Adaptive Control of Robotic Arm under Time-varying Uncertainties

MECH5808A - Nonlinear Systems Analysis

Final Project Report

Author

Lakshay Arora

101212387

Presented to Faculty

Dr. Mojtaba Ahmadi

Department of Mechanical and Aerospace Engineering

Carleton University

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1 Introduction

In recent years, the trajectory control of manipulator robots has been the subject of much research, due to the robots' increasingly frequent use in dangerous or inaccessible environments, where human beings can hardly intervene. The robotic manipulators have become an integral part of various research areas such as process industries, space control applications like free floating space manipulators, medical and healthcare like limb rehabilitation manipulators, nuclear plants etc,. That is why there is a need of selecting an appropriate method for control has become really crucial while performing any kind of manipulation.

The choice of controllers depends mainly on the presence of uncertainties. These uncertainties can be characterized by variation in payload, model imprecision of link parameters, inaccuracies present in torque constants of actuators, etc. The primary consideration in designing and accomplishing a fundamental required task of a robot manipulator is to plan the trajectory for this robot manipulator moving from its current position to a different set or series of points which eventually leads to it's final destination while carrying a payload. The trajectory control of robot arm in carrying constant and time varying load especially in service robot and industry fields is important. The changes in the payload may not be known apriori. Different control approaches have been employed for nonlinear systems in the last 2-3 decades. Control architectures depend on the system model or structure. These controllers not only aim to guarantee system robustness but also, stability as well as fast convergence. They can solve many problems such as external disturbance invariance to system uncertainties.

Deriving the control law which includes and deals with the uncertainties has gained a huge interest among researchers. The literature consists of various nonlinear control techniques such as feedback linearization, robust control, backstepping control, Lyapunov stability based robust control, adaptive control, and sliding mode control for the robotic manipulator. Traditional controllers like, PD controllers are unable to accommodate the uncertainties discussed above. Such a controller drastically reduce the system's performance and may even become unsatisfactory depending on the degree of changes[2]. It is well known that adaptive controller is capable of catering systems with constant uncertainties. In [7], an adaptive control of n-Degree of Freedom (DOF) manipulators with time-dependent uncertainties is presented by linearly parametrizing the manipulator dynamic model. However, adaptive controller requires a huge computation power for regressor matrix in order to express the robot dynamics in a linearly parameterized form while dealing with unknown time varying uncertainties. Moreover, sometimes it is difficult to represent these uncertainties in a paramaterized form.

Function Approximation Technique (FAT) is a regressor-free adaptive control for manipulators operating under time-varying uncertainties[5][3]. The basic idea is to represent the general uncertainties by using a set of known basis function weighted by a set of unknown coefficients. The uncertainties are expressed by FAT equations such as Fourier Series, Bessel and Taylor polynomials. There are many studies based on the same FAT adaptive control[6, 4]. In this report, FAT adaptive control scheme for 2-DOF robot arm carrying uncertain time-varying payload presented in [1] is implemented and also tested for different desired trajectories and cases to check tracking performance of the controller.

2 Dynamic model for Robot Manipulator

The dynamic model of n-link robot manipulator can be represented using Lagrange equation which can be expressed as

$$\mathbf{M(q)\ddot{q}(t)} + \mathbf{C(q,\dot{q})\dot{q}(t)} + \mathbf{G(q)} = \boldsymbol{\tau} \tag{1}$$

where $\mathbf{q} \in \mathbb{R}^n$, $\dot{\boldsymbol{q}} \in \mathbb{R}^n$, and $\ddot{\boldsymbol{q}} \in \mathbb{R}^n$ denote the link position, velocity, and acceleration vectors, respectively, $\boldsymbol{M(q)} \in \mathbb{R}^{n\times n}$ is the symmetric nonsingular inertia matrix, $\boldsymbol{C(q,\dot{q})} \in \mathbb{R}^{n\times n}$ is the Coriolis and centrifugal force matrix, $\boldsymbol{G(q)} \in \mathbb{R}^n$ is the vector of gravitational torques and $\boldsymbol{\tau} \in \mathbb{R}^n$ is the control torque applied to the joints.

3 Regressor-free Adaptive Control based on FAT

Since the inertia matrix, Coriolis matrix, and gravity vector are functions of q, which is continuous, which therefore satisfy the Dirichlet conditions. This allows us to use Fourier series as our orthonormal basis functions. The Adaptive Function Approximation Technique controller framework represents the inertia matrix, Coriolis matrix, and gravity vector as

$$\begin{aligned} M(q(t)) &= W_M^T Z_M(t) + \varepsilon_M(t) \\ C(q(t),\dot{q}(t)) &= W_C^T Z_C(t) + \varepsilon_C(t) \\ G(q(t)) &= W_G^T Z_G(t) + \varepsilon_G(t) \end{aligned} \tag{2}$$

where $W_D \in \mathbb{R}^{n^2\beta_D\times n}$, $W_C \in \mathbb{R}^{n^2\beta_C\times n}$, and $W_G \in \mathbb{R}^{n\beta_G\times n}$ are the constant weight matrices. $Z_D(t) \in \mathbb{R}^{n^2\beta_D\times n}$, $Z_C(t) \in \mathbb{R}^{n^2\beta_C\times n}$, and $Z_G \in \mathbb{R}^{n\beta_G}$ are matrices of basis functions. $\varepsilon_D(t) \in \mathbb{R}^{n\times n}$, $\varepsilon_C(t) \in \mathbb{R}^{n\times n}$, and $\varepsilon_D(t) \in \mathbb{R}^n$ are time-varying approximation errors. β_D, β_C, and β_G denote the number of basis functions used for the inertia matrix, Coriolis matrix, and gravity vector respectively.

