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Controller Design and Simulation High-Gain Nonlinear Observer for Three-Joint PUMA Robot Regards to Adaptive Fuzzy Sliding Mode Controller with Uncertainly Condition

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Abstract

In this study, a novel sliding mode adaptive controller is developed for three-link PUMA robot, regards to high-gain fuzzy observer in an uncertainty condition. The studied system has uncertain nonlinear functions, multiple inputs and outputs, and non-measurable scenarios, and therefore requires an observation design. To design the controller, fuzzy systems were initially utilized to approximate non-linear uncertain functions, and then a supposable observer is available to estimate non-measurable system states. Finally, by combining the adaptive fuzzy controller and feedback linearization method, a high-gain observer-based fuzzy control was developed. In order to this approach is used as enhance performance indicators of the control system. Fuzzy Takagi-Sugeno systems were employed to find the control gain. In the proposed control method, the convergence of tracking the desired reference signal of the system can be guaranteed by designing the adaption's parameters. The simulation results demonstrated the validity of the control method.

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1. Introduction

Robots have profound impacts on human life, they can perform multiple tasks on industry [1,2]. Nowadays, people need to produce high-quality, and high productive materials by using robot in widely range [3,4]. In this process robot should be operated uniformly, reliably, and impunity. But, Robotic manipulators perforce numerous problematics including uncertainties, because of unknown dynamic models, nonlinear static phrases, outside disturbances, or external noise. Studied have shown that tracking control of robot is essential factor, and need to great degree of inaccuracy in hypothetical and functional claims [5,6].In 1940, Khalil showed control assumption about High-gain observers as an essential instrument for the propose of output feedback control in nonlinear systems. This design was not completely useful in some general conditions [7,8].

High-gain observers were used earlier by Wang, Chen, and Shi for designing robust observers in linear systems [9]. Two years later, wang provided an accreted technique that was flourished individually by a large group of researchers [10]. They progress an approach that control by sliding mood adaptive fuzzy controller for nonlinear system [11]. At the same time, guan designed adaptive fuzzy mechanism to estimate the unknown uncertainties in the model, and high-gain terms to refund the approximation errors [12].

In recent years designing the observers and estimating the states and internal variables in nonlinear systems are among the most important and challenging issues in the control field [13,14]. Although several papers have explored the design of non-linear observers [15,16], in many real-life applications, it is not possible for designer to measure state variables completely, this method is uneconomically [17,18]. For example, all variables in the state may be non-physical, or it may be difficult to measure them because of their large size

[19,20]. In some situations, measurements made for feedback may not be appropriate due to excessive noise [21]. Therefore, it is mandatory to estimate state variables. In this case, observers or estimators should be applied, which are measured using the input signal and output, and estimate the unknown parameters along with a dynamic model of the system [22]. A major problem in the design of the observer in practical applications is the uncertainty in the model due to changes in its constant parameters [23]. Fuzzy observers have been suggested to solve this problem [24]. Fuzzy observers have the ability to simultaneously estimate the vector variables of the state and vector of parameters [25]. Some design methods include a nonlinear observer of the method including the Lyapunov theory, a high-gain observer, a developed Kalman filter, design techniques based on state-dependent Riccati equation, and a method of feedback linearization [26]. A solution to this problem is the linearization of the observer error equations around the equilibrium point of the system [27].

Another method for estimating the states for non-linear systems is to find the transformation that allocates the existing technique to be outlook as the original form of the design and simplify the design of the observer. The problem with both of these methods is that the nonlinear parts of the system are combined directly or indirectly with the observer dynamics [28,29]. For the decomposition and design, the Takagi-Sugeno fuzzy model system is introduced, which is a desirable demonstration for a particular category of nonlinear systems. A fuzzy system is a general estimator for nonlinear systems [30,31]. Researchers have examined the comparative observer. In general, the convergence of the parameters required the realization of the conditions of the system's stimulating signal, which is typically faced with problems [32,33]. When discussing a hybrid observer, the dependence on the convergence of parameters is an important problem. In order to solve this problem, the comparator-mode observer will pay special attention to estimating system states despite the convergence of the parameter error. In this case, to consider the new conditions of the non-linear system, it is necessary to estimate the state variables despite the lack of convergence and uncertainty of the system parameters [34].

High-gain observer is professional technique to design nonlinear output feedback control. This method was innovated into control output feedback for a group of nonlinear systems. Subsequently Long and Zhao proposed a modern structure for high-gain observers, which was suitable for stabilizing linearizable systems with an unknown parameter [35].

In this study, we addressed a new high-gain observer by using T-s method and develop this scheme by combining a novel adaptive law and sliding mode controller for robot. Robot dynamics are containing uncertainties in environmental disturbances, and sliding mode control has a great many appealing aspects including unknown parameters which are robustness and they are not insensitivity into unknown external disturbance. On the other hand, this technique brings many limitations including chattering phenomena. By combining Adaptive control with sliding mode method, we are able to overcome to parameter variations.

The main contributions of this paper can be highlighted as follows:

1) Robot dynamics are containing unknown and unavailable external disturbances, that high gain observer estimated them by using T-s control Model, and put tracking error near zero.

2) The adaptive laws are able to update adaptive parameters, and estimate uncertainly, and external disturbances. Adaptive control can enhance close- looped system robustness.

3) By using Lyapunov’s method control system are able to guarantee boundless of control system.

The remainder of this paper is organized as follows. In section II the mathematical robot's model and dynamic are designed. In Section III, the sliding mode control view as a powerful method to control robot' position. In Section IV the adaptive sliding mode control are designed, in this section adaptive parameters are designed true and false. Section V the adaptive sliding mode control regards to output feedback control are designed by using T-s system to estimate unknown parameters in robot dynamics, and unknown time-variant external disturbances, the velocities of robot are not available. Section VI Finally, the conclusions are drawn in.

2. Robot modeling

Control of mobile robot is currently among the main subjects of scientific research in robotic area.

Robot manipulators are containing mechanical part with serial or parallel links. The dynamical structure of the three-link PUMA rigid robot manipulator with unstructured uncertainty is formulated by following equations that famous to Euler-Lagrange lemma [36,37]:

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = U \tag{1}$$

Where $q(t)\in R3*1$ is an angular joint positions vector, it is assumed that this vector is unavailable to measurement. Moreover, $\dot{q}\in R3*1$ and $\ddot{q}\in R3*1$ denote joints angular, velocities, and accelerations;

M(q)∈R3*3 represents the link inertia matrix; $C(q,\dot{q},\ddot{q})\dot{q}$∈R3*3 is the Coriolis's vector or centripetal torques; and G(q)∈R3*1 is gravitational torque's vector. Also, U∈R3*3 control inputs vector with an indefinite structure. The outputs to be controlled are the angular positions. In the functional implementation of the adaptive law, external uncertainty, including errors in system structure, parametric uncertainty, and estimation errors, must be taken into consideration when modeling the robot. Readers are referred to main article for further information on robot's structure. (Chen at al., 2016).

$$\begin{cases} \|C(q,\dot{q})\| \leq \Im\|\dot{q}\| \\ s^T(\dot{M}(q) - 2C(q,\dot{q}))s = 0 \end{cases} \tag{2}$$

