning algorithms as the arm is commanded to execute a prescribed task accurately even in the presence of disturbances. Given suitable initial conditions of these parameters and as the robot arm starts to perform the desired task, the iterative learning algorithms (ILA1 and ILA2) will compute the next value of the parameters from the current input value based on the resulting track error and suitable learning constants. Figure 1 is a graphic representation showing the mechanism of the proposed control scheme. Note that ILA1 and ILA2 use different types of learning algorithms to compute the required parameters.

As time increases, the learning mechanism causes the track error to gradually converge approaching zero datum and the process is iteratively repeated until a small and acceptable error margin is achieved. Consequently, the $K_p$, $K_d$ and **IN** are said to have been optimized and having appropriate values to be effectively used by the system.

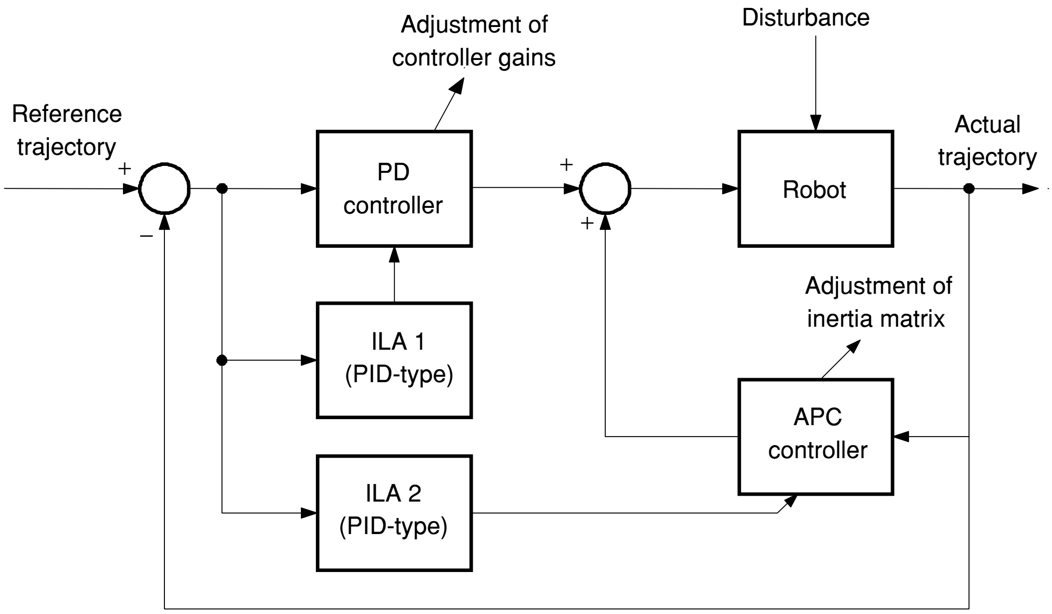


**Figure 1** Mechanism of the Proposed Control Scheme

In the following sections, the fundamentals of both AFC and iterative learning methods are briefly highlighted so that a better understanding of the overall control scheme can be derived.

## 3.0 ACTIVE FORCE CONTROL AND ITERATIVE LEARNING CONCEPTS

### 3.1 Active Force Control (AFC)

It has been shown that disturbances can be effectively eliminated via the compensating action of the AFC strategy [4, 9]. The detailed mathematical analysis of the AFC scheme can be found in [9]. The paper will only highlight the essentials of the AFC applied to control a robotic manipulator arm. Figure 2 shows a schematic of this scheme.

