Fuzzy adaptive state-feedback control for a revolute-prismatic-revolute robot manipulator

N. Nejadkourki and M. J. Mahmoodabadi

Abstract: In this work, a fuzzy adaptive state-feedback control is designed for the stabilization of a three-degree of freedom revolute-prismatic-revolute (RPR) robot manipulator. At first, the forward kinematic equations are derived and its workspace is investigated. The Lagrange method is applied to find the dynamical equations, and the inverse dynamic approach is utilized to design a state-feedback controller for the regulation of the joint positions. The gradient descent scheme and the sliding surface relations are implemented to adaptively define the control gains. Moreover, a fuzzy system based on the linguistic if-then rules is used to tune the control parameters. The time responses of the joint variables for the introduced scenario are simulated and compared with those of other recently published methods.

Subjects: Automation; Robotics; Intelligent Systems; Systems & Controls

Keywords: State-feedback control; adaptive control; fuzzy system; manipulator; workspace; dynamical equations

1. Introduction
From the last decades, demands for using the robots have been increasingly growing. The main reason for their usage growth in industries is for increasing the speed and accuracy of producing, as well as decreasing the costs. Today, the hard works are not for humans, and new industrial
systems used the robots as labors. Many robots and manipulators inspire from human physiology and other properties. Their fabrication contains a series of rigid bodies that are connected by different types of joints. The considered RPR manipulator in this work is typically one of these robots which is applicable for high speed and accurate processes with a limit space. In the recent years, a lot of researchers have studied these robots from many different points of views. To name but a few, the forward kinematic analysis of a 3-RPR parallel manipulator has been presented in (Nag, Mohan, & Bandopadhyay, 2017). Modeling and experimental of a new 3-RPR parallel micro-manipulator have been studied in (Dong, Gao, & Yue, 2016). Determination of cusp points of 3-RPR parallel manipulators has been performed in previous literature (Moroz, Rouiller, Chablat, & Wenger, 2010). Further, the reliable motion planning for a parallel manipulator has been investigated in a previous literature (Lins Vieira, Wajnberg, Teófilo Beck, & Martins da Silva, 2019). In (Wu & Bai, 2019), the design and kinematic of a 3-RPR parallel manipulator reconfigured with four-bar linkages have been analyzed.

On the other hand, the state-feedback control as one of the simplest and most applicable controllers has been widely implemented in the sciences and technologies. For instance, position domain nonlinear control of contour tracking of robotic manipulator has been studied in (Ouyang, Pano, Tang, & Yue, 2018). Formalization of fractional-order PD control systems has been investigated in (Zhao & Li, 2018). Moreover, performance analysis for bounded persistent disturbances has been done for PD/PID-controlled robotic systems with its experimental demonstrations (Kim, Hur, & Oh, 2018).

Besides, in order to timely adapt the control gains, the adaptive methods have been successfully employed in different control approaches, such as, backstopping adaptive control (Ouyang, Shi, Shan, & Spencer, 2019), adaptive T-S fuzzy control (Mirzajani, Aghababa, & Heydari, 2019), adaptive integral line-of-sight guidance law (Nie & Lin, 2019) and universal adaptive control (Wang, Liu, Wang, Dong, & Tenberge, 2019).

Finally, the fuzzy logic helps researchers to insert the human knowledge and linguistic variables to define the system parameters, especially control ones. For instance, in (Zhai & Karimi, 2019), an adaptive fuzzy iterative control strategy has been developed for the wet-clutch filling of automatic transmission. Yuguang and Fan have introduced dynamic modeling and adaptive fuzzy sliding mode control for multi-link underwater manipulators (Yuguang & Fan, 2019). Zohoori et al. have suggested monitoring production time and cost performance by combining earned value analysis and adaptive fuzzy control (Zohoori, Verbraeck, Bagherpour, & Khakdaman, 2019).

The contribution of the work could be mentioned as follows. A novel fuzzy adaptive state-feedback control is introduced for stabilization of a three-degree of freedom RPR robot manipulator. To this end, the forward kinematics, dynamical equations, and workspace of the manipulator are investigated. The inverse dynamic approach is utilized to design a state-feedback controller for the regulation of the joint positions. In order to adaptively define the control gains, the gradient descent scheme and the sliding surface relations are implemented. Moreover, a fuzzy system based on the linguistic if-then rules is utilized to regulate the control parameters.