Uncertainties in this system, including error can be added by Δ(.) to the nominal value, and symbolize by (.)0, to achieve the actual evaluate of system elements. Therefore, in following equation the matrices are rewritten as:

$$\begin{cases} M(q)\ddot{q} = M_0(q)\ddot{q} + \Delta M\ddot{q} \\ C(q,\dot{q})\dot{q} = C_0(q,\dot{q})\dot{q} + \Delta C\dot{q} \\ G(q) = G_0(q) + \Delta G \end{cases} \tag{3}$$

Moreover, the friction Fr(t)∈R3, considered as an un-modeled quantity, where b(t)∈R3 is disturbances, and it can be added to the robot model (1). It becomes

$$(M_0(q) + \Delta M)\ddot{q} + (C_0(q,\dot{q}) + \Delta C)\dot{q} + G_0(q) + \Delta G + F_r(t) = U + b \tag{4}$$

Then, after a little mathematical simplification, robot model structure is given by (5), and η is uncertainty in robot model and defined by:

$$\begin{cases} M_0(q)\ddot{q} + C_0(q,\dot{q})\dot{q} + G_0(q) = U + \eta(\ddot{q},\dot{q},q,b) \\ \eta = -[\Delta M\ddot{q} + \Delta C\dot{q} + \Delta G + F_r - b] \end{cases} \tag{5}$$

where η is contained unmolded parameters, uncertainties in structure, and environmental dist-urbances.

3. Sliding-Mode Control design for the PUMA Robot

A sliding mode controller comprises two parts: the sliding surface, and the off-surface dynamics. The first step to derive this controller is to decide the expression of error. s should only be a function of e and its first derivative ė.The simplest function that guarantees e→0 and t→∞ is (6). The sliding surface is not singular and it is chosen for 3-link robot as (6).

Consequently, if s is driven near zero, then e will be driven to zero, where λ is a positive constant, and e is tracking error.

$$\begin{cases} s = \dot{e} + \lambda e \\ \lambda = diag[\lambda_1, \lambda_2, \lambda_3], \lambda \geq 0 \end{cases} \tag{6}$$

Where q,q̇,q̈∈n×1 are respectively symbolize the position vector, velocity vector, and acceleration vector of the robot's joints. Where qd is input trajectory or robot position vector, to control the robot position or trajectory of robot, q must be following qd, where e, ė and ë, are defined as dynamic error in equation (6) can be rewritten as (7) [38]:

$$\begin{cases} e = q - q_d, e \in R^{3*1} \\ \dot{e} = \dot{q} - \dot{q}_d \\ \ddot{e} = \dot{q} - \ddot{q}_d \end{cases} \tag{7}$$

Speed and velocity are describing as:

$$\begin{cases} \dot{q}_r = \dot{q} - s = \dot{q}_d - \lambda e \\ \ddot{q}_r = \ddot{q} - \dot{s} = \ddot{q}_d - \lambda\dot{e} \end{cases} \tag{8}$$

Proof: The closed-loop system is uniformly ultimately bounded (UUB), where K∈R3*3 is defined as a positive and constant vector. Furthermore, where $\widehat{M}(\hat{q})$ and $\widehat{C}(\hat{q},\dot{\hat{q}})$ are respectively estimated value of robot arm mass, and vector of the Coriolis. Where $\widehat{G}(\hat{q})$ is also the estimated value of the vector of gravitational torques [39].

$$U = \widehat{M}(\hat{q})\ddot{q}_r + \hat{C}(\hat{q},\dot{\hat{q}})\dot{q}_r + \hat{G}(\hat{q}) - Ksign(s) \tag{9}$$

Stability analyze is approved in two main parts, and $\widehat{U}$ and Us are defined as follows:

$$\begin{cases} U = \widehat{U} - U_s \\ \widehat{U} = \widehat{M}(\hat{q})\ddot{q}_r + \hat{C}(\hat{q},\dot{\hat{q}})\dot{q}_r + \hat{G}(\hat{q}) \\ U_s = Ksign(s) \end{cases} \tag{10}$$

By placing relations (8) in (9), we will have:

$$U = \widehat{M}(\hat{q})(\ddot{\hat{q}} - \dot{s}) + \hat{C}(\hat{q},\dot{\hat{q}})(\dot{\hat{q}} - s) + \hat{G}(\hat{q}) - Ksign(s) \tag{11}$$

By placing Relations (11) in (1), we will have:

$$\widehat{M}(\hat{q})\ddot{\hat{q}} - M(q)\ddot{q} + \hat{C}(\hat{q},\dot{\hat{q}})\dot{\hat{q}} - \hat{C}(q,\dot{q})\dot{q} + \hat{G}(\hat{q}) - G(q) - \widehat{M}(\hat{q})\dot{s} - \hat{C}(\hat{q},\dot{\hat{q}})s - Ksign(s) = 0 \tag{12}$$

By placing the relations (5) and (11) in (13), we will have:

$$\widehat{M}(\hat{q})\dot{s} = \eta - \hat{C}(\hat{q},\dot{\hat{q}})s - Ksign(s) \tag{13}$$

By choosing the following Lyapunov candidate based on errors in the closed-loop system and consider sustainability:

$$V = \frac{1}{2}s^T\widehat{M}(\hat{q})s \tag{14}$$

$\dot{V}$ is the time derivative of V or Lyapunov function that defined in (15).

$$\begin{aligned} \dot{V} = s^T(\eta - C(\hat{q},\dot{\hat{q}})s - Ksign(s) + \frac{1}{2}s^T\dot{\widehat{M}}(\hat{q})s \\ = s^Ts + s^T(\eta - Ksign(s)) \\ + s^T\left(\frac{1}{2}\dot{\widehat{M}}(\hat{q}) - \hat{C}(\hat{q},\dot{\hat{q}})\right)s \end{aligned} \tag{15}$$

$$\frac{1}{2}\dot{\widehat{M}}(\hat{q}) - \hat{C}(\hat{q},\dot{\hat{q}}) = 0$$

By placing Relations (15) in (13), and by considering the anti-symmetry property of (2), we will have:

$$\begin{cases} \dot{V} = -s^T s + \sum_{i=1}^{3} s_i\,(\eta - K_i sign(s)) \\ \qquad K \geq \eta \end{cases} \tag{16}$$

Where $\dot{V}$ is negative semi definite, and close loop system being asymptotic stability.

Where S is robust control surface and it is available to estimate the unavailable states of systems. The stability analysis is maintaining to demonstrate the stability of control system, quick adaptation, excellent robustness, and effective input chattering reduction. Therefore, the development control design are able to retain the sliding-mode error near the sliding surface.

4. Fuzzy Adaptive Robust Controller Structure

In this section, we addressed a new Takagi-Sugeno fuzzy model for nonlinear systems. Consequently, there are two main methods for creating Takagi-Sugeno fuzzy models: (1) identification, and (2) derivation structure that used to make nonlinear equations. In this article we used to second method.

$$\eta(\ddot{q}, \dot{q}, q, b) = \Delta + \sum_{i=1}^{3} \theta_i^{*T} \varphi_i(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) \tag{17}$$

The $\eta(\ddot{q}, \dot{q}, q, b)$ is approximated using the Takagi-Sugeno fuzzy systems. In (18), θ*T is a fuzzy optimal vector matrix, φ(•)=[φ1(•),φ2(•),φ3(•)] is a fuzzy regress or vector, and Δ=[Δ1,Δ2,Δ3] is the vector of minimum fuzzy modeling error assumed positive and vounded. The vector of the fuzzy modeling error (Δ) is assumed to be below a boundary with fixed and indeterminate boundaries.