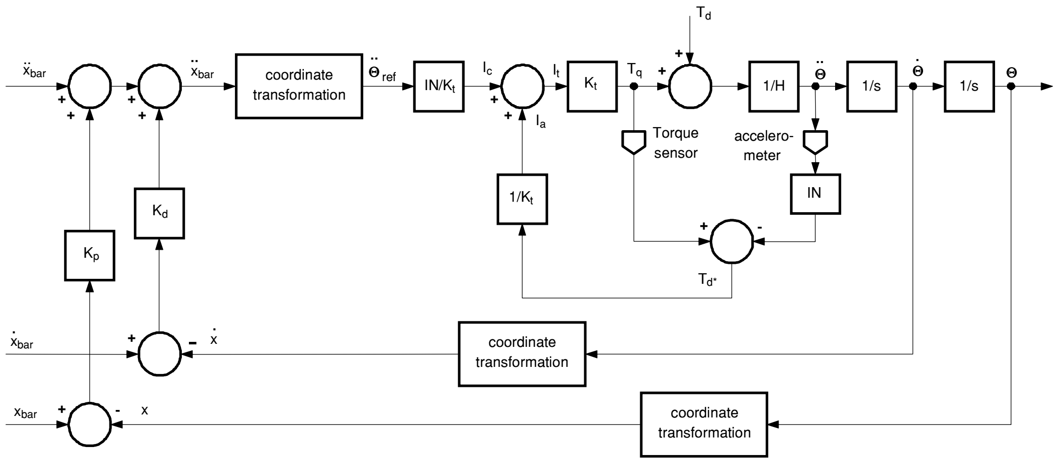


**Figure 2** The AFC Scheme Applied to a Robot Arm

In AFC, it is essential that we obtain the physical measurements of the joint acceleration ($\ddot{\theta}$) of the arm and the actuated torque ($\boldsymbol{T_q}$) using accelerometer and torque sensor respectively as can be seen in Figure 2. Next, the estimated inertia matrix of the arm (**IN**) has to be appropriately identified by suitable means. In this way, we could estimate the disturbance torques $\boldsymbol{T_d}$*****, based on the measured or estimated values of the variables. A mathematical expression to represent this is as follows:

$$\boldsymbol{T_d}^* = \boldsymbol{T_q} - \mathbf{IN}\ \ddot{\theta} \tag{1}$$

Eq. (1) can be further simplified as

$$\boldsymbol{T_d}^* = K_t\, \boldsymbol{I_t} - \mathbf{IN}\ \ddot{\theta} \tag{2}$$

where

$$\boldsymbol{T_q} = K_t \, \boldsymbol{I_t} \tag{3}$$

In this case, instead of measuring the torque directly, we measure the torque current $\boldsymbol{I_t}$ and then multiply it with the torque constant $K_t$ which of course gives the value of the required actuated torque. While the measurement part is obvious, the inertial parameter can be obtained using a number of methods such as crude approximation, reference of a look-up table or intelligent means using neural network and iterative learning algorithms [6]. The last method was chosen and implemented in the paper.

In addition to the above, a PD controller employing resolved motion acceleration control (RMAC) as described in [9] which can improve the overall performance of the control scheme is included. RMAC is governed by the following equation:

$$\ddot{\boldsymbol{x}}_{\boldsymbol{ref}} = \ddot{\boldsymbol{x}}_{\boldsymbol{bar}} + K_d(\dot{\boldsymbol{x}}_{\boldsymbol{bar}} - \dot{\boldsymbol{x}}) + K_p(\boldsymbol{x}_{\boldsymbol{bar}} - \boldsymbol{x}) \tag{4}$$

Eq. (2) is then transformed into $\ddot{\theta}_{ref}$ by means of inverse *Jacobian* manipulation to be fed forward into the AFC control loop. The controller gains in Eq. (4) are adaptively obtained via the iterative learning algorithm.