The estimates/approximates are expressed as

$$\begin{aligned}\hat{M}(q(t)) &= \hat{W}_M^T Z_M(t) \\ \hat{C}(q(t),\dot{q}(t)) &= \hat{W}_C^T Z_C(t) \\ \hat{G}(q(t)) &= \hat{W}_G^T Z_G(t)\end{aligned} \tag{3}$$

Now defining the following

$$\begin{aligned}v &= \dot{q}_d - \lambda e_q \\ a = \dot{v} &= \ddot{q}_d - \lambda \dot{e}_q \\ e = \dot{q} - v &= \dot{e}_q + \lambda e_q\end{aligned} \tag{4}$$

where $q_d \in \mathbb{R}^n$ is the reference trajectory, $\lambda \in \mathbb{R}^{n\times n}$ is a tunable diagonal matrix with positive diagonal entries, and $e_q = q - q_d$.

The adaptive FAT control law is

$$\tau = \hat{W}_M^T Z_D a + \hat{W}_C^T Z_C v + \hat{W}_G^T Z_G - Ke \tag{5}$$

where $K \in \mathbb{R}^{n\times n}$ is a tunable diagonal matrix with positive diagonal entries. The update laws are given as

$$\begin{aligned}\dot{\hat{W}}_D &= -Q_D^-1(Z_D a e^T + \sigma_D \hat{W}_D) \\ \dot{\hat{W}}_C &= -Q_C^-1(Z_C v e^T + \sigma_C \hat{W}_C) \\ \dot{\hat{W}}_G &= -Q_G^-1(Z_G e^T + \sigma_G \hat{W}_G)\end{aligned} \tag{6}$$

where $Q_D \in \mathbb{R}^{n^2\beta_D \times n^2\beta_D}$, $Q_C \in \mathbb{R}^{n^2\beta_C \times n^2\beta_C}$, and $Q_G \in \mathbb{R}^{n\beta_G \times n\beta_G}$ are tunable diagonal matrices with positive diagonal entries, and $\sigma(.)$ are positive numbers.

The stability of this FAT control law is proved by introducing a Lyapunov-like function in the next section for 2-DOF robot manipulator adaptive control.

4 FAT Adaptive Control for 2-DOF Robotic Arm

In this section, an adaptive control strategy and it's update law to compensate for unknown time-varying payload is employed for 2-DOF Robotic arm[1].

A 2-DOF planar robotic arm as depicted by Figure 1, can be denoted by $\boldsymbol{M_2(q)}$, $\boldsymbol{C_2(q,\dot{q})}$ and $\boldsymbol{G_2(q)}$ which is expressed as

$$\begin{aligned} M_2(q) &= M_{m_1}(q) + m_2(t)P_M(q) \\ C_2(q,\dot{q}) &= m_2(t)P_C(q,\dot{q}) \\ G_2(q) &= G_{m_1}(q) + m_2(t)P_G(q) \end{aligned} \tag{7}$$

and

$$\mathrm{q} = \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix}, \dot{q} = \begin{bmatrix} \dot{\theta}_1 \\ \dot{\theta}_2 \end{bmatrix}, \ddot{q} = \begin{bmatrix} \ddot{\theta}_1 \\ \ddot{\theta}_2 \end{bmatrix}, M_{m_1}(\mathrm{q}) = \begin{bmatrix} \frac{1}{3}\mathrm{m}_1 l_1^2 & 0 \\ 0 & 0 \end{bmatrix}, G_{m_1}(q) = \begin{bmatrix} \frac{1}{2}\mathrm{m}_1 g l_1 \cos\theta_1 \\ 0 \end{bmatrix},$$

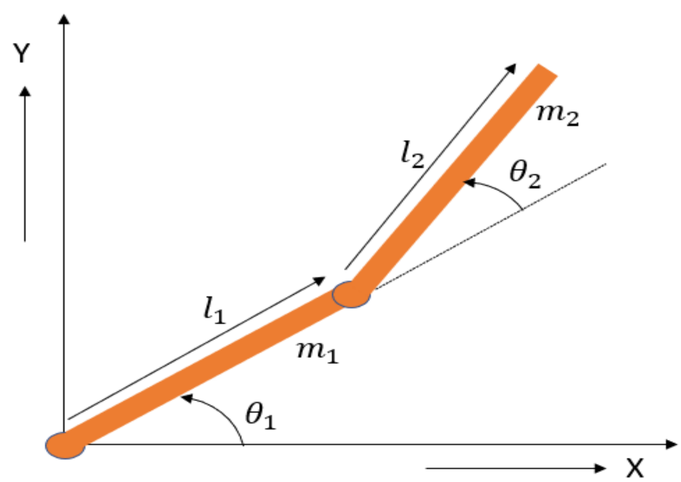

Figure 1: 2-DOF Planar Robotic Arm

$$P_M(q) = \begin{bmatrix} l_1^2 + \frac{1}{3}l_2^2 + l_1 l_2 \cos\theta_2 & \frac{1}{3}l_1^2 + \frac{1}{2}l_1 l_2 \cos\theta_2 \\ \\ \frac{1}{3}l_1^2 + \frac{1}{2}l_1 l_2 \cos\theta_2 & \frac{1}{3}l_2^2 \end{bmatrix}$$