(18)

Now, the Lyapunov function is defined according to (19). After investigating the function's stability, the appropriate adaptation law is obtained for making asymptotic stability conditions and the tracking error.

$$V = \frac{1}{2} s^T \widehat{M}(\hat{q}) s + \sum_{i=1}^{3} \frac{1}{2} \tilde{\theta}_i^{\,T} F^{-1} \tilde{\theta}_i \tag{19}$$

$\dot{V}$ is the time derivative of V or Lyapunov function that follow as:

$$\dot{V} = \frac{1}{2} \dot{s}^T \widehat{M}(\hat{q}) s + \frac{1}{2} s^T \widehat{M}(\hat{q}) \dot{s} + \frac{1}{2} s^T \dot{\hat{M}}(q) s + \frac{1}{2} \sum_{i=1}^{3} \dot{\tilde{\theta}}_i^{\,T} F^{-1} \tilde{\theta}_i + \tilde{\theta}_i^{\,T} F^{-1} \dot{\tilde{\theta}}_i = s^T \widehat{M}(\hat{q}) \dot{s} + \frac{1}{2} s^T \dot{\hat{M}}(q) s + \sum_{i=1}^{3} \tilde{\theta}_i^{\,T} F^{-1} \dot{\tilde{\theta}}_i \tag{20}$$

where $\tilde{\theta}$ is the matrix error of adaption parameters, $\tilde{\theta}$ is estimation error of the adaption parameter and θ* is the efficiency matrix. In addition, the matrix of F=FT≥0 is the gain of adaption. We now have a derivative of the Lyapunov function by considering the anti-symmetry property of:

$$\begin{cases} \left|\eta - \theta^{*T} \varphi^T\right| \leq \delta_i \\ \tilde{\theta} = \theta^{*T} - \hat{\theta}^T \\ \tilde{\theta}^T\, \tilde{\theta} \geq 0 \\ F = F^T \geq 0 \end{cases} \tag{21}$$

$$\begin{cases} \dot{V} = s^T(\eta - \hat{C}(\hat{q}, \dot{\hat{q}}) s - K sign(s) + \frac{1}{2} s^T \dot{\hat{M}}(\hat{q}) s + \sum_{i=1}^{3} \tilde{\theta}_i^{\,T} F^{-1} \dot{\tilde{\theta}}_i \\ = s^T(\eta - K sign(s)) + s^T(\frac{1}{2} \dot{\hat{M}}(\hat{q}) - \hat{C}(\hat{q}, \dot{\hat{q}})) s + \sum_{i=1}^{3} \tilde{\theta}_i^{\,T} F^{-1} \dot{\tilde{\theta}}_i \end{cases} \tag{22}$$

By placing (17) in (22) and considering the anti-symmetry property of (2), (23) is obtained:

$$\begin{cases} \dot{V} = s^T(\eta - \hat{C}(\hat{q}, \dot{\hat{q}}) s - \beta) + \frac{1}{2} s^T \dot{\hat{M}}(\hat{q}) s + \sum_{i=1}^{3} \tilde{\theta}_i^{\,T} F^{-1} \dot{\tilde{\theta}}_i = \\ \dot{V} = s^T s + s^T(\eta - \beta) + s^T(\frac{1}{2} \dot{\hat{M}}(\hat{q}) - \hat{C}(\hat{q}, \dot{\hat{q}})) s + \sum_{i=1}^{3} \tilde{\theta}_i^{\,T} F^{-1} \dot{\tilde{\theta}}_i \end{cases} \tag{23}$$

Where $\dot{V}$ is negative semi definite function, and closed-loop system is also asymptotic stability. Because all signals in this assumption control system are bounded. Now, the input control and low control are achieved as follows:

$$\begin{cases} \Gamma = -\gamma s - \sum_{i=1}^{3} \hat{\theta}_i^{\,T} \varphi_i(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) \\ \dot{\hat{\theta}}_i = F[\sum_{i=1}^{3} \varphi_i(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r)\, s - \sum_{i=1}^{3} \delta \hat{\theta}_i] \\ \beta_i = \theta_{B_i}^{\,T} \varphi_{\eta_i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) + \theta_{B_i}^{\,T} \varphi_{\eta_i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) \end{cases} \tag{24}$$

where γ, F=FT>0 and δ=δT>0 are the control gain adaption matrix gain and sigma factor correction, respectively. By placing (24) in (23), we will have:

$$\begin{cases} \dot{V} = -s^T s - \sum_{i=1}^{3} \hat{\theta}_i^{\,T} F^{-1} \varphi_i(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) + \sum_{i=1}^{3} s_i(\eta_i - \hat{\theta}_{\beta i}^{\,T} F^{-1} \varphi_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) + \hat{\theta}_{\beta id}^{\,T} F^{-1} \varphi_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r)) \\ = \\ -s^T s + \sum_{i=1}^{3} s_i(\eta_i - \hat{\theta}_{\beta i}^{\,T} F^{-1} \varphi_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) + \\ + \sum_{i=1}^{3} -s_i \hat{\theta}_{\beta i}^{\,T} F^{-1} \varphi_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) + \sum_{i=1}^{3} \hat{\theta}_{\beta id}^{\,T} F^{-1} \varphi_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) + \\ \sum_{i=1}^{3} -s_i \hat{\theta}_{\beta i}^{\,T} \varphi_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) + \sum_{i=1}^{3} \tilde{\theta}_{\beta i}^{\,T} F^{-1} \tilde{\theta}_{\beta i}^{\,T} = \\ -s^T s + \sum_{i=1}^{3} s_i(\eta_i - \hat{\theta}_{\beta i}^{\,T} F^{-1} \varphi_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) \\ + \sum_{i=1}^{3} -s_i \tilde{\theta}_{\beta i}^{\,T} \varphi_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) + \tilde{\theta}_{\beta i}^{\,T} F^{-1} \tilde{\theta}_{\beta i}^{\,T} \\ -s^T s + \sum_{i=1}^{3} s_i(\eta_i - \hat{\theta}_{\beta id}^{\,T} F^{-1} \varphi_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) + \\ \sum_{i=1}^{3} \tilde{\theta}_{\beta i}^{\,T}[-s_i \varphi_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) + \dot{\tilde{\theta}}_{\beta i}] \end{cases} \tag{25}$$