### 3.2 Iterative Learning

One of the early proposer of the iterative learning method applied to robotic control is *Suguru Arimoto* who proposes a number of learning algorithms and at the same time provides analytical proof for their convergence, stability and robustness [10, 11]. *Arimoto et al*. has shown that the track error effectively converges to zero with the increase in time via the iterative learning scheme applied to the control of robot arm. A slightly modified learning algorithm [6] to suit our application is employed. In this study, the following learning rules are adopted:

$$y_{k+1} = y_k + (\phi + \Gamma \, d/dt) \; \boldsymbol{TE_k} \tag{5i}$$

$$y_{k+1} = y_k + (\phi + \Gamma \, d/dt + \Psi \textstyle\int dt) \; \boldsymbol{TE_k} \tag{5ii}$$

In the study, the estimated inertia matrix **IN** is substituted in place of $y$ in Eq. (5i) while the controller gains, $K_p$ and $K_d$ are similarly substituted in Eq. (5ii). Since the learning parameters are represented in the form of '*proportional*' ($\phi$) and '*derivative*' ($\Gamma$) constants for the first case, the algorithm is conveniently described as a PD-type learning algorithm as shown in Figure 3i. The other algorithm which contains an additional '*integral*' ($\Psi$) term shall be described as a PID-type learning algorithm (Figure 3ii).

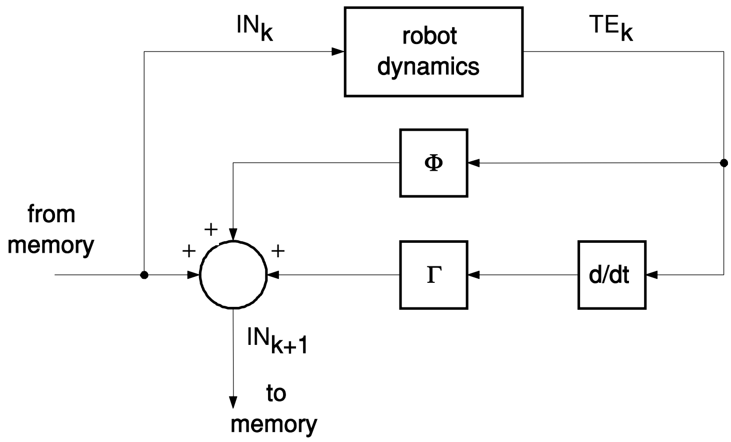


**Figure 3(i)** A PD-type Learning Algorithm

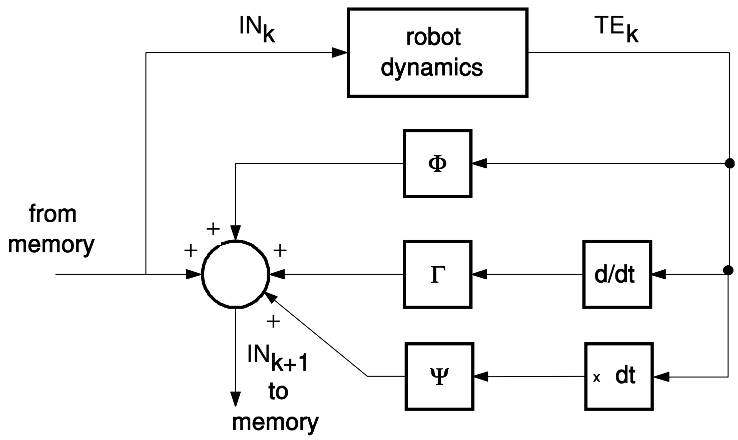


**Figure 3(ii)** A PID-type Learning Algorithm

## 3.3 The Proposed Control Scheme

Figure 4 shows how the PD and PID-type learning algorithms are incorporated into the system. It is obvious that two PID-type algorithms were implemented in ILA1 while a PD-type was used instead in ILA2 as shown in Figure 4. The integration of both the AFC scheme and the iterative learning algorithms making it the core of the proposed scheme is also shown. From the figure, it is obvious that the iterative learning algorithms are easily and readily embedded into the overall control scheme with the track error vector *TE* serving as the input to the learning algorithms section while the gains ($K_p$ and $K_d$) and the estimated inertia matrix (**IN**) are treated as the outputs. Consequently, a simulation study of the above scheme was performed considering various loading conditions and changes in the robotic parameters.