$$P_C(q,\dot{q}) = \begin{bmatrix} 0 & -\frac{1}{2}l_1 l_2 \sin\theta_2\dot{\theta}_2 \text{ - } l_1 l_2 \sin\theta_2\dot{\theta}_1 \\ \\ \frac{1}{2}l_1 l_2 \sin\theta_2\dot{\theta}_1 & 0 \end{bmatrix}$$

$$P_G(q) = \begin{bmatrix} \frac{1}{2}gl_1\cos\theta_1 + \frac{1}{2}gl_2\cos(\theta_1+\theta_2) \\ \frac{1}{2}gl_2\cos(\theta_1+\theta_2) \end{bmatrix}$$

where g is the gravitational acceleration, l_1, l_2 are the lengths of arm links, θ_1, θ_2 are the angular displacements of the links, $\dot{\theta}_1$,$\dot{\theta}_2$ are the angular velocities of the links, $\ddot{\theta}_1$,$\ddot{\theta}_2$ are the angular accelerations of the links. Here, m_1 is the mass of the first link and $m_2(t)$ represents the total mass of link 2 and the uncertain payload since the unknown time-varying payload is regarded as a part of link 2. The following properties are utilized for the derivation of the adaptive control law:

- The inertia matrix, $M_2(q)$ is a symmetric positive definite matrix
- $\dot{M}_2(q) - 2C_2(q,\dot{q})$ is a skew symmetric matrix

The joint tracking error vector can be described as $e_q = q(t) - q_d(t)$, where $q_d(t) \in \mathbb{R}^2$ is the desired trajectory and is assumed to be twice differentiable. As shown by Equation (4), setting the reference velocity error as e and the reference joint velocity as v, the adaptive control law for 2-DOF robotic arm is given by

$$\tau = \hat{M}_2(q)a + \hat{C}_2(q,\dot{q})v + \hat{G}_2(q) - Ke \tag{8}$$

where $K \in \mathbb{R}^{2\times2}$ is the positive diagonal matrix, $a,v \in \mathbb{R}^2$ are the reference joints acceleration and reference joints velocity, respectively. From Equation (7), the estimations are described as

$$\begin{aligned}\hat{M}_2(q) &= M_{m_1}(q) + \hat{m}_2(t)P_M(q)\\ \hat{C}_2(q,\dot{q}) &= \hat{m}_2(t)P_C(q,\dot{q})\\ \hat{G}_2(q) &= G_{m_1}(q) + \hat{m}_2(t)P_G(q)\end{aligned} \tag{9}$$

where $\hat{M}_2(q), \hat{C}_2(q,\dot{q})$ and $\hat{G}_2(q)$ are the estimates.

From above, it is seen that $m_2(t)$ is unknown, contributing to the uncertainties in $\hat{M}_2(q), \hat{C}_2(q,\dot{q})$ and $\hat{G}_2(q)$ matrices. Selecting the update law as

$$\dot{\hat{W}}_{m_2} = -Q_{m_2}^{-1}[Z_{m_2}e^TP_M(q)a + Z_{m_2}e^TP_C(q,\dot{q})v + Z_{m_2}e^TP_G(q)] \tag{10}$$

where $\dot{\hat{W}}_{m_2}$ is the vector of the constant weighting function of the FAT representation that is to be estimated, $m_2(t)$ is the vector of the time-varying basis function of the FAT representation that is chosen and Q_{m_2} is the adaptive gain matrix.

5 Stability Proof for FAT

The stability proof for the proposed control strategy in Equation (8) and its update law (Equation (10)) is described as follows.

Substituting Equation (8) into the mathematical model of the robot manipulator for 2-DOF is given by

$$M_2(q)\ddot{q} + C_2(q,\dot{q})\dot{q} + G_2(q) = \hat{M}_2(q)a + \hat{C}_2(q,\dot{q})v + \hat{G}_2(q) - Ke \tag{11}$$

Subtracting $(M_2(q)a + C_2(q.\dot{q})v)$ from both sides of above equation and utilizing Equation (9) and replacing $\dot{q} - v$ with e, yields

$$M_2(q)\dot{e} + C_2(q,\dot{q})e = \tilde{m}_2[P_M(q)a + P_C(q,\dot{q})v + P_G(q)] - Ke \tag{12}$$

$\tilde{m}_2$ is the estimation error representing the difference between the actual payload, $m_2(t)$ and its estimation is $\hat{m}_2(t)$. The actual and uncertain payload, $m_2(t)$ and $\hat{m}_2(t)$, is expressed using FAT in terms of multiplication of constant unknown weighting function and the slected time-varying function function, which is given as

$$\begin{aligned} m_2 &= W_{m_2} Z_{m_2} + \varepsilon_{m_2} \\ \hat{m}_2 &= \hat{W}_{m_2} Z_{m_2} \end{aligned} \tag{13}$$

where $W_{m_2} \in \mathbb{R}^{1\times n_b}$ is the true value of the weighing function, $Z_{m_2} \in \mathbb{R}^{n_b \times 1}$ is the basis function (Fourier/Taylor series), $\hat{W}_{m_2} \in \mathbb{R}^{1\times n_b}$ is the estimated weighting function, n_b is the number of the basis function in the FAT representation and ε_{m_2} is the approximation error matrix which are assumed to be zero.