Yang's inequality is as follows [40,41]:

$$x^T y \leq \frac{1}{2} \|x\|^2 + \frac{1}{2} \|y\|^2 \tag{26}$$

$$\begin{cases} s^T \Delta \leq \|s\|\|\Delta\| \leq \frac{1}{2} s^T s + \frac{1}{2}\rho^{*2} \\ \dot{\tilde{\theta}}_{Bi} = {s_i}^T \gamma s_i \varphi_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) \\ \sum_{i=1}^{3} {\tilde{\theta}_i}^T \delta \hat{\theta}_i = \sum_{i=1}^{3} {\tilde{\theta}_i}^T \delta({\theta_i}^* - \tilde{\theta}_i) \leq \sum_{i=1}^{3} (\frac{\delta}{2}\|{\theta_i}^*\|^2 - \frac{\delta}{2}\|\tilde{\theta}_i\|^2) \end{cases}$$

Using Young's inequality and (25), we will have:

$$\begin{aligned} &\dot{V} = -{s_i}^T \gamma s_i - \sum_{i=1}^{3} s_i(\eta_i - {\hat{\theta}_{\beta i}}^T \varphi_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r)) \\ &\left|\eta_i - {\hat{\theta}_{\beta i}}^T \varphi_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r)\right| \leq \delta_i \leq \gamma_i |s_i| \\ &= s_i \left|\eta_i - {\hat{\theta}_{\beta i}}^T \varphi_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r)\right| \leq \gamma_i |s_i|^2 = \gamma_i {s_i}^2 \\ &\dot{V} \leq s^T s + \sum_{i=1}^{3} \gamma_i {s_i}^2 \end{aligned} \tag{27}$$

For simplification and avoiding complexity α and β are assumed as follows:

$$\begin{cases} \alpha = \min\left\{ s^T(\gamma - \frac{1}{2}I)s, \frac{1}{2}\|\delta\|\tilde{\theta}(F) \right\} \\ \beta = \sum_{i=1}^{3} \frac{\delta}{2}\left\|{\theta_i}^*\right\|^2 + \frac{1}{2}\rho^{*2} \\ \dot{V} \leq \sum_{i=1}^{3}(-s_i^2 + \gamma_i^2) = -s^T(I - \gamma)s \leq 0 \\ I \geq \gamma \end{cases} \tag{28}$$

Barbalat's Lemma [42]: where φ(t) is defined as a uniformly continuous valid function. For $t \geq 0$, presume that $\lim_{t\to\infty} \int_0^t \phi(\tau)d\tau$ already is existed and limited. Then, φ(t)→0, t→t. Lyapunov lemma can be achieve by Using Barbalat's lemma.

Lemma Rayleigh-Ritz theorem: where A ∈R×n is a valid, symmetric, positive-definite matrix; where λmin is minimum and λmax is maximum eigenvalues of A vector and all these vectors are positive and valid. Then for ∀x ∈ Rn, we have λmin||x||2 ≤ xT Ax ≤ λmax||x||2, where || · || denotes the standard Euclidean norm.

Lyapunov - Lemma: where v is scalar function, lower bound of $\dot{V}$ is a negative semi-definite function. $\dot{V}$ is uniformly continuous in time (The A is an adequate position, that $\ddot{V}$ is bounded); v →0 then, t →∞.

Given Ritz's relationship, we will have: the control system is designed as semi-continuous and bounded, and the whole of closed-loop signals are fainted. By choosing the appropriate design parameters, the traceability error convergence can be set to a very small field around zero [43].

$$\begin{cases} \lim_{t\to\infty} \dot{V} \leq -\alpha V + \beta \leq 0, \lim_{t\to\infty} \dot{V} = 0 \\ \ddot{V} = -\dot{s}_i{}^T \gamma s_i - s_i{}^T \gamma \dot{s}_i - \sum_{i=1}^{3} \dot{s}_i \eta_i + (\dot{s}_i \hat{\theta}_{\beta i}{}^T \varphi_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r)) - s_i{}^T \dot{\hat{\theta}}_{\beta i}{}^T \varphi_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) - s_i{}^T \hat{\theta}_{\beta i}{}^T \dot{\varphi}_{\eta i}(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) \end{cases} \tag{29}$$

$$\begin{aligned} &\lim_{t\to\infty} \|e\|^2 = 0 \\ &\lim_{t\to\infty} s = \lim_{t\to\infty}(\dot{e} + \lambda e) = 0 \\ &\lim_{t\to\infty} \hat{q} = \dot{q}_d \end{aligned} \tag{30}$$

The control system is designed as a semi-continuous boundary finite, and all closed-loop signals are infinite. Therefore, by selecting the appropriate design parameters, the traceability error convergence can be set to a very small field around zero.

5. Constructive Adaptive Controlling Design Based on Output Feedback

In this part, we enhance a new adaptive fuzzy controller in the previous part, it was assumed that we could quickly access each of the three robot arms in addition to the position of the robot arms. This will increase the limits and also the cost of the designed control system. The fifth assumption [44]: In this part of the paper, it is assumed that the control system is not capable of measuring the velocity of Puma's arms.

In addition, to conquer this complication in the Adaptive controlling design, a high-gain observer can be designed to compute the uncertain speeds in PUMA robot. The robot's position vector is not available and the robot's velocity vector is not accessible, therefore we must be used high-gain observer, to estimate these inaccessible vectors in robot's dynamic, including unknown and external disturbances. In the following equation there is a lemma about the high-gain observer (32). Where y(t) is system's output , and assumed that first n-1 derivatives are infinite, that is, │y(k)│≤yk (k=1, 2, …, n-1). Where yk is a positive and constant [45].

$$\begin{cases} \varepsilon \dot{\hat{q}}_i = \hat{q}_{i+1}, i = 1,2,\ldots,n-1 \\ \varepsilon \dot{\hat{q}}_n = -\bar{\lambda}_1 \hat{q}_n - \bar{\lambda}_2 \hat{q}_{n-1} - \cdots - \bar{\lambda}_{n-1}\hat{q}_2 - \hat{q}_1 + q_1 \end{cases} |\dot{q} \leq Q| \tag{31}$$

In previous equation where ε assumed small positive constant, and εi (i=1, 2, …, n) are the state variables of the observer. Selecting λ1, λ2, …., λn-1 parameters in the polynomial (33). This equation is Hurwitz, and it is containing following properties [46]:

$$s^n + \bar{\lambda}_1 s^{n-1} + \ldots + \bar{\lambda}_{n-1} s + 1 \tag{32}$$

$$\begin{aligned} &\varepsilon \dot{\pi}_i = \pi_{i+1}, i = 1,2,\ldots,n-1 \\ &\varepsilon \dot{\pi}_n = -\bar{\lambda}_1 \pi_n - \bar{\lambda}_2 \pi_{n-1} - \cdots - \bar{\lambda}_{n-1}\pi_2 - \pi_1 + x_1(t) \\ &\xi_k = \frac{\pi_k}{\xi^{k-1}} - {x_1}^{(k-1)} = -\varepsilon \bar{\psi}^{(k)}, k = 1,\ldots,n-1 \\ &||\xi_k|| \leq \varepsilon h_k, t \geq t^* \\ &\psi = \pi_n + \bar{\lambda}_1 \pi_{n-1} + \cdots + \bar{\lambda}_{n-1}\pi_n \\ &\zeta_k = \frac{\hat{q}_{k+1}}{\varepsilon^{k-1}} - {q_1}^{(k)} = -\varepsilon \psi^{(k+1)} \\ &k = 1,\ldots,n-1 \end{aligned} \tag{33}$$

where t* and bk are positive constants which related on Yk-1, ε (k=1,2,…,n) and λi (i=1,2,…,n-1) we assumption that for all t≥t*, $|\psi(k)| \leq b_k$ and $|\xi_{k+1}| \leq \epsilon_k$ Converges to $|y(k)|$ with infinite error if y and its first the derivatives are bounded; thus, $\hat{q}/\epsilon^{k+1}$ (k=1,2,…,n) this factor can be estimated unmeasured derivatives of the output up to the$(n-1)$ th order.