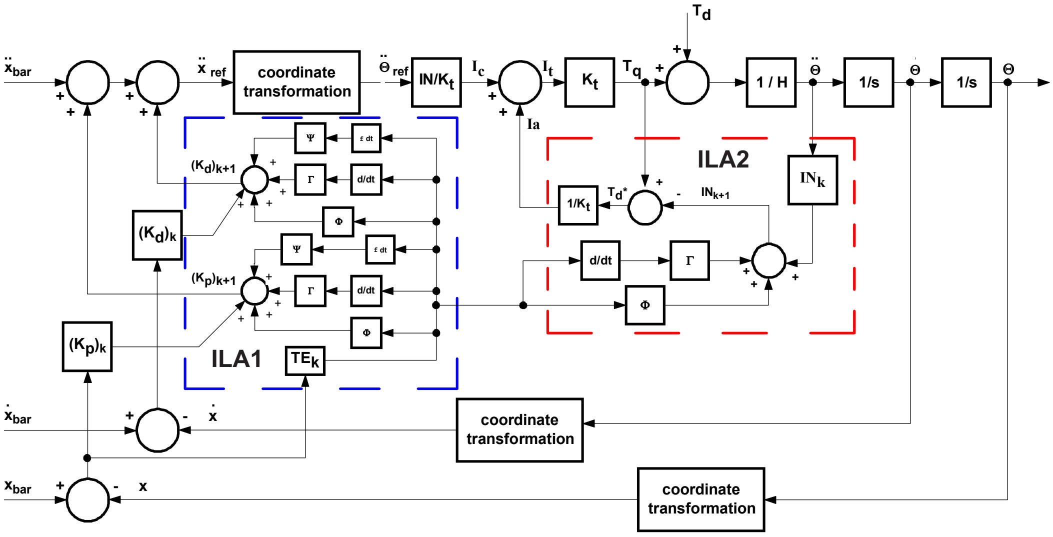


**Figure 4** A Schematic of the Proposed Control Scheme

It is important to note that throughout the study, only the diagonal elements of the estimated inertia matrix **IN** (a 2 × 2 square matrix) were considered. For convenience, the inertia terms are denoted as $IN_{11} = IN_1$ and $IN_{22} = IN_2$. The off-diagonal terms, $IN_{12}$ and $IN_{21}$ are disregarded since it has been shown in [9] that this coupling term may be ignored by the AFC strategy.

## 4.0 MATHEMATICAL MODEL OF THE ROBOT ARM

The dynamic model or the general equation of motion of a robot manipulator [12] can be described as follows:

$$\boldsymbol{T_q} = \mathbf{H}(\theta)\ddot{\theta} + \boldsymbol{h}(\theta, \dot{\theta}) + \boldsymbol{G}(\theta) + \boldsymbol{T_d} \qquad (6)$$

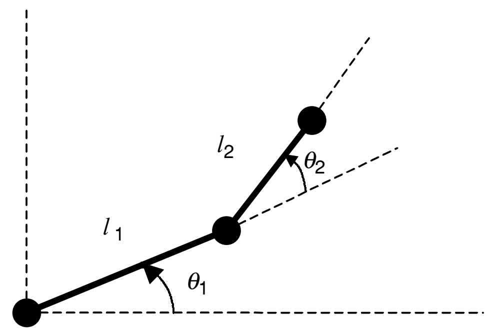


**Figure 5** A Representation of a Rigid Two-Link Planar Arm

Figure 5 shows a representation of a rigid two-link horizontal planar manipulator under study. The gravitational term can be ommitted here since the arm is assumed to move in a horizontal plane. Thus, the dynamic model is reduced to

$$\boldsymbol{T_q} = \mathbf{H}(\theta)\ddot{\theta} + \boldsymbol{h}(\theta, \dot{\theta}) + \boldsymbol{T_d} \tag{7}$$

## 5.0 SIMULATION

Simulation work was performed using the MATLAB and SIMULINK software packages. Figure 6 shows the SIMULINK block diagram of the proposed scheme.