The FAT representation $W_{m_2} Z_{m_2}$ in Equation (13), is chosen as any orthonormal function such as Taylor Series, Fourier Series, Bessel functions and Legendre polynomials.

Defining the estimation error for the weighing function which is given as $\tilde{W}_{m_2} = \hat{W}_{m_2} + W_{m_2}$ and replacing it into Equation (12), yields

$$M_2(q)\dot{e} + C_2(q,\dot{q})e = \tilde{W}_{m_2} Z_{m_2}[P_M(q)a + P_C(q,\dot{q})v + P_G(q)] - Ke \tag{14}$$

Now, defining a Lyapunov-like function

$$V(e,\tilde{W}_{m_2}) = \frac{1}{2}e^T M_2(q)e + \frac{1}{2}\tilde{W}_{m_2} Q_{m_2} \dot{\tilde{W}}_{m_2} \tag{15}$$

Differentiating Equation (15) and using Equation (14), the derivative is obtained as

$$\dot{V}(e,\tilde{W}_{m_2}) = -e^T Ke + \tilde{W}_{m_2} Q_{m_2} \dot{\tilde{W}}_{m_2} + \tilde{W}_{m_2} Z_{m_2} e[P_M(q)a + P_C(q,\dot{q})v + P_G(q)] \tag{16}$$

Putting Equation (10) into Equation (16), the Lyapunov derivative becomes

$$\dot{V}(e,\tilde{W}_{m_2}) = -e^T Ke \tag{17}$$

From Equation (15), $V > 0$ (positive definite), and from Equation (17), $\dot{V} \leq 0$ (negative semi-definite), $\tilde{W}_{m_2}$ and e are bounded and then differentiating Equation (17),

$$\ddot{V}((e,\tilde{W}_{m_2}) = -2e^T K\dot{e} \tag{18}$$

Therefore, $\ddot{V}$ is also bounded and by using Barbalat Lemma, $\lim_{t\to\infty} \dot{V} = 0$. This implies, $\lim_{t\to\infty} e = 0$ from Equation (17). Also, e_q and $\dot{e}_q$ asymptotically converge to zero.

Therefore, under the control strategy (Equation (8)) and update law (Equation (10)), the actual robotic arm trajectory tends to the desired trajectory as time tends to infinity despite the time-varying uncertainity of the payload mass, $m_2(t)$. So, the highlight of this method is that the need of linear parameterization is eliminated and since only one adaptation gain matrix that is needed to be tuned in the update law, it leads to the simplification of the control law implementation.

6 Simulation and Conclusion

Simulation of the proposed method in [1] is implemented in this section. The simulation for 2-DOF robotic arm is done in MATLAB 2020a using ode45 as the solver. The aim is to track the desired trajectories which are as follows

1. $\theta_{1d} = \theta_{2d} = \sin t$ [1]
2. $\theta_{1d} = 0, \theta_{2d} = \sin t$

The robotic arm is required to track these desired trajectories, under three different unknown time-varying payload conditions which are

- Case 1: $m_2(t) = \sin t + 3$ [1]
- Case 2: $m_2(t) = 3kg$ (constant)
- Case 3: $m_2(t) = 0.5 \sin 3t + 3$ (Amplitude as 0.5 and Frequency 3 times faster than Case 1)

The robotic arm parameters and tuned controller parameters are taken same as in the reference paper [1]. Therefore, the parameters taken are taken as $l_1 = 0.18m$, $l_2 = 0.26m$, $m_1 = 0.8kg$, $K = diag[10 \quad 10]$, $\lambda = [100 \quad 100]^T$ and the adaptation gain matrix as $Q_{m_2} = 10I_{11}$. The uncertain payload, $\hat{m}_2$ given by Equation (13) have been approximated by the first 11 terms of Fourier series, where

$$\hat{W}_{m_2} = \begin{bmatrix} \hat{w}_{m_2,0} & \hat{w}_{m_2,1} & \hat{w}_{m_2,2} & \hat{w}_{m_2,3} & \hat{w}_{m_2,4} & \hat{w}_{m_2,5} & \hat{w}_{m_2,6} & \hat{w}_{m_2,7} & \hat{w}_{m_2,8} & \hat{w}_{m_2,9} & \hat{w}_{m_2,10} \end{bmatrix} \tag{19}$$

$$Z_{m_2} = \begin{bmatrix} \frac{1}{2} & \cos\frac{\pi t}{5} & \sin\frac{\pi t}{5} & \cos\frac{2\pi t}{5} & \sin\frac{2\pi t}{5} & \cos\frac{3\pi t}{5} & \sin\frac{3\pi t}{5} & \cos\frac{4\pi t}{5} & \sin\frac{4\pi t}{5} & \cos\frac{5\pi t}{5} & \sin\frac{5\pi t}{5} \end{bmatrix}^T \tag{20}$$

Therefore, $\hat{m}_2(t)$ becomes

$$\begin{aligned} \hat{m}_2(t) = \frac{\hat{w}_{m_2,0}}{2} &+ \hat{w}_{m_2,1}\cos\frac{\pi t}{5} + \hat{w}_{m_2,2}\sin\frac{\pi t}{5} + \hat{w}_{m_2,3}\cos\frac{2\pi t}{5} + \hat{w}_{m_2,4}\sin\frac{2\pi t}{5} + \hat{w}_{m_2,5}\cos\frac{3\pi t}{5} + \\ &\hat{w}_{m_2,6}\sin\frac{3\pi t}{5} + \hat{w}_{m_2,7}\cos\frac{4\pi t}{5} + \hat{w}_{m_2,8}\sin\frac{4\pi t}{5} + \hat{w}_{m_2,9}\cos\frac{5\pi t}{5} + \hat{w}_{m_2,10}\sin\frac{5\pi t}{5} \end{aligned} \tag{21}$$