Furthermore, U does not include information about mathematical model of robot structure It has contain unavailable states, that depends on the available output signals in robot system. High-gain observers are able to estimate these parameters. It is appeal to design the output feedback control design for a group of nonlinear systems with uncertain dynamics and external disturbances.

$$U = \hat{M}(\hat{q})(\ddot{\hat{q}} - \dot{s}) + \hat{C},.(\hat{q},\dot{\hat{q}})(\dot{\hat{q}} - s) + \hat{G}(\hat{q}) - \beta \tag{34}$$

Proof: closed-loop technique is defined as (35), in which β is the upper bound of the uncertainties and defined as (36):

$$\beta_i = \theta_i{}^T \varphi_i(\hat{q}, \dot{\hat{q}}, \ddot{\hat{q}}_r) \tag{35}$$

$$\hat{M}(\hat{q})\ddot{\hat{q}} - M(q)\ddot{q} + \hat{C}(\hat{q},\dot{\hat{q}})\dot{\hat{q}} - C(q,\dot{q})\dot{q} + \hat{G}(\hat{q}) - G(q) - \hat{C}(\hat{q})\dot{s} - \hat{C}(\hat{q},\dot{\hat{q}})s - Ksign(s) = 0 \tag{36}$$

ased on (37) and (7), (38) defined as:

$$\hat{M}(\hat{q})\dot{s} = \eta - \hat{C}(\hat{q},\dot{\hat{q}})s - \beta \tag{37}$$

where L is a positive design parameter. The fuzzy regress or vector is bounded.

$$\begin{cases} \left\|\varphi(\hat{q},\dot{\hat{q}},\ddot{\hat{q}}_r)\right\|^2 \le L \\ \left|\eta - \theta^T\varphi(\hat{q},\dot{\hat{q}},\ddot{\hat{q}}_r)\right| \le \delta \end{cases} \tag{38}$$

The adaptation error is as the following relation:

$$\begin{cases} \tilde{\theta} = \hat{\theta} - \theta^* \\ \eta = -s_1 - k_2\hat{s}_2 + \hat{\theta}^T s(\hat{z}) \\ \dot{\hat{\theta}}_i = -\Gamma_i(s_i(\hat{z})\hat{\delta}_{2,i} + \delta_i\hat{\theta}_i \\ s_1 \in R^n, \|s_1\| \le \sqrt{D} \\ s_2 \in R^n, \|s_1\| \le \sqrt{\dfrac{D}{\lambda\min(M)}} \\ \tilde{\theta} \in R^{l\times n}, \|\tilde{\theta}\| \le \sqrt{\dfrac{D}{\lambda\min(\Gamma^{-1})}} \\ D = 2(V(0) + \dfrac{C}{\rho}) \end{cases} \tag{39}$$

where D defined as D = 2 (V (0) + C/ρ), ρ and C are positive and constants parameters. A positive definite function is constructed as:

$$\begin{cases} V = \frac{1}{2}s_1{}^T s_1 + \frac{1}{2}s_2{}^T\hat{M}(\hat{q})s_2 + \frac{1}{2}\sum_{i=1}^{3}\tilde{\theta}_i{}^T\Gamma^{-1}\tilde{\theta}^*{}_i \\ s \ne 0 \end{cases} \tag{40}$$

The time derivative of V becomes:

$$\dot{V} \le -s_1{}^T k_1 s_1 - s_2{}^T(k_2 - \tfrac{1}{2}I)s_2 - s_2{}^T k_2\tilde{s}_2 + \sum_{i=1}^{3} s_{2,i}[\hat{\theta}_i{}^T s_i(\hat{z}) - \theta^*{}_i s_i(z)] - \sum_{i=1}^{3}[\tilde{\theta}_i{}^T s_{2,i}s_i(\hat{z}) + \delta_i\tilde{\theta}^T{}_i\hat{\theta}_i] + \tfrac{1}{2}\|\varepsilon\|^2 \tag{41}$$

Based on (32) and (34), (39), Equation (43) becomes:

$$\begin{aligned} &\xi = \frac{\pi_2}{\varepsilon} - \dot{q}_1 = -\varepsilon\psi^{(2)} \\ &\|\xi_2\| \le \varepsilon h_2 \\ &\psi = \pi_2 + \lambda_1\pi_1 \\ &\tilde{s}_2 = \hat{s}_2 - s_2 = \tfrac{\pi_2}{\varepsilon} - F(q) - \dot{q}_1 + F(q) = \xi_2 \end{aligned} \tag{42}$$

According to Young lema:

$$\begin{aligned} \dot{V} \le & -s_1{}^T k_1 s_1 - s_2{}^T(k_2 - \frac{1}{2}I)s_2 - s_2{}^T k_2\tilde{s}_2 \\ & - \sum_{i=1}^{3} s_{2,i}\tilde{\theta}_i{}^T s_i(\hat{z}) - \sum_{i=1}^{3}\theta^*{}_i{}^T s_{2,i} \\ & + \sum_{i=1}^{3}\frac{\delta_i}{2}\left\|\tilde{\theta}_i\right\|^2 + \frac{1}{2}\|\varepsilon\|^2 \\ & + \sum_{i=1}^{3}\frac{\delta_i}{2}\left\|\tilde{\theta}_i\right\|^2 \end{aligned} \tag{43}$$

$$\begin{aligned} &\sum_{i=1}^{3} s_{2,i}\theta^*{}_i{}^T \le \frac{1}{2}s_2{}^T s_2 + \sum_{i=1}^{3}\frac{\|\theta^*{}_i\|^2\varepsilon^2\|s_{ti}\|^2}{2} \\ &\quad - \sum_{i=1}^{3}\tilde{\theta}^T s_i(\hat{z}_i) = \\ &-\sum_{i=1}^{3}\frac{\sqrt{\delta_i}\tilde{\theta}_i}{\sqrt{2}}\frac{\sqrt{2}}{\sqrt{\delta_i}}s_i(\hat{z})s_{2,i} \\ &\quad \le \sum_{i=1}^{3}\frac{\delta_1\left\|\tilde{\theta}_i\right\|^2}{4} \\ &\quad + \sum_{i=1}^{3}\frac{2\|s_i(\hat{z}_i)\|^2}{\delta_i}\frac{1}{2}s_2{}^T s_2 \end{aligned} \tag{44}$$