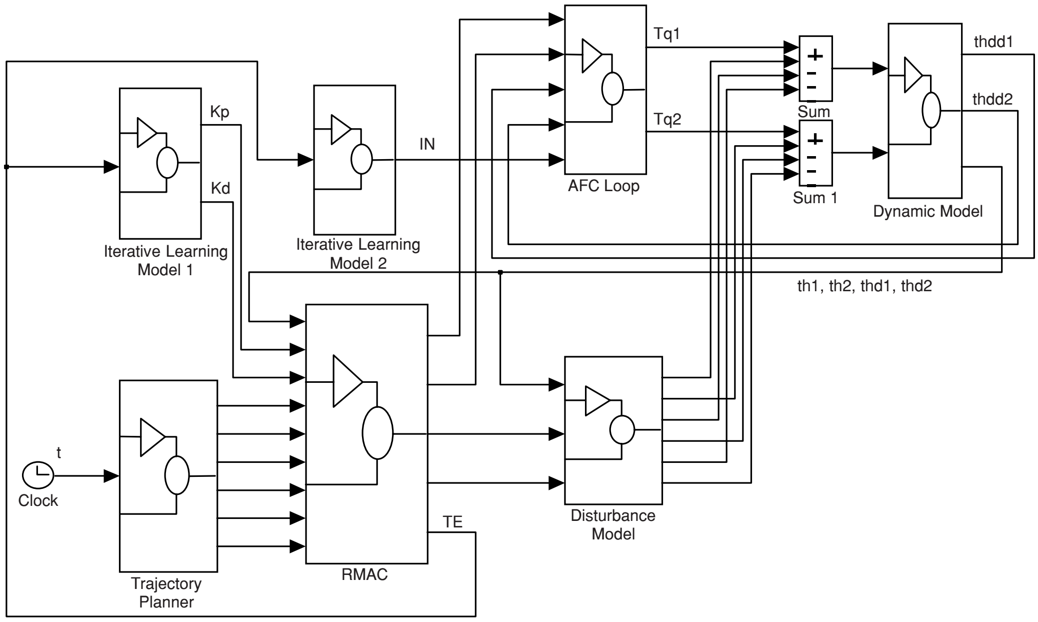


**Figure 6** A SIMULINK Representation of the Control Scheme

### 5.1 Simulation Parameters

The following parameters were used in the simulation study.

**Robot parameters:**

Link length: $l_1 = 0.25$ m $l_2 = 0.2236$ m

Link mass: $m_1 = 0.25$ kg $m_2 = 0.2236$ kg

Payload mass: $m_{pl} = 0.01$ kg

**Actuator parameter:**

Motor torque constant: $K_t = 0.263$ Nm/A

**Iterative learning parameters:**

*ILA 1*:

Proportional term: $\phi = 350\ (K_p),\ 250\ (K_d)$

Derivative term: $\Gamma = 250\ (K_p),\ 250\ (K_d)$

Integral term: $\phi = 450\ (K_p),\ 450\ (K_d)$

*ILA 2*:

Proportional term: $\phi = 0.0175$

Derivative term: $\Gamma = 0.00008$

**Other parameters:**

Sampling time: 0.01 s

Initial conditions of
parameters to be computed: $IN_1 = IN_2 = 0$ kgm$^2$
$K_p = K_d = 0$

Endpoint tangential velocity: $\boldsymbol{V_{cut}} = 0.5$ m/s

$K_t$ is derived from the actual data sheet for a dc torque motor [13] considered in the study. Note that the learning constants for the learning algorithms were heurestically assumed prior to the actual simulation study. Simulation was performed taking into account specific introduced disturbance to test the system's robustness.