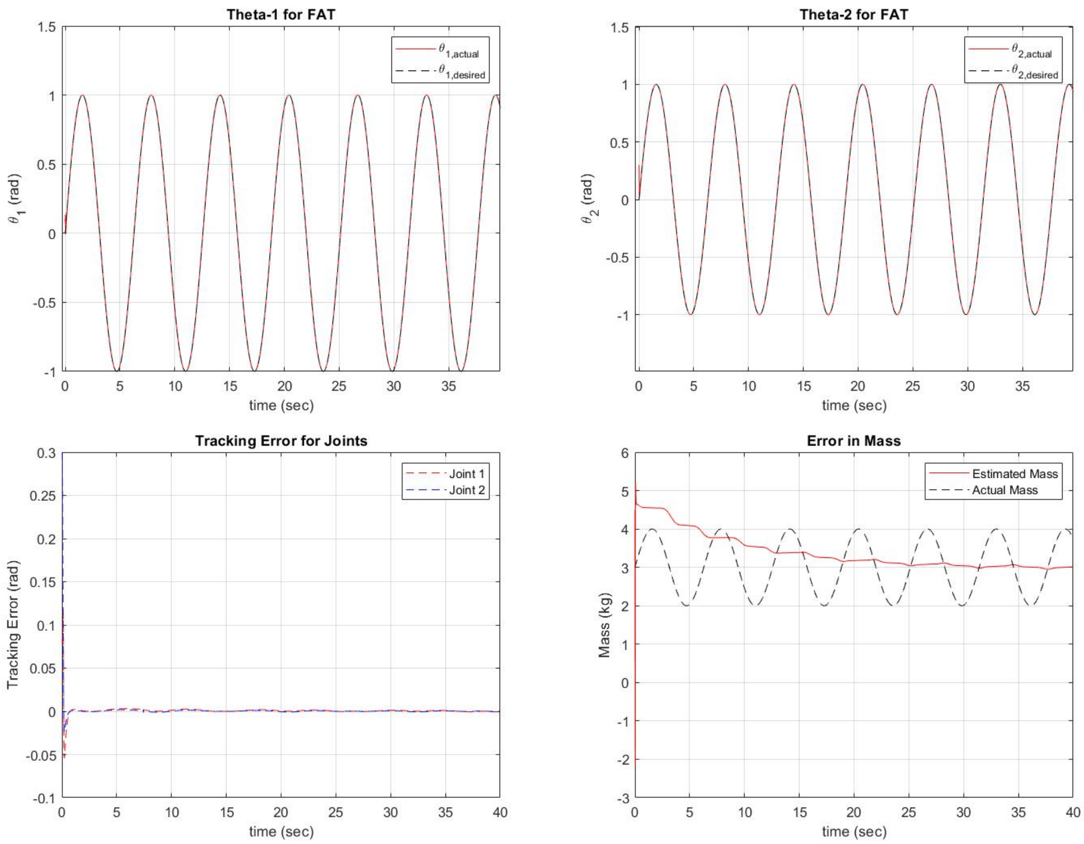

Figure 2: Results for desired trajectory 1- Case 1

The initial conditions are taken as $\hat{\theta}_1 = 0.08rad$, $\hat{\theta}_2 = 0.3rad$, $\hat{\dot{\theta}}_1 = 0.08$, $\hat{\dot{\theta}}_2 = 0.3$ and $\hat{m}_2 = 4.5kg$ for the solver. Figure 2 the tracking response of joint 1 and joint 2 of the robotic arm under the influence of the proposed controller, tested under Case 1 with desired trajectory as number 1, where the unknown mass varies sinusoidally with an amplitude of 1 kg and period of 2 seconds. From the figure it can be observed that the robotic arm follows the desired trajectory accurately even though the exact value of the payload is not known exactly in advance. Moreover, it shows the tracking error of both the joints and mass error between the actual and the estimated payload.