Based on (42) and (43), Equation$s_2{}^T k_2\tilde{s}_2 \le \frac{1}{2}s_2{}^T s_2 + (k_2\tilde{s}_2)^T k_2\tilde{s}_2$ becomes:

$$\begin{aligned} \dot{V} \le & -s_1{}^T k_1 s_1 - s_2{}^T(k_2 - I)s_2 - s_2{}^T k_2\tilde{s}_2 \\ & + \sum_{i=1}^{3}\frac{\delta_i\left\|\tilde{\theta}_i\right\|^2}{4} - \sum_{i=1}^{3}(\frac{\varepsilon^2}{2}\|s_{ti}\|^2 \\ & + \frac{\delta_i}{2})\|\theta^*{}_i\|^2 \\ & \sum_{i=1}^{3}\frac{2}{\delta_i}\|s_i(\hat{z})\|^2\frac{1}{2}s_2{}^T\tilde{s}_2 + \frac{1}{2}\|\varepsilon\|^2 \end{aligned} \tag{45}$$

$$\begin{aligned} \dot{V} \le & -s_1{}^T k_1 s_1 - s_2{}^T(k_2 - \frac{3}{2}I)s_2 - \frac{1}{2}\|\varepsilon\|^2 \\ & - \sum_{i=1}^{3}\frac{\delta_i\left\|\tilde{\theta}_i\right\|^2}{4} + \\ & \lambda_{max}\quad (k_2{}^T k_2 + daig[\frac{2l_i}{\delta_i}] \\ & + \frac{1}{2}\varepsilon^T h_2^2\frac{1}{2}\sum_{i=1}^{3}(\varepsilon^2\|s_{ti}\|^2 \\ & + \delta_i)\|\theta^*{}_i\|^2 \le -\rho V + c \end{aligned} \tag{46}$$

where ρ and C are two constants defined as

$$\begin{aligned} &\rho = \min(2\lambda\min(k_1), \\ &\frac{2\lambda\min(k_2 - \frac{3}{2}I)}{\lambda\max}, \min(\frac{\delta_i}{2\lambda\max\Gamma^{-1}{}_i}) \end{aligned} \tag{47}$$

Now, by rewriting the control relationship (control law, and adaptive law) obtained in the previous section for design regards on the output feedback. The property of the principle of equality and the principle of reparability:

Where K1 and K2 are control gains, and select to satisfy (48) equation, and $\rho > 0$ is positive.

$$c = \frac{1}{2}\sum_{i=1}^{3}(\varepsilon^2 \|s_{ti}\|^2 + \delta_i)\|\theta^*{}_i\|^2 +$$
$$\lambda_{max} \quad (k_2^T k_2 + daig[\frac{2l_i}{\delta_i}]\frac{1}{2}\varepsilon^T h_2^2 + \frac{1}{2}\|\varepsilon^2\|^2 \quad (48)$$
$$\lambda_{min} \quad (k_1) \geq 0$$
$$\lambda_{min} \quad (k_2 - \tfrac{3}{2}I) \geq 0$$

$\dot{V}$is a negative semi-definite, and the closed-loop system has asymptotic stability. According to the Lasal lemma, the vector of the sliding surface converges to zero.

$$\lim_{t\to\infty} s = \lim_{t\to\infty}(\dot{e} + \lambda e) = 0$$

$$\begin{cases} \lim_{t\to\infty}\dot{\hat{q}} = \dot{q}_d \\ \lim_{t\to\infty}\hat{q} = q_d \end{cases} \quad (49)$$

As mentioned earlier, the fuzzy system used in this paper has two inputs and one output and consists of five trapezoidal triangle membership functions with the names

$$\mathrm{BP, SP, Zero, BN, SN} \quad (50)$$

An error derivative is defined for input. It is noteworthy that the range of changes is also considered for fuzzy membership functions for the interval. In addition, the non-fuzzy maker is also used in control system. In this study, we addressed (17) fuzzy rules, that they are contain the number of it, then rules. Exit membership functions describe the gain control behaviour. Membership functions were considered on a [-30, + 30] interval. The inputs of the fuzzy system are considered, thus representing the trace error vector and the derivative of the trace error.

6. Simulation Results

In this paper, the robot has three degrees of freedom. Consequently, three controllers are used for their control and identification. The structure of the three controllers is exactly the same. As shown in fig. 1, there is a large fuzzy interest observer inside each controller. The PUMA robot is in an uncertain presence (parametric-nonparametric). In the first part of the simulation, the simulation assumes that the probes are manually tested and error-free, and the speed and position of the robot arm are available. In the second part, it is assumed that the robot arm speed is not available and is obtained by the observer of large interest. In the final section, using the slip-mode control method, a robust adaptive fuzzy observer has great interest in estimating the speed of the robot arm.

In figs. 2, 3, and 4, q1, q2 and q3 outputs of the robot are investigated in the sliding mode. In less than 6 seconds, the desired and real outputs converge to each other.

Figs. 5, 6 and 7 plot tracking error of q1, q2 and q3 arms of the robot in the sliding mode in the existence of uncertainty. The error has a small boundary around zero. In the Simulation Results, the tracking error has been shown to converge and join a diminutive neighbourhood of the base.

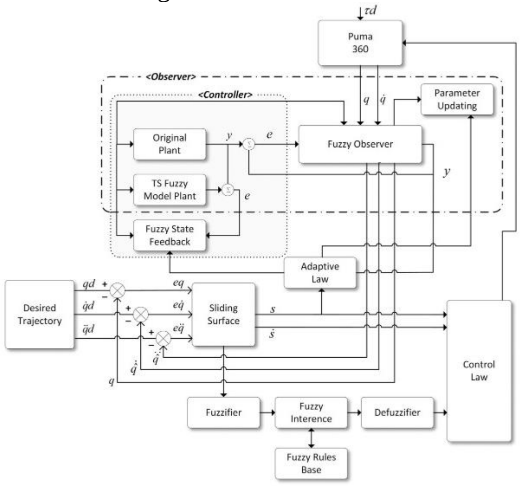

Fig. 1. Internal controller structure

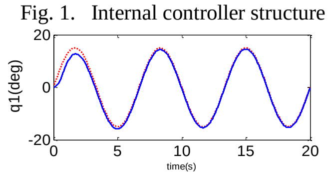

Fig. 2. Output of q1 sliding mode

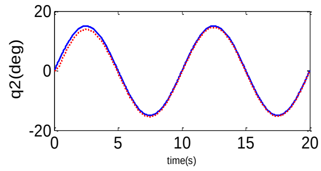

Fig. 3. Output of q_2 sliding mode

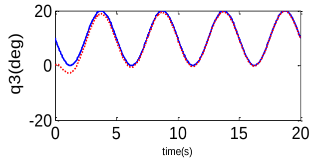

Fig. 4. Output of q3 sliding mode

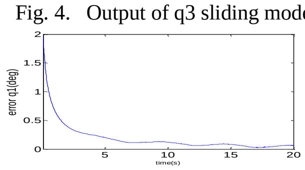

Fig. 5. Tracking error of q1

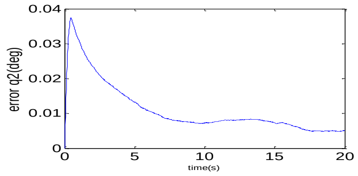

Fig. 6. Tracking error of q2 sliding mode in uncertainty

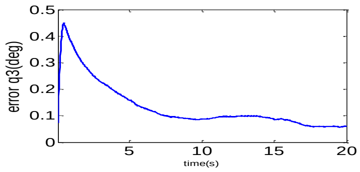

Fig. 7. Tracking error of q3 sliding mode in uncertainty

If the remaining error is proper to be minor, it can be decrease including C/ρ in two Theorems 1 and 2 reduce. By developing K1, K2 the reduction is attained, to estimate accuracy of the adaptive parameters, and the high-gain observer, the real amount of $1/\varepsilon$ is positive and constant. In figs. 8, 9, and 10, the k_1, k_2 and k_3 parameters are shown in the sliding mode control figs, 11, 12, and 13, the λ_1, $\lambda_2$and $\lambda_3$parameters are shown in the sliding mode control.