## 5.2 The Prescribed Trajectory

The prescribed trajectory considered in the simulation study is a circular path. It serves as the reference trajectory that the arm should accurately track via the control strategy. The trajectory coordinates in *Cartesian* space can be described as follows:

$$\mathbf{x_1} = 0.25 + 0.1 \sin\left(\boldsymbol{V_{cut}}\ \boldsymbol{t}/0.1\right) \quad (8)$$

$$\mathbf{x_2} = 0.1 + 0.1 \cos\left(\boldsymbol{V_{cut}}\ \boldsymbol{t}/0.1\right) \quad (9)$$

## 5.3 Loading Conditions

In the process of investigating the effectiveness and robustness of the system, three different loading conditions were considered. The performance study was performed under the following conditions:

a. The system is free from any external disturbance.
b. A constant force of magnitude 30 N is acting horizontally at the end of the second link.
c. A constant disturbance torque of magnitude 10 Nm is acting at each joint.

## 6.0 Results and Discussion

The trajectory track performance of the arm under the three different operating and loading conditions are depicted in Figure 7 through Figure 12. It is evident that in the first two cycles, the trajectories of the arm are highly distorted in all the three cases. Nevertheless, as time progresses, the performance rapidly improved as can be seen from the superior trajectory track performance at the later stage when the learning is said to be completed. Figure 10 through Figure 12 show that the trajectories tracked in the last two cycles resemble the desired one with only small deviations. The effectiveness of the iterative learning process is clearly demonstrated in Figure 13 through Figure 15 where the large initial track error rapidly converges to near zero datum in all the three cases as time increases. The fast convergence of the track error to values under 0.001 m margin within 4 s of operation signifies the excellent learning capability of the algorithm. In other words, the control system is able to give robust performance in less than three cycle period (one cycle period is equivalent to the time taken by the end effector to describe a complete reference circular trajectory; one cycle period = 1.257 s) with the end-point velocity, $\boldsymbol{V_{cut}}$ = 0.5 m/s. Considering a circular path trajectory of 0.2 m in diameter, the error value of 0.001 m corresponds to about 0.5% deviation from the desired trajectory.