The rest of the paper is organized as follows. Section 2 presents the forward kinematics and workspace of the robot. Section 3 denotes the driving of the dynamical equations using the Lagrange method. The inverse dynamic based state-feedback control is stated in Section 4. The adaptive state-feedback control and its fuzzy version are represented in Sections 5 and 6, respectively. Section 7 shows the simulation of the results and the related discussions. Finally, Section 8 concludes the paper.

2. Forward kinematics
In order to determine the position of the end-effector using the joint variables, the forward kinematic methods could be implemented. In Figure 1, the geometrical situations and coordinate
assignments for the considered RPR manipulator are illustrated. Based on the Denavit–Hartenberg conventions (Spong, Hutchinsom, & Vidyasagar, 2005), the related parameters are stated in Table 1.

Based on the introduced parameters in Table 1, the forward kinematic equation could be written as follows.

\[
T_0^3 = \begin{bmatrix}
\cos \theta_1 \cos \theta_3 & -\cos \theta_1 \sin \theta_3 & -\sin \theta_1 & -(d_2 + d_3) \sin \theta_1 \\
\sin \theta_1 \cos \theta_3 & -\sin \theta_1 \sin \theta_3 & \cos \theta_1 & (d_2 + d_3) \cos \theta_1 \\
0 & 0 & 0 & d_1 \\
0 & 0 & 0 & 1
\end{bmatrix}
\]

(1)

where \( \theta_1, d_2, \) and \( d_3 \) denote the joint variables of the robot. Moreover, \( d_3 \) as a constant shows the distance between the end effector and joint 3. Using Equation (1), the workspace of the robot end-effector is depicted in Figure 2.

3. Dynamical equations

Using the Denavit–Hartenberg parameters mentioned in the previous section and Lagrange relations (Spong et al., 2005), the dynamical equations of the robot manipulator could be displayed as follows (Mahmoodabadi & Roshandel, 2019).

\[
\tau_1 = \left(I_1 + I_2 + I_3 + (m_1 + m_2 + m_3)(d_2 + d_3)^2\right)\ddot{\theta}_1 + 2(d_2 + d_3)(m_1 + m_2 + m_3)\ddot{d}_2
\]

(2)

| Link | \( a_i \) | \( \alpha_i \) | \( d_i \) | \( \theta_i \) |
|------|---------|---------|---------|---------|
| 1    | 0       | -90     | \( d_1 \) | \( \theta_1^* \) |
| 2    | 0       | 0       | \( d_2 \) | 0       |
| 3    | 0       | 0       | \( d_3 \) | \( \theta_3^* \) |
where $I_i$ and $m_i$ ($i = 1, 2, 3$) denote the inertia moment and the mass of the links, respectively. In this work, the following values are used for these parameters.

$$m_1 = 0.8; m_2 = 1; m_3 = 0.5; d_1 = 0.5; d_3 = 0.5; I_1 = 0.05; I_2 = 0.08; I_3 = 0.01.$$  \hspace{1cm} (5)

If the state variables are regarded as follows:

$$z_1 = \dot{\theta}_1; z_2 = d_2; z_3 = \dot{\theta}_3; z_4 = \dot{\theta}_1; z_5 = \dot{d}_2; z_6 = \dot{\theta}_3;$$  \hspace{1cm} (6)

then, the state-space equations could be written as follows:

$$\dot{z}_1 = z_4;$$  \hspace{1cm} (7)

$$\dot{z}_2 = z_5;$$  \hspace{1cm} (8)

$$\dot{z}_3 = z_6$$  \hspace{1cm} (9)

$$\dot{z}_4 = \left( \frac{r_1 + (z_2 + d_1)(m_1 + m_2 + m_3)z_4 z_5}{I_1 + I_2 + I_3 + (m_1 + m_2 + m_3)(z_2 + d_3)^2} \right)$$  \hspace{1cm} (10)

$$\dot{z}_5 = \left( \frac{f_2 + (d_2 + d_3) \times (m_1 + m_2 + m_3)z_4^2}{m_2 + m_3} \right)$$  \hspace{1cm} (11)

$$\dot{z}_6 = \left( \frac{r_3}{I_3} \right)$$  \hspace{1cm} (12)

4. Inverse dynamic based state-feedback control

The general form of the system dynamical equation is regarded as the following equation.