Figs. 14, 15, and 16 demonstrate the robot outputs for q1, q2 and q3 angles and the tracing error has a large boundary. Plot the output based on the control law in (24). It shows that the associated position error remains in the prescribed bound (32) to claim the containment control with the prescribed accomplishment (35) development in part 4.

Fig. 17 shows the control input without fuzzy adaption in which the input is turbulent. In fig. 18, the error has a large boundary.

In fig. 19, at second 8, adaptive parameters are detected and the output reaches the desired value. The position of shoulder joint and elbow joint using fuzzy adaptive controller are shown in figs. 20, 21 and 22.

The tracking errors in every one joints are elucidated in Fig. 23. Control inputs have shown in Fig. 24. The evolution of the adaptive parameters is elucidated in fig. 25 is considerably stable. In fig 26, we can also visit the real positions that are converged to the desired trajectories. Input torques are shown in fig. 27, they are limited and permanent.

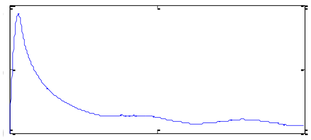

Fig. 8. Parameter k1 in the sliding mode

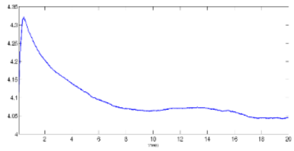

Fig. 9. Parameter k2 in the sliding mode

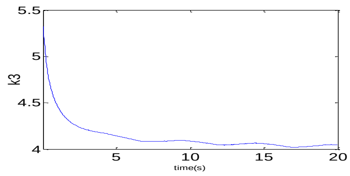

Fig. 10. Parameter k3 in the sliding mode

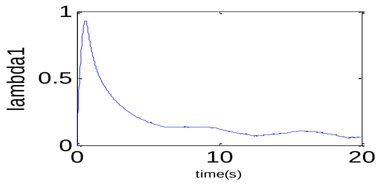

Fig. 11. Parameter λ1 in the sliding mode

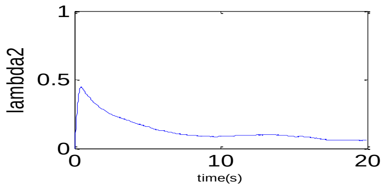

Fig. 12. Parameter λ2 in the sliding mode

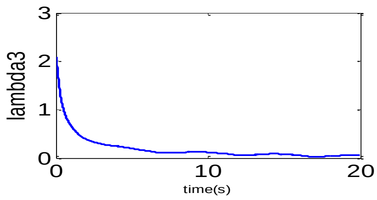

Fig. 13. . Parameter λ3 in the sliding mode

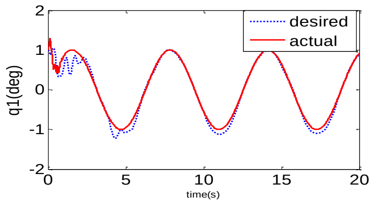

Fig. 14. Output of q1 without fuzzy adaption

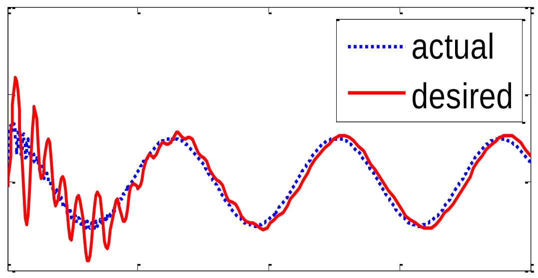

Fig. 15. Output of q2 without fuzzy adaption

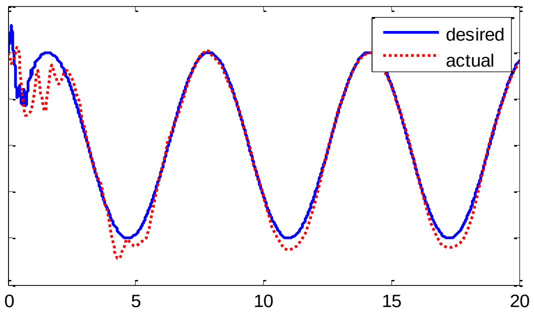

Fig. 16. Output of q3 without fuzzy adaption

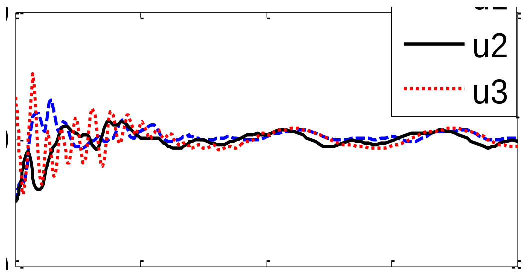

Fig. 17. Control input signal

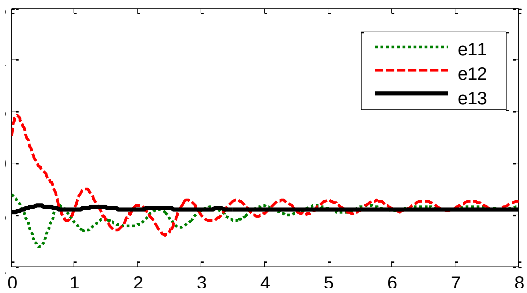

Fig. 18. Tracking errors without observer

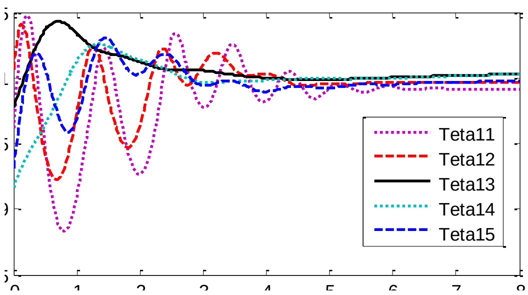

Fig. 19. Adaptive parameters without observer

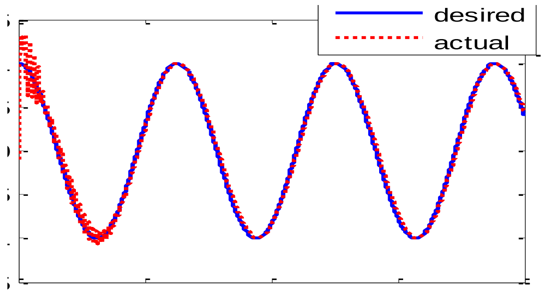

Fig. 20. Output of q1 fuzzy adaption

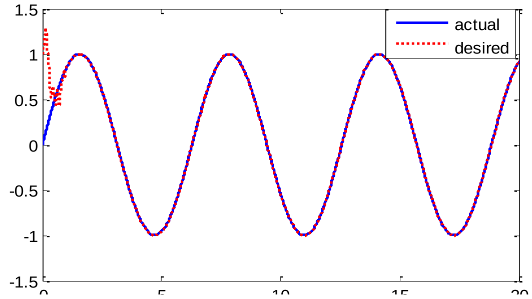

Fig. 21. Output of q2 fuzzy adaption

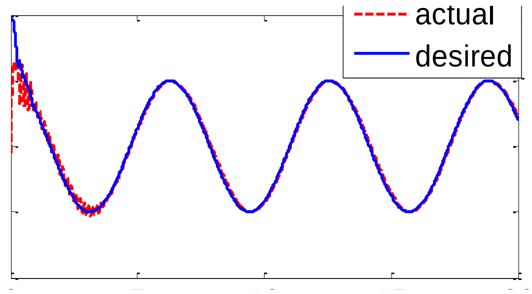

Fig. 22. Output of q3 fuzzy adaption

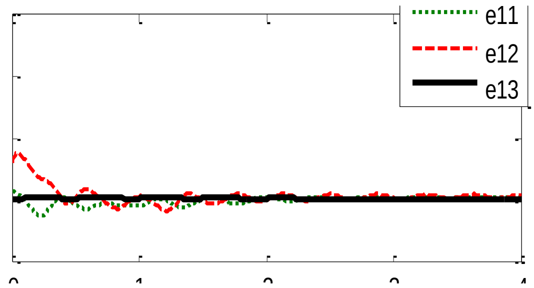

Fig. 23. Tracking error- based adaptive law design

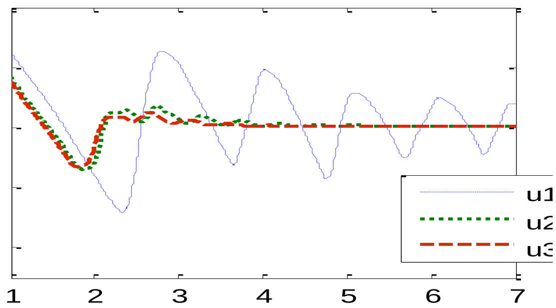

Fig. 24. Control input signal

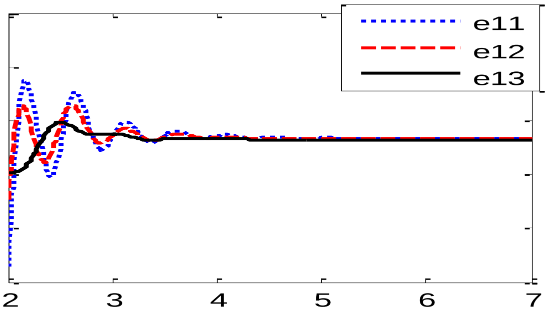

Fig. 25. Adaptive Parameters fuzzy adaption

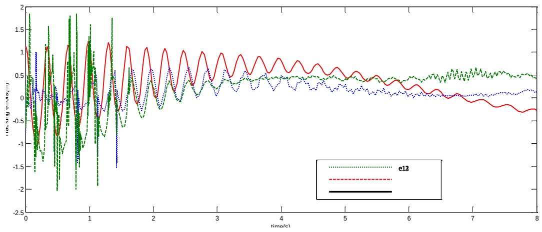

Fig. 26. Tracking errors without observer

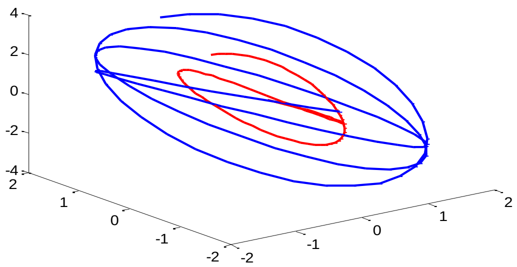

Fig. 27. Cartesian path

Figs. 20-22 elucidated control output, it is stable and the tracking performance is acceptable during lack of data about the velocity in measurement tools. The proper controller is more functional rather than controller without fuzzy adaption, by reason of, its more economical, do not need to velocity measurement sensors.

This study addressed a novel sliding-mode adaptive fuzzy controller for nonlinear systems with uncertainty, and unknown control directions with input saturation, lack of full state measurements. A high-gain fuzzy observer was designed to estimate unknown parameters in system. The Adaptive fuzzy controller guaranteed the semi-global uniform ultimate bounded-ness (SGUUB) the whole of signals in the closed-loop are bonded, and the tracking error in output can be converted to a small neighbourhood of the origin by the appropriate selection in the design parameters.