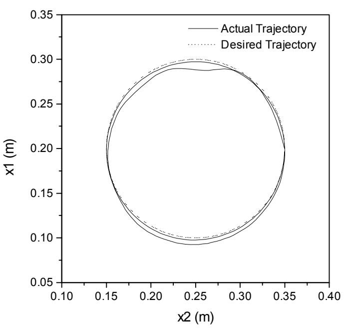


**Figure 7** The Trajectory of the Arm in the First Two Cycles (no disturbance)

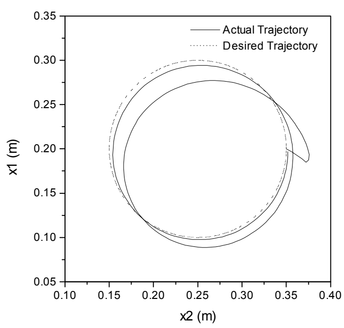


**Figure 8** The Trajectory of the Arm in the First Two Cycles ($A$ = 30 N)

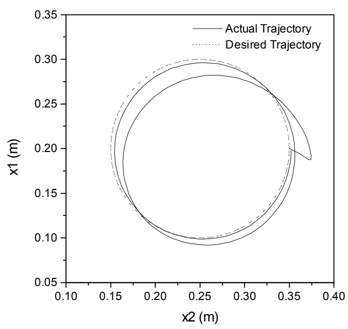


**Figure 9** The Trajectory of the Arm in the First Two Cycles ($T_d$ = 10 Nm)

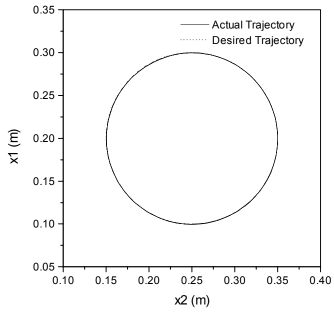


**Figure 10** The Trajectory of the Arm in the Last Two Cycles (no disturbance)

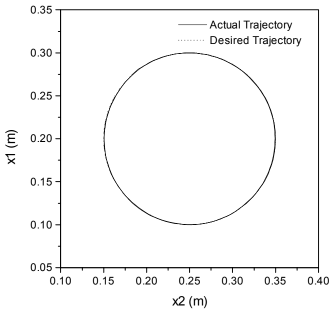


**Figure 11** The Trajectory of the Arm in the Last Two Cycles ($A$ = 30 N)

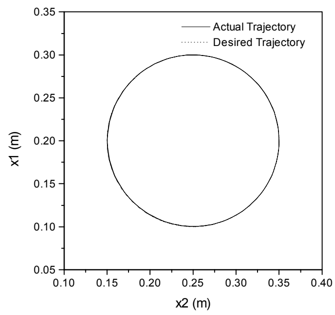


**Figure 12** The Trajectory of the Arm in the Last Two Cycles, ($T_d$ = 10 Nm)

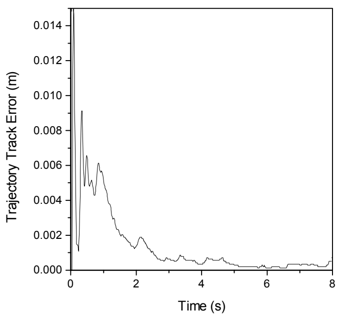


**Figure 13** The Trajectory Track Error (no disturbance)

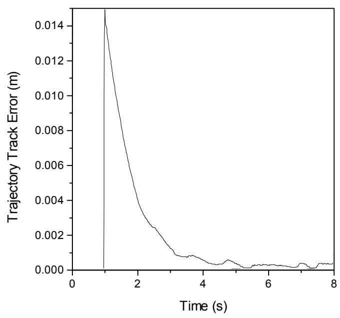


**Figure 14** The Trajectory Track Error ($A$ = 30 N)

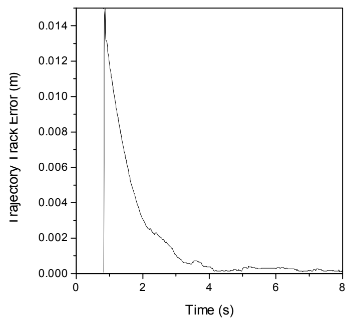


**Figure 15** The Trajectory Track Error ($T_d$ = 10 Nm)

The iterative learning algorithms applied at the RMAC section (PD controller) adaptively compute the controller gains $K_p$ and $K_d$ as the robot operates in task space. Figure 16 through Figure 18 show the patterns generated against time. The initial part of the graphs shows a quick non-linear transient response followed by almost a straight and linear pattern having positive gradient. The characteristics of the computed values can be attributed to the nature of the learning algorithm itself. On top of that, the computed value produces only positive definite value since it is a function of the track error (in the study, this error is assigned to be positive definite). The gradient of the curves are however influenced by the learning constants, $\phi$, $\Gamma$ and $\Psi$ as already discussed in the previous study [6]. A good choice of these learning parameters is essential to ensure excellent control performance. The types of disturbances also affect the gradient of the slope; the constant force and the disturbance torques applied to the system produce steeper slopes because of their larger initial track errors.

The other learning algorithm employed to approximate the estimated inertia matrix of the arm (**IN**) via the AFC controller produces results as shown in Figure 19 through Figure 21. The graphs exhibit curves, each of which is characterized by a