$$D(z) \dot{z} + c(z, \dot{z}) + g(z) = u$$  \hspace{1cm} (13)

where $z = [z_1, z_2, z_3]^T$. The inverse dynamic method is applied to change the nonlinear variables to linear one (Mahmooodabadi & Ziaei, 2019) and designed a state-feedback controller (Shim, Jang,
Suh, Noh, & Lee, 2018; Zhao & Li, 2018; Zou & Li, 2017) as follows:

\[ \tau = D(z)a_z + c(z, \dot{z}) + g(z) \]  

(14)

\[ a_q = -k_p \dot{z} - k_d \ddot{z} + r \]  

(15)

\[ k_p = [k_{p1}, k_{p2}, k_{p3}] \]  

(16)

\[ k_d = [k_{d1}, k_{d2}, k_{d3}] \]  

(17)

If

\[ r(t) = \dot{z}(t) + k_p \dot{z}^2(t) + k_d \ddot{z}^2(t), \]  

(18)

then

\[ \ddot{e}(t) + k_d \dot{e}(t) + k_p \dot{e} = 0. \]  

(19)

Therefore, the asymptotic stability of the controller is guaranteed.

5. Adaptive state-feedback control

The adaptive methods (Al-Fahdawi, Barroso, & Soares, 2019; Ding et al., 2018; Zhang, Cai, & Li, 2019) are used to timely regulate the control parameters. In this work, the considered adaptive approach uses a dynamic sliding surface to tune the gains. For an n-order nonlinear system, the sliding surface is defined as Equation (20).

\[ R(z, t) = \left( \frac{d}{dt} + \delta \right)^{-1} \]  

(20)

where \( \delta \) is a positive definite real number. For the considered robot manipulator, three sliding surfaces are defined for the three joint variables.

\[ \mathbf{R}_1 = \dot{e}_1 + \delta_1 e_1 \]  

(21)

\[ \mathbf{R}_2 = \dot{e}_2 + \delta_2 e_2 \]  

(22)

\[ \mathbf{R}_3 = \dot{e}_3 + \delta_3 e_3 \]  

(23)

In these equations, \( e_1, e_2, \) and \( e_3 \) are the errors of the system, and \( \dot{e}_1, \dot{e}_2, \) and \( \dot{e}_3 \) are, respectively, their derivatives formulated as follows:

\[ e_1 = z_1^f - z_1 \]  

(24)

\[ e_2 = z_2^f - z_2 \]  

(25)

\[ e_3 = z_3^f - z_3 \]  

(26)

\[ \dot{e}_1 = \dot{z}_1^f - \dot{z}_1 \]  

(27)

\[ \dot{e}_2 = \dot{z}_2^f - \dot{z}_2 \]  

(28)

\[ \dot{e}_3 = \dot{z}_3^f - \dot{z}_3 \]  

(29)
where $z_1^d$, $z_2^d$, and $z_3^d$ are the desired values for the state variables, and $\dot{z}_1^d$, $\dot{z}_2^d$, and $\dot{z}_3^d$ are their derivatives, respectively. Based on the gradient descent method and the chain rule, the adaptation Law for $k_{p1}$ can be easily obtained as the following steps.

$$\dot{k}_{p1} = -\gamma_{11} \frac{\partial R_1 R_3}{\partial k_{p1}} = -\gamma_{11} \frac{\partial R_1 R_3}{\partial \tau_1} \frac{\partial \tau_1}{\partial k_{p1}}$$  \hspace{1cm} (30)$$

where $\gamma_{11}$ is a positive constant and

$$\frac{\partial \tau_1}{\partial k_{p1}} = e_1$$  \hspace{1cm} (31)$$

$$\frac{\partial \dot{R}_1}{\partial \tau_1} = \frac{\partial \dot{R}_1}{\partial \tau_1} R_1 + R_1 \frac{\partial \dot{R}_1}{\partial \tau_1} = 0 + R_1 \frac{\partial e_1}{\partial \tau_1} = R_1 \frac{\partial \dot{z}_d}{\partial \tau_1}$$

$$\frac{\partial \dot{R}_1}{\partial \tau_1} = \frac{I_1 + I_2 + I_3 + (m_1 + m_2 + m_3)(z_4 + d_3)^2}{I_1}$$ \hspace{1cm} (32)$$

hence,

$$\dot{k}_{p1} = -\gamma_{11} R_1 e_1$$  \hspace{1cm} (33)$$

Moreover, applying the similar procedure for the other control gains gives:

$$\dot{k}_{d1} = -\gamma_{12} R_1 e_1$$  \hspace{1cm} (34)$$

$$\dot{k}_{p2} = -\gamma_{21} R_2 e_2$$  \hspace{1cm} (35)$$

$$\dot{k}_{d2} = -\gamma_{22} R_2 e_2$$  \hspace{1cm} (36)$$

$$\dot{k}_{p3} = -\gamma_{31} R_3 e_3$$  \hspace{1cm} (37)$$

$$\dot{k}_{d3} = -\gamma_{32} R_3 e_3$$  \hspace{1cm} (38)$$

where $\gamma_{ij} i,j = 1,2,3$ are positive constants. As it can be seen from the above equations, the control gains are calculated by solving the above time derivative equations. Hence, those need the initial conditions which are found by try and error processes in this research.

$k_{p1}(0) = 500; k_{p2}(0) = 50; k_{p3}(0) = 100; k_{d1}(0) = 5; k_{d2}(0) = 0; k_{d3}(0) = 5$

6. Fuzzy adaptive state-feedback controller

The fuzzy logic initially introduced by Zadeh in 1965 was not appeared out of universities until 1985, because its actual concept had been not recognized. The most important advantage of the fuzzy logic is the implementation of the linguistic Language to design complicated systems. In this paper, in order to regulate the introduced gains of the adaptive controller in the previous section, a proper fuzzy system is suggested. For this purpose, a singleton fuzzifier, a product inference engine, and a center average defuzzifier are utilized and combined as Equation (39).
Figure 3. Input membership functions.

| Table 2. Fuzzy rule base for variable δ₁ |
|-----------------------------------------|
| ε₁ | S  | M  | B  |
| S  | 79 | 79.5 | 79.8 |
| M  | 80.5 | 80 | 80.5 |
| B  | 80.2 | 79.5 | 80.5 |

| Table 3. Fuzzy rule base for variable γ₁1 |
|-----------------------------------------|
| ε₁ | S  | M  | B  |
| S  | 230 | 210 | 195 |
| M  | 200 | 201 | 200 |
| B  | 201 | 195 | 205 |

| Table 4. Fuzzy rule base for variable γ₁2 |
|-----------------------------------------|
| ε₁ | S  | M  | B  |
| S  | 10.001 | 9.999 | 10 |
| M  | 10.3 | 10.02 | 10 |
| B  | 9.99 | 9.9 | 10 |

| Table 5. Fuzzy rule base for variable δ₂ |
|-----------------------------------------|
| ε₂ | S  | M  | B  |
| S  | 14.55 | 15.2 | 15 |
| M  | 14.9 | 14.8 | 15.3 |
| B  | 15 | 14.6 | 15.1 |
fuzzy parameter \( \frac{\sum_{i_1=1}^{N_1} \sum_{i_2=1}^{N_2} y^{-h_{i_1}} (\mu_{A_1}^{i_1}(z_1)\mu_{A_2}^{i_2}(z_2))}{\sum_{i_1=1}^{N_1} \sum_{i_2=1}^{N_2} (\mu_{A_1}^{i_1}(z_1)\mu_{A_2}^{i_2}(z_2))} \) \( (39) \)

**Table 6. Fuzzy rule base for variable \( \gamma_{21} \)**

| \( e_2 \) | S | M | B |
|---|---|---|---|
| S | 60 | 50 | 15 |
| M | 21 | 18 | 20 |
| B | 19 | 18 | 20 |

**Table 7. Fuzzy rule base for variable \( \gamma_{22} \)**

| \( e_2 \) | S | M | B |
|---|---|---|---|
| S | 9.8 | 10.2 | 9.90 |
| M | 10.1 | 10 | 10.1 |
| B | 10 | 9.8 | 10.1 |

**Table 8. Fuzzy rule base for variable \( \delta_3 \)**

| \( e_3 \) | S | M | B |
|---|---|---|---|
| S | 70 | 71 | 69.5 |
| M | 71 | 70 | 71 |
| B | 70 | 69 | 70 |

**Table 9. Fuzzy rule base for variable \( \gamma_{31} \)**

| \( e_3 \) | S | M | B |
|---|---|---|---|
| S | 1100 | 1110 | 1000 |
| M | 950 | 900 | 1000 |
| B | 1010 | -1060 | 1000 |

**Table 10. Fuzzy rule base for variable \( \gamma_{32} \)**

| \( e_3 \) | S | M | B |
|---|---|---|---|
| S | 9.8 | 10.1 | 9.9 |
| M | 10.2 | 10 | 10.1 |
| B | 10 | 9.8 | 10.1 |
Figure 4. Time responses of the first joint of the RPR manipulator.