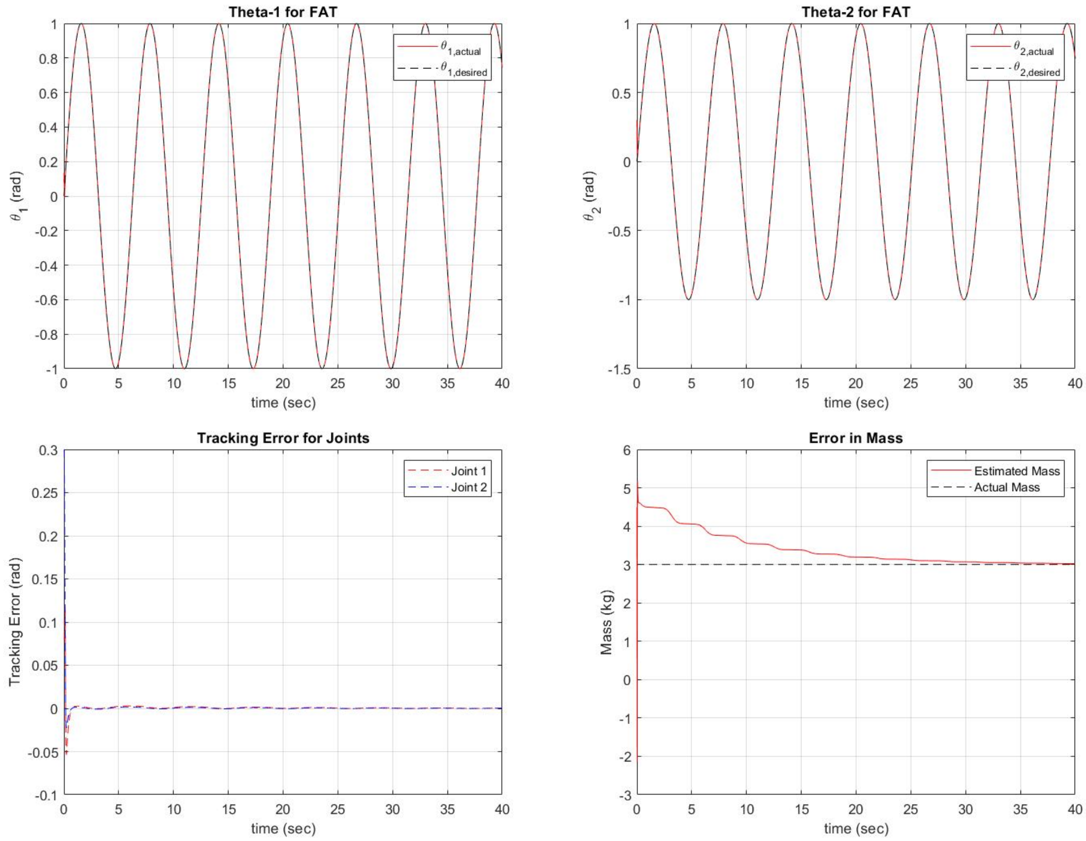

Figure 3: Results for desired trajectory 1 - Case 2

The initial conditions remain same for Case 2. Figure 3 represents the the tracking response of joint 1 and joint 2 of the robotic arm under the influence of the proposed controller, tested under Case 2 with desired trajectory as number 1, where the unknown mass remains constant value of 3 kg. Here as well the robotic arm follows the desired trajectory accurately. Moreover, it shows the tracking error of both the joints and the mass error plot shows that the estimated mass converged fairly well with the true mass.

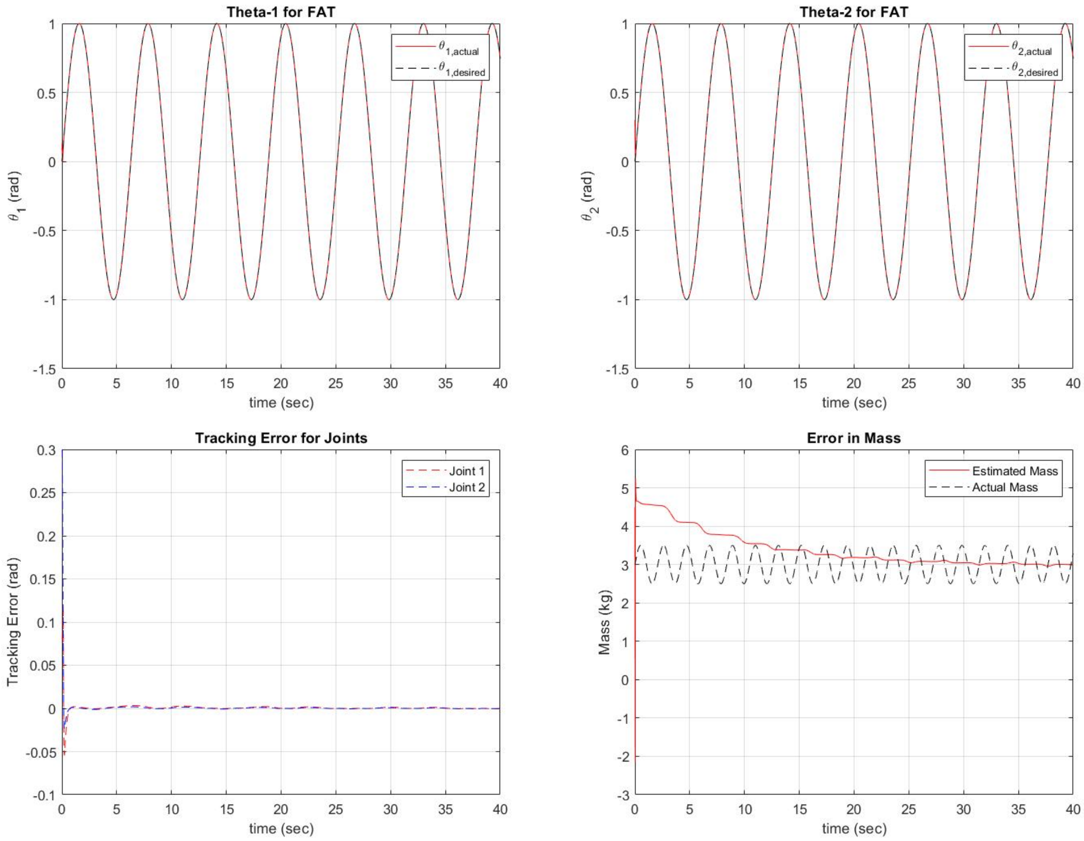

Figure 4: Results for desired trajectory 1 - Case 3

The initial conditions remain same for Case 3. Figure 4 represents the the tracking response of joint 1 and joint 2 of the robotic arm under the influence of the proposed controller, tested under Case 3 with desired trajectory as number 1, where the unknown mass remains constant value of 3 kg. Here as well the robotic arm follows the desired trajectory accurately. Moreover, it shows the tracking error of both the joints but the estimated mass does not able to converge fairly well with the true mass. That might be because of several reasons including the choice of the initial conditions, tuning of the diagonal and adaptive gain matrices. But, as shown in the figure it is still able to track the desired trajectory really well.

