



Nonlinear Tracking Control of Parallel Manipulator Dynamics with Intelligent Gain Tuning Scheme

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Abstract

This paper presents modelling and control of highly nonlinear dynamics parallel manipulator system using neural network-based gain tuning technique in a model-based feedback linearization controller. Adaptive gain tuning approach is implemented for conventional computed torque control scheme. The proposed controller has very simple structure and takes little computational time while tracking a trajectory. A feed forward model is implemented to achieve the gains corresponding to the errors and their derivatives. The results are illustrated for a circular trajectory. Simulation results for a 3-RRR planar parallel manipulator show that the intelligent gain tuning technique has better performance than conventional computed torque control in terms of controllability and stability. An experimental analysis is presented for straight line trajectory.

Keywords: Computed torque control, Lyapunov stability, Online gain tuning, Planar parallel manipulator, Sliding mode control.

1. Introduction

Parallel manipulators are dynamically coupled, time-varying and highly nonlinear systems that are extensively used in high speed, high accuracy operations for various industrial tasks (Jun et al., 2011 & Patel and George, 2012). With these requirements, the accurate position control of the manipulator end-effector is a challenging task and also it is difficult to make use of parallel manipulators in real time tasks (Zubizarreta et al., 2013 & Xue et al., 2013). Model based controllers designed with known dynamics of parallel manipulators and it is a difficult task to design with an acceptable performance index (e.g., minimum error, better tracking capability and external disturbance rejection). Most popular approaches of model based controller are the augmented PD (APD) (Wei and Shuang, 2014) and computed-torque control (CTC) (Amin et al., 2012 & Li and Wu 2004), which are appropriate for trajectory tracking control with external disturbance rejection and system uncertainties. Many researchers combined robust classical techniques (e.g. Computed torque control) with non-classical methods (e.g. fuzzy and neural networks (NN)). Some other works proposed different online self-gain tuning approaches using hybrid techniques with function approximation capabilities using some advanced robust control techniques to achieve good tracking performance and stability of the system (Amin and Musa, 2012 & Tien et al., 2013). Zuoshi et al., 2005 developed a combined computed torque and fuzzy control. Likewise a nonlinear PD control was

proposed by (Francisco et al., 2014), where the gains are auto tuned using fuzzy controller. Lyapunov theorem is used for stability analysis to get guaranteed asymptotic convergence to zero for both tracking error and error rate. (Muller and Hufnagel, 2012) proposed a CTC and augmented PD technique in redundant coordinates as an alternative to coordinate switching method. Many recent works also employed sliding mode control approach (Farzin and Nasri, 2012 & Wen and Chien, 2014) due to its robustness in the adjustment of instabilities. Adaptive, Hybrid PID and PD SMCs were proposed for robotic manipulators (Acob et al., 2013 & Ouyang et al., 2014) to estimate error uncertainties, here the decentralized PID controller acts as a feedback system to enhance the stability of the close-loop mechanism.

Artificial Neural Networks are progressively identified as a successful tools for controlling nonlinear dynamic systems because of their advantages such as the ability to approximate arbitrary linear or nonlinear mapping through learning, less formal statistical training and ability to identify complex nonlinear relationships between dependent and independent variables and strong interaction between predicted variables. In this regard, self gain tuning techniques has been proposed to enhance the execution of such controllers. (Tien et al., 2013) proposed an online self gain tuning method using neural networks with nonlinear PD-CTC that achieves good tracking performance in 5-bar parallel manipulator.

But in this approach, they did not consider the external disturbances or un-modelled dynamics. An indirect disturbance observer was implemented by (Vinoth et al., 2014) to compensate the external disturbances prior to the controller design. Very few works applied the gain tuning approaches to higher degree of freedom parallel manipulators, due to its complex nonlinear dynamics. Present work proposes a neural network based auto-tuned PD-CTC for the 3-RRR planar manipulator. Here, the nonlinear PD-CTC is achieved by combining a conventional CTC and an intelligent gain tuning method using a two layer neural network in presence of model uncertainties and external disturbances. The advantages of the proposed controller over the conventional controllers have been illustrated.

2. Dynamics of Planar Parallel Manipulator

As shown in figure 1, a three degree of freedom 3-RRR planar parallel mechanism has three active and six passive joints connecting a mobile platform with fixed base using three limbs. The fixed frame XOY is attached to the base frame and moving frame X'PY' is considered on the mobile platform.