Figure 5. Time responses of the second joint of the RPR manipulator.
where \( y^{i_1i_2} \) denote the centers of the output membership functions. \( \mu_{A_1}^{i_1} \) and \( \mu_{A_2}^{i_2} \) are the input membership functions considered as triangular shapes (Figure 3). Further, the IF-THEN fuzzy rules for each control gains are illustrated in Tables (2–10).

7. Simulation and discussion

In order to challenge the performance of the suggested control strategy, the initial conditions for the joint variables are regarded as \( \theta_1(0) = 45^\circ, \theta_2(0) = 0.9 \) and \( \theta_3(0) = 45^\circ \). Moreover, the desired paths are considered as \( \dot{\theta}_1^d = \sin 2t, \dot{\theta}_2^d = \sin 4t \) and \( \dot{\theta}_3^d = \sin 3t \).

Figures 4–6 depict the time responses of the robot joints controlled by the proposed fuzzy adaptive state-feedback method, the optimum fuzzy PD controller introduced in (Mahmoodabadi & Roshandel, 2019) and PD controller. In Figure 4, the proposed method stabilizes the first link in less than 0.1 (s); but, the method of (Mahmoodabadi & Roshandel, 2019) and PD controller perform this in more than 0.6 (s) and 2 (s), respectively. In Figure 5, the fuzzy adaptive state-feedback approach forces the robot to track the desired trajectory in less than 0.2 (s), while the optimum fuzzy PD and PD controllers achieve this in about 0.8 (s) and 0.7 (s), respectively. Furthermore, Figure 6 shows that the method of this work is able to control the third joint in about 0.2 (s); however, the method of (Mahmoodabadi & Roshandel, 2019) and PD controller, respectively, stabilize the link in more than 0.5 (s) and 1.8 (s). For more visibility, Figures 7–9 are added to portray the errors of the joints for the schemes of this work and (Mahmoodabadi & Roshandel, 2019). These figures clearly prove the effectiveness and superiority of the fuzzy adaptive state-feedback control in comparison with the optimum PD control.

Finally, the most significant advantage of the introduced control approach could be discovered from Figures 10–12 which, respectively, demonstrate the control efforts \( \tau_1, f_2, \) and \( \tau_3 \). Numerically, the maximum control efforts for \( \tau_1, f_2, \) and \( \tau_3 \) obtained via the proposed scenario in this work are, respectively, as 1100 N.m, 140 N and 3.9 N.m. However, the optimum fuzzy PD approach
Figure 7. Changing of the first joint error over time for the RPR manipulator.

Figure 8. Changing of the second joint error over time for the RPR manipulator.
Figure 9. Changing of the third joint error over time for the RPR manipulator.

Figure 10. Control effort $\tau_1$ over time for the RPR manipulator.
Figure 11. Control effort $f_2$ over time for the RPR manipulator.

Figure 12. Control effort $\tau_3$ over time for the RPR manipulator.
introduced in (Mahmoodabadi & Roshandel, 2019) uses more values for these functions as 1700 N. m, 560N, and 5.1 N.m, respectively.

8. Conclusions
In this research, a novel intelligent fuzzy adaptive scheme was introduced to control the joints of a three-degree of freedom RPR manipulator from an initial condition to the sinusoidal desired paths. At first, the workspace of the robot was studied via driving the forward kinematic equations. Then, the dynamical equations of the robot motion have been found using the Lagrange approach. Moreover, the inverse dynamic method was utilized to linearize the nonlinear equations of motion using the variable changing. The stability of the system was guaranteed via a state-feedback controller. The adaptation laws based on the sliding mode relations and the gradient descent method were successfully implemented to timely regulate the control gains. Finally, a simple and efficient fuzzy system was designed to tune the adaptive parameters and enhance the performance of the controller. Time responses of the joint variables and changing of the errors were simulated and compared with those of a recently published work and a conventional method to show the feasibility and effectiveness of the proposed scenario.

The future works of this research could be summarized as follows: (1) adding the integral components to the controller in order to have a complete linear stabilizer (PID); (2) applying an evolutionary optimization algorithm to improve the controller performance; (3) employing integral sliding surfaces to robust the stabilizer; and finally, (4) directing the neural networks to handle the system uncertainties.

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