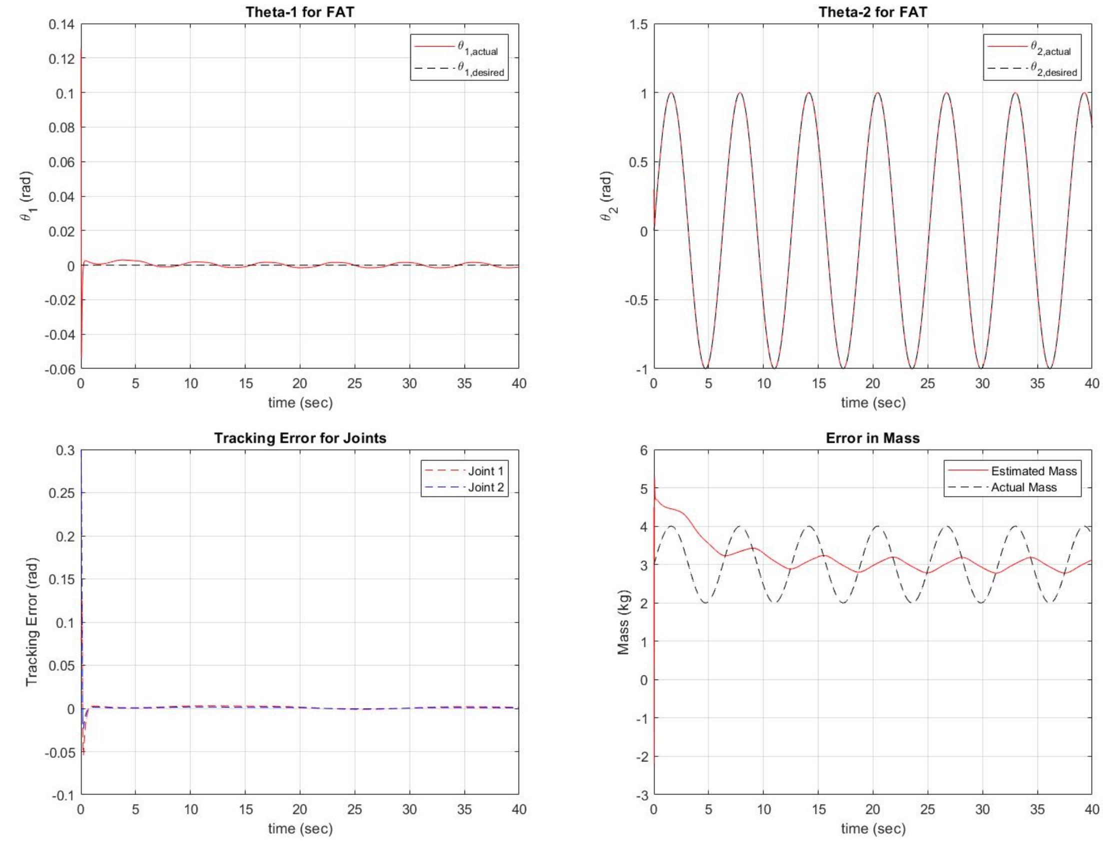

Figure 5: Results for desired trajectory 2 - Case 1

The initial conditions for desired trajectory 2 are taken as $\hat{\theta}_1 = 0.08rad$, $\hat{\theta}_2 = 0.3rad$, $\dot{\hat{\theta}}_1 = 0.08$, $\dot{\hat{\theta}}_2 = 0.3$ and $\hat{m}_2 = 4.5kg$ for the solver. Figure 5 the tracking response of joint 1 and joint 2 of the robotic arm under the influence of the proposed controller, tested under Case 1 with desired trajectory as number 1, where the desired tracking response of joint 1 is taken as 0. Here, the unknown mass varies sinusoidally with an amplitude of 1 kg and period of 2 seconds. From the figure it can be observed that the robotic arm follows the desired trajectory accurately even though the exact value of the payload is not known exactly in advance for both the joints. Notice, even though the desired trajectory is zero, the controller is able to converge pretty well to the path. Moreover, it shows the tracking error of both the joints and mass error between the actual and the estimated payload.

Likewise, Case 2 and Case 3 for desired trajectory 2 figures are shown by Figure 6 and Figure 7 respectively.

Here as well, the controller is able to track the desired trajectory accurately despite time varying payload.