The tracking error are elucidated to converge, it remained in small neighbourhood of the base. The remaining error is appropriated to be minimum. In fig. 26 the tracking performance in closed-loop system for 3 joints robot is shown. According to this figure, tracking is successfully done and the system error is converging to a small value near to zero. On the other hand, to design controller we need to totally-known structure in control system, which is hard to achieve in profession. By looking on the simulation consequence also indicate that the fuzzy adaption can be estimated the unknown parameters in system and guarantee the control performance. The tracking error is reduced conform to expand in the fuzzy adaptation gains. The simulation consequence proves that bounded-ness of the adaptation gains with increased convergence rate. The control inputs are shown in fig. 24. They getting influenced by the Gaussian noise, it is appearing in oscillation on the control inputs. Specifically, the high-gain observer cannot be increased the control inputs, thus offering an adequacy method to design the output feedback control.

It is observed about Figs that the control simulation performance in the three different controllers for the same robot are not resembling. Table I obviously displays that the adaptive fuzzy controller demonstrates greater transient and steady-state accomplishment for the robot. Because adaptive fuzzy controller manipulates to estimate the uncertain speeds of the PUMA robot.

The proposed controller in this paper is able to recompense uncertainties in robot structure including un-modelled dynamics or external disturbances by using the adaptive fuzzy controller, by combining the adaptive law estimate disturbance bound, whereas High- Gain adaptive fuzzy controller is created regards to estimate the robot dynamic with unknown parameters without the adaptive skill to change parameters. These obviously illustrate the adaptive ability and the robustness of our adaptive output to the parameter changes and external disturbances.

Table.1.
Time and Control Performance Comparison of the Three Methods

Control parameters	*Sliding Mood*	*Fuzzy observer*	*Without observer*
Percentage of permanent mode error	0.5	0.3	3
Time (s)	0.2	0.5	2.5

7. Conclusion

In this study, a robust adaptive fuzzy high gain estimation observer is created for continuous-time systems with exact (Takagi-Sugeno) representations with uncertainty, unmeasured states, and external disturbance. Using the Lyapunov function and robust adaptive fuzzy algorithms, the parameters were estimated. Therefore, the results can be extended to the measurement of disturbances. Our design method is general in the sense that the same design procedure is applied for any fault vector. The simulation consequences revealed that the convergence of the state observation errors was ensured step by step in finite time for three observers. Finally, it was demonstrated through an example that the efficiency of the sliding-mode observer overcomes the occurrence of the chattering phenomenon.

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