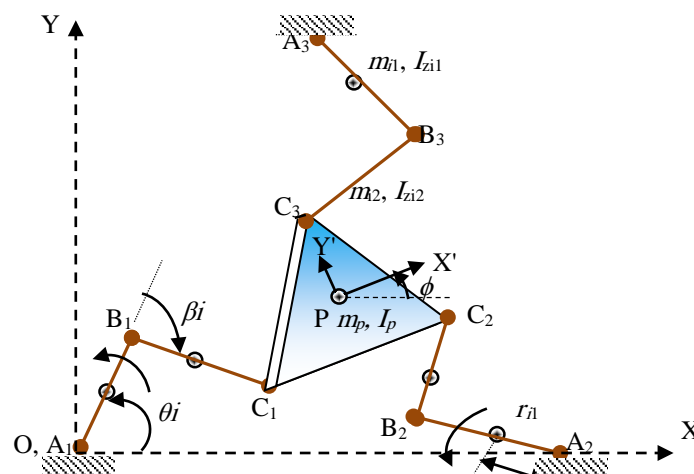


Figure 1: Kinematic Structure of 3-RRR Planar Parallel Manipulator

Two translations x_p, y_p and one rotation ϕ about Z axis constitute the end-effector (platform center P) coordinates. The active and passive joint vectors are respectively denoted by $q_a = [\theta_1, \theta_2, \theta_3]^T$, $q_p = [\beta_1, \beta_2, \beta_3]^T$ and l_{i1} and l_{i2} are the active and distal link lengths. The mass of the links m_{i1} and m_{i2} are concentrated at the centroid of each link about the axis normal to the XOY-reference plane. Also, their

moments of inertia are considered as I_{zi1} and I_{zi2} , m_p is the mass of the mobile platform located at the centroid of the equilateral triangle P, and I_p is the moment of inertia about an axis equally oriented.

The dynamic model of open-loop system of the 3-RRR mechanism can be expressed as:

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

where $q = (q_a, q_p, X_p)^T \in \mathbb{R}^{9 \times 1}$ is the joint vector, $X_{mp} = (x_p, y_p, \phi)$ is the end-effector vector $\tau_t = (\tau_a, \tau_p, F_p)^T \in \mathbb{R}^{9 \times 1}$ is the torque vector $\tau_a = (\tau_{a1}, \tau_{a2}, \tau_{a3})^T$ is the input joint torque vector of active joints, $\tau_p = (\tau_{p1}, \tau_{p2}, \tau_{p3})^T = (0, 0, 0)^T$ is the input torque vector of passive joints and $F_{mp} = (f_x, f_y, \tau_{mp})^T$ is the applied wrench vector of the end-effector. $M(q)$ and $C(q, \dot{q}) \in \mathbb{R}^{9 \times 9}$ are the inertial and coriolis matrices respectively, which are given in the matrix form below and $N(q) \in \mathbb{R}^{9 \times 1}$ is the vector of actuated torque. The above dynamic model can be simplified by considering external disturbances at the active joints. The loop closure constraints are considered using a Jacobian matrix. From D'Alembert's principle and the principle of virtual work, the configuration space can be smoothly parameterized by the actuator joint vector q_a .

$$\tau_a = W^T \tau_t \tag{2}$$

where

$$W = \begin{bmatrix} I \\ \frac{\partial q_p}{\partial q_a} \\ \frac{\partial q_a}{\partial q_a} \end{bmatrix} \tag{3}$$

W is the Jacobian matrix. By using the matrix W from the equation (3) the dynamic model of equation (1) can be transformed into the closed-loop kinematic structure as:

$$W^T M(q)\ddot{q} + C(q, \dot{q})\dot{q} + N(q) = \tau_a \tag{4}$$

Thus, they are expressed in terms of active joint coordinates. The complete dynamics of the closed-loop mechanism can be written as:

$$\widehat{M}(q_a)\ddot{q}_a + \widehat{C}(q_a, \dot{q}_a)\dot{q}_a + \widehat{N}(q_a) = \tau_a \tag{5}$$

where $\widehat{M} = W^T M W, \widehat{C} = W^T M \dot{W} + W^T C W, \widehat{N} = W^T N$

Accordingly the active joint torques can be computed. The dynamic model of equation (5) should have the following properties:

Property 1: \widehat{M} is positive definite and symmetric.

Property 2: $\widehat{M} - 2\widehat{C}$ is a skew-symmetric.