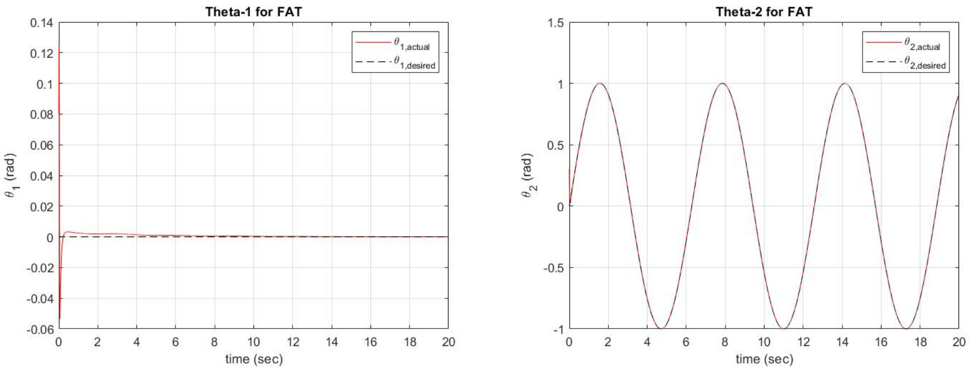

Figure 6: Tracking response for for desired trajectory 2 - Case 2

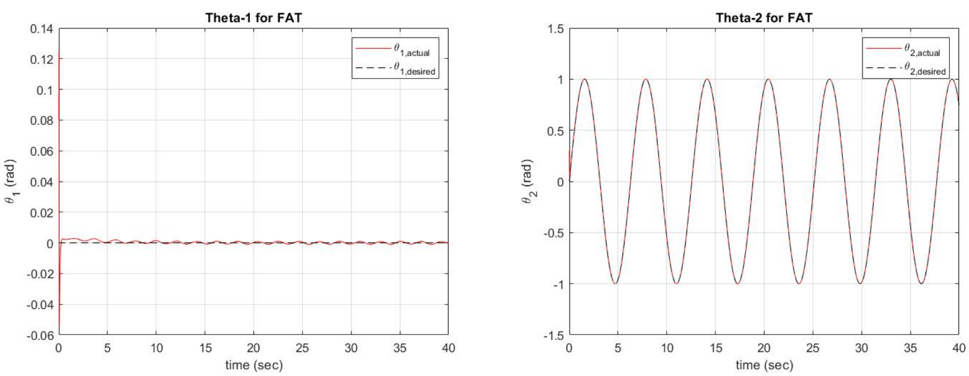

Figure 7: Tracking response for desired trajectory 2 - Case 3

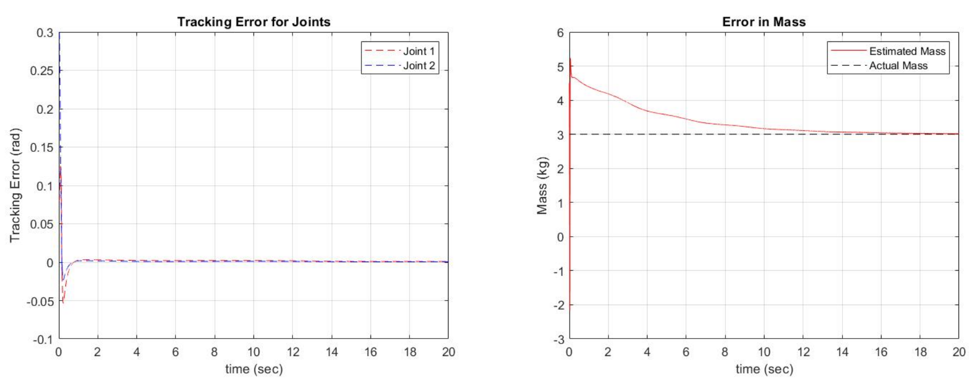

Figure 8: Tracking error and Mass error for desired trajectory 2 - Case 2

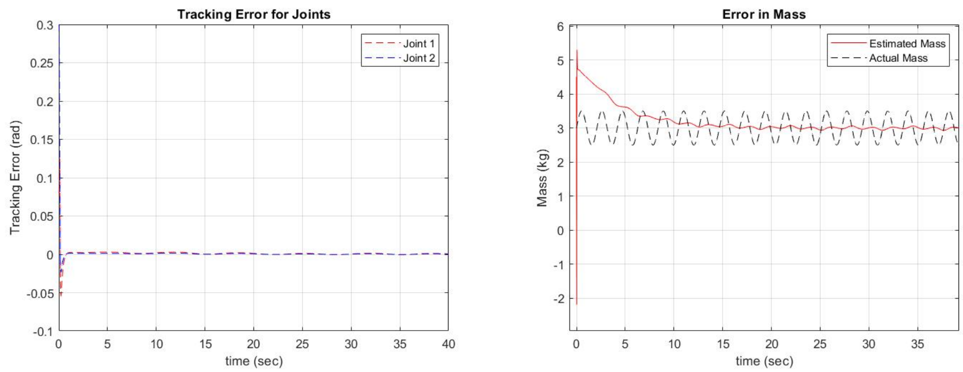

Figure 9: Tracking error and Mass error for desired trajectory 2 - Case 3

Conclusion

In this report, a FAT-based adaptive control strategy is presented to compensate for uncertain time-varying payload in a 2-DOF planar robotic arm. In this method, since the mass is on the second link, the total mass of link 2 is assumed to be the sum of the masses of link 2 and the mass of object. The payload is considered to be the part of the link 2 only. The uncertain mass is then written as a FAT expression in a form of Fourier series expansion. This approximates the mass in terms of sine and cosine functions, which makes it easier to work on a differential equation. The control law is derived as a normal adaptive law control law that utilized the estimated models and reference errors. The controller is so designed that there is only one adaptive gain matrix to be tuned in the update law. The proposed control technique is successfully implemented to track desired path of the robotic arm under time-varying uncertainties with less tracking error which is proven by the simulation results.

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