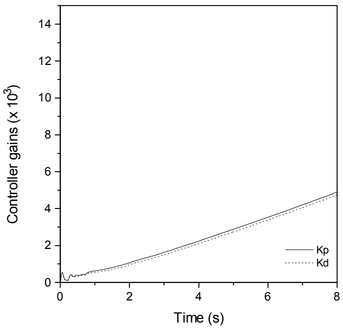


**Figure 16** The Controller Gains (no disturbance)

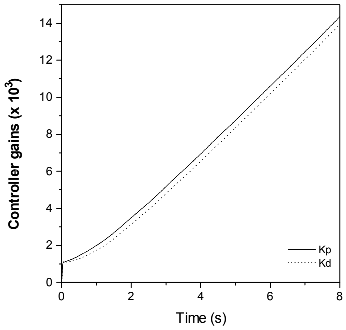


**Figure 17** The Controller Gains ($A$ = 30 N)

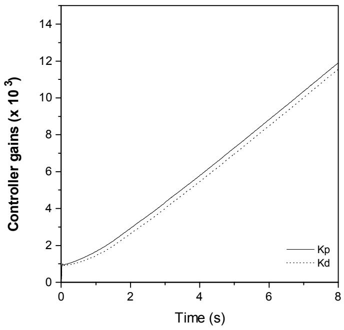


**Figure 18** The Controller Gains ($T_d$ = 10 Nm)

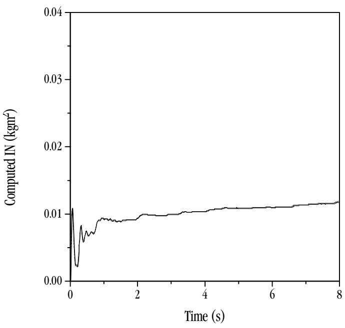


**Figure 19** The Estimated Inertia Matrix (no disturbance)

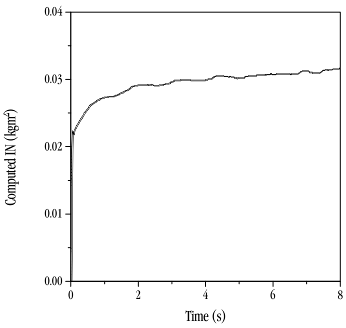


**Figure 20** The Estimated Inertia Matrix ($A$ = 30 N)

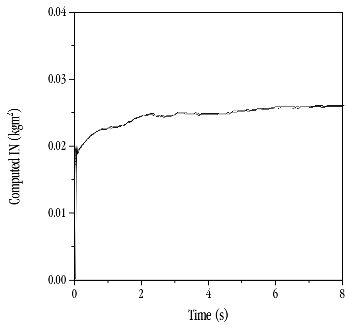


**Figure 21** The Estimated Inertia Matrix ($T_d$ = 10 Nm)

steep slope at the initial stage. At the intermediate stage, it negotiates a sharp bend and towards the end of the simulation period produces a positive gradual incremental slope. It should be noted that the diagonal terms, $IN_1$ and $IN_2$ of the inertia matrix **IN** are in fact having the same numerical values since they both have identical initial conditions. In other words, a single curve shown in Figure 19 through Figure 21 actually signifies two inertial parameters of exactly the same quantity that are computed by the control algorithm. It can be deduced that the computed values at the later stage of the simulation period have 'optimized' the parameter and thus having appropriate values that are effectively used by the proposed control scheme. These curve patterns once again show that the system exhibits excellent 'all-round' performances under various operating conditions even in the presence of disturbances considering the relatively very small track error generated by the system towards the end of the simulation period.

## 7.0 CONCLUSION

The proposed control scheme has been shown to give excellent trajectory track control performances by generating the required estimated parameters via the iterative learning algorithms. Both the PD-controller gains and the estimated inertia matrix are successfully computed signifying that the the AFC and iterative learning algorithms combine readily to yield robust and effective characteristics even under the influence of the applied disturbances. A distinct feature of the control scheme is that the learning process is accomplished automatically, continuously and on-line and at a fast rate while the robot is performing the task. The fast convergence of the trajectory track errors to acceptable marginal values within a reasonable period indicates that the learning mechanism is effectively taking place as predicted and that the parameters are identified and optimized. Further investigation of the system performance employing the proposed control scheme should take into account the stopping criteria necessary to ensure the systematic convergence of the computed values.

## ACKNOWLEDGEMENTS

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