The exact dynamic model of the parallel manipulator will be never known due to nonlinear uncertainties in the system. If the modelling errors caused by these uncertainties are bounded, the actual dynamics can be expressed by combining the modelling errors and estimated dynamics in the following equation:

$$\widehat{M}_a(q_a)\ddot{q}_a + \widehat{C}_a(q_a, \dot{q}_a)\dot{q}_a + \widehat{N}(q_a) = \tau_a \tag{6}$$

Where $\widehat{M}_a = \widehat{M} + \Delta\widehat{M}_a$ and $\widehat{C}_a = \widehat{C} + \Delta\widehat{C}_a$ are the actual dynamic parameters of the parallel manipulators; and $\Delta\widehat{M}_a$ and $\Delta\widehat{C}_a$ are the bounded modelling errors.

The vector of unknown external disturbances and uncertainties at the active joints can be expressed as follows:

$$\Delta\tau_a = \Delta\widehat{M}_a(q_a)\ddot{q}_a + \Delta\widehat{C}_a(q_a, \dot{q}_a)\dot{q}_a + \widehat{N}(q_a) + D(t) \tag{7}$$

where $D(t) \in \mathfrak{R}^{3 \times 1}$ is the vector of the external disturbances.

From equations (6) and (7), the actual dynamic equation of the planar parallel manipulator in the active joint space as:

$$\widehat{M}(q_a)\ddot{q}_a + \widehat{C}(q_a, \dot{q}_a)\dot{q}_a + \Delta\tau_a = \tau_a \tag{8}$$

The dynamic model of equation (8) of the manipulator in the active joint space, which is similar as serial manipulator. But, the presences of uncertainties $\Delta\tau_a$ are enormous and highly nonlinear because of closed-loop constraints and the variation of the parameters.

3. Design of Controllers

Dynamic equation (6) of the manipulator is highly nonlinear due to the dynamic coupling between the kinematic links. In order to achieve a good performance of parallel manipulators in trajectory tracking problems different control techniques from nonlinear control theory are required.

3.1. Computed Torque Control

In computed torque control, the nonlinear dynamic equations of motion are reduced to linear form in terms of dynamic errors. Utilizing the computed torque control approach with a proportional-derivative (PD) outer control loop, the applied actuator torques are calculated at each time step using the following computed torque law as given in (Zuoshi et al., 2005).

$$\tau_c = \widehat{M}(q_a)(\ddot{q}_d + K_p e + K_v \dot{e}) + \widehat{C}(q_a, \dot{q}_a)\dot{q}_a \tag{9}$$

where τ_a is the computed torque applied to input links, K_p and K_v are the diagonal matrices of the proportional and derivative gains, and e and \dot{e} are the array of the position and velocity errors of the input links, $e = q_d - q_a$ and $\dot{e} = \dot{q}_d - \dot{q}_a$. Figure 2 shows the complete CTC approach.

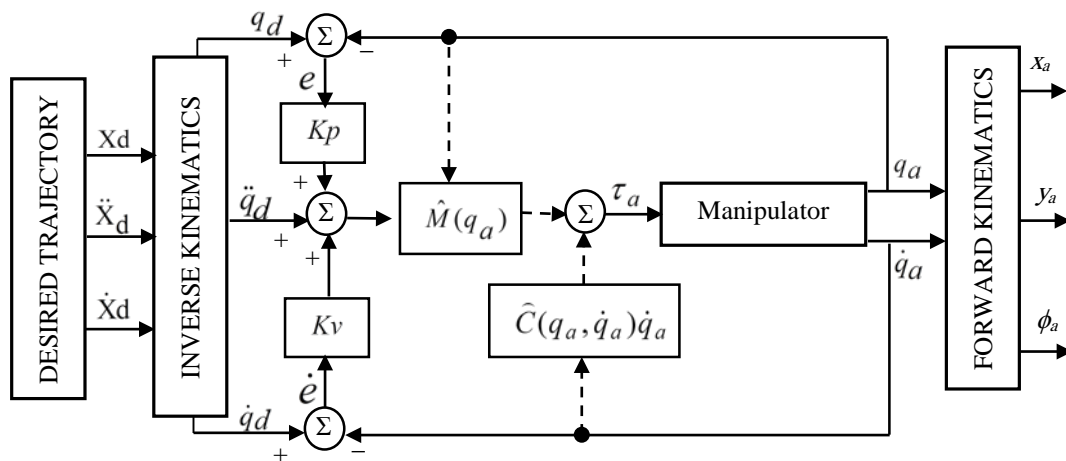


Figure 2: Schematic diagram of the general CTC scheme

3.2. Design of Hybrid Sliding Mode Control

The first step in the design of the SMC is the design of sliding surface function of the system (9) as:

$$s = \dot{e} + \lambda e = \dot{q}_a - (\dot{q}_d - \lambda e) = \dot{q}_a - \dot{q}_d \tag{10}$$

where $\lambda = \text{diag} [\lambda_1, \lambda_2, \lambda_3]$ with $\lambda_i (i=1, 2, 3)$ are the positive constants, which determines the motion feature in the sliding surface; and using dynamics written in terms of the new parameter of sliding surface as follows:

$$\tau_c = \widehat{M}(q_a)\ddot{q}_d + \widehat{C}(q_a, \dot{q}_a)\dot{q}_a + \widehat{M}(q_a)(K_p e + K_v \dot{e} + K_s \text{sat}(s, \psi)) \tag{11}$$

where $K_s = \text{diag}[K_{s1}, K_{s2}, K_{s3}]$ is positive definite and represents the SMC gain. Also the saturation (Ouyang et al., 2014):

$$\text{sat}(s, \psi) = \begin{cases} \text{sign}(s) & \text{if } |s| > \psi \\ s/\psi & \text{if } |s| \leq \psi \end{cases} \quad (12)$$

In the above equation ψ is a diagonal matrix that determines the boundary layer of the sliding surfaces and $\text{sign}()$ is the Signum function.

This control law replaces the model-dependent part of the SMC law with the linear feedback of the computed torque control law and retains the switching term of the SMC law. Because this control law only contains feedback control, it is more robust and less sensitive to changes in the dynamics of the system than pure SMC. With this, a model-free law is obtained with nonlinear feedback control for rigid robotic manipulators.

3.3. Design of Intelligent Gain Tuning Technique

The conventional control techniques which mentioned in literature achieve rarely the required performance in trajectory tracking with the presence of modeling errors and external disturbances with constant gain matrices K_p and K_v . In order to improve the performance of conventional control schemes, different nonlinear control techniques are employed. In the present paper, the nonlinear PD-CTC is considered, which has the similar structure of CTC. The control law for the proposed scheme as follows:

$$\tau_c = \widehat{M}(q_a)(\ddot{q}_d + K_p e + K_v \dot{e}) + \widehat{C}(q_a, \dot{q}_a)\dot{q}_a = \widehat{M}(q_a)q'' + \widehat{C}(q_a, \dot{q}_a)\dot{q}_a \quad (13)$$

where $q'' = \ddot{q}_d + K_p e + K_v \dot{e}$; and K_p and K_v are time-varying gain matrices. $K_p = \text{diag}[K_{p1}, K_{p2}, K_{p3}]$; $K_v = \text{diag}[K_{v1}, K_{v2}, K_{v3}]$. For tuning the gain matrices K_p and K_v in nonlinear CTC controller equation (13), an intelligent tuning system proposed by Tien et al., 2013 is applied. Here, the output of the NN is the input to the nonlinear PD-CTC:

$$q_i'' = f(x_i), \quad i = 1, 2, 3. \quad (14)$$

in which x_i is the input of sigmoid function, $f(x_i)$ is defined in the following equation:

$$f(x_i) = \Psi \times \frac{(1 - e^{-Z})}{(1 + e^{-Z})} \quad i = 1, 2, 3. \quad (15)$$

where $\Psi = 2/Y_g$, $Z = 2x_i Y_g$, Y_g represents the sigmoid function's shape. Here the sigmoid function is the dependent of parameter Y_g (Tu and Kyoung, 2006). Figure 3 shows the block diagram of NN model which is used in the intelligent gain tuning. In this, the NN has a single neuron, which is used to update the gains. Here, the input of the sigmoid function is considered as the output of the NN, which can be formulated as follows:

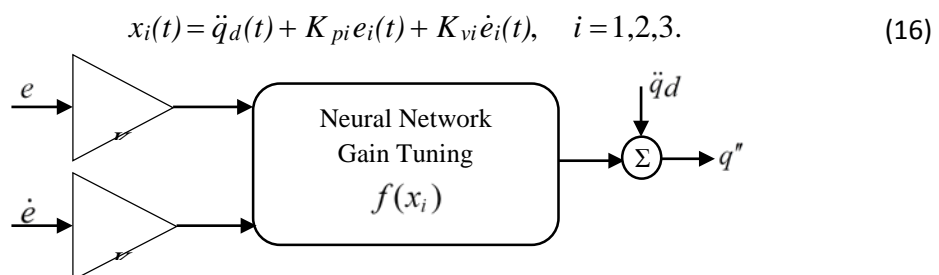


Figure 3: Intelligent Gain Tuning using Neural Network

The gains K_{pi} and K_{vi} in equation (16) are automatically updated by NN in order to minimize the error which is defined as:

$$E_i = \frac{1}{2}(q_{di} - q_{ai})^2 \quad (17)$$

The following equations are updated gains:

$$K_{pi}(t+1) = K_{pi}(t) + \Delta K_{pi}(t) \quad (18)$$

$$K_{vi}(t+1) = K_{vi}(t) + \Delta K_{vi}(t) \quad (19)$$

In which the change of gains $\Delta K_{pi}(t)$ and $\Delta K_{vi}(t)$ can be computed by the steepest descent method (Tien et al., 2013):

$$\Delta K_{pi}(t) = \mu_p e_i^2 \frac{4e^{-Z}}{(1+e^{-Z})^2}, \Delta K_{vi}(t) = \mu_v e_i \dot{e}_i \frac{4e^{-Z}}{(1+e^{-Z})^2} \quad (20)$$

The online self gain tuning technique should satisfy the conditions which were presented in (Tu and Kyoung, 2006). The proof of the exponential stability of the parallel manipulator system controlled by the proposed controller (13) with intelligent gain tuning technique (19), (20) is described below.

3.4. Stability Analysis

To show that the computed torque control technique linearizes the controlled system, the torques computed by (9) are substituted into in (5), yielding

$$\widehat{M}(q_a)\ddot{q}_a = \widehat{M}(q_a)(\ddot{q}_d + K_p e + K_v \dot{e}) \quad (21)$$

Premultiplying each term of the equation (21) by \widehat{M}^{-1} , and substituting the relationship, $\ddot{e} = \ddot{q}_d - \ddot{q}$. Provides the following linear relationship for the error:

$$K_p e + K_v \dot{e} + \ddot{e} = 0 \quad (22)$$

The above relation can be used for selecting the gains to get the desired nature of the closed-loop error response. Since the error equation (22) is linear, it is easy to select K_p and K_v so that the overall system is stable and $e \rightarrow 0$ exponentially as $t \rightarrow \infty$. Generally, if let $K_v = k_v I$, $K_p = k_p I$ with $s^2 + k_v s + k_p$ Hurwitz polynomial, then the control law (13) implemented to the system (21) results in exponential trajectory tracking. The system is parameterized by the end-effector coordinates in the control law (21).

4. Simulations

In order to demonstrate the effectiveness and robustness of the proposed control law, simulation results are presented in this section. To demonstrate robustness, several different cases are considered and the tracking performances of CTC, Hybrid SMC and proposed intelligent gain tuning technique are compared. The properties used for the manipulator are listed in Table 1.

Table 1: Geometric parameters of the 3-RRR planar manipulator

S.No.	Parameter	Length (m)	Mass (kg)	Inertia (kg-m ²)
1	Active link (l_{i1})	0.2500	0.4680	2.4380×10^{-3}
2	Passive link (l_{i2})	0.1667	0.3120	0.7220×10^{-3}
3	Mobile platform(m_p)	0.1250	0.2340	1.8281×10^{-3}
4	Base platform	0.5000	-	-

A circular trajectory in XY plane is tracked using different controller schemes. The desired trajectory is defined as follows:

$$\text{Circular Trajectory: } \{x_d = x_p - r \times \cos(t), y_d = y_p + r \times \sin(t)\} \tag{23}$$

where $r=0.01\text{m}$ is the radius, $(x_p, y_p, \phi)^T = (0.21, 0.21, 0)^T$ is the center of the circle and $t \in [0, 6.3]$. The orientation of the mobile platform is maintained constant throughout the trajectory ($\phi=0^\circ$). In simulations, the control gains for CTC: $K_p=1000, K_v=63.25$, Hybrid SMC: $\lambda=10, K_s=\text{diag}(100,50,25), \psi=\text{diag}(0.08,0.06,0.02)$ are selected. The proposed controller parameters are set as the tuning speed parameters $\mu_p=50000, \mu_v=100$, sigmoid function's shape identifier, i.e., $Y_g=0.01$, initial control gains for without external disturbance: $K_p=800; K_v= 50$, and with external disturbance: $K_p=500; K_v= 50$ are considered.

4.1. Tracking Control without External Disturbances

First of all, the proposed intelligent gain tuning technique is applied for the tracking control for a prescribed trajectory, and the comparisons with conventional CTC and Hybrid SMC are presented in figure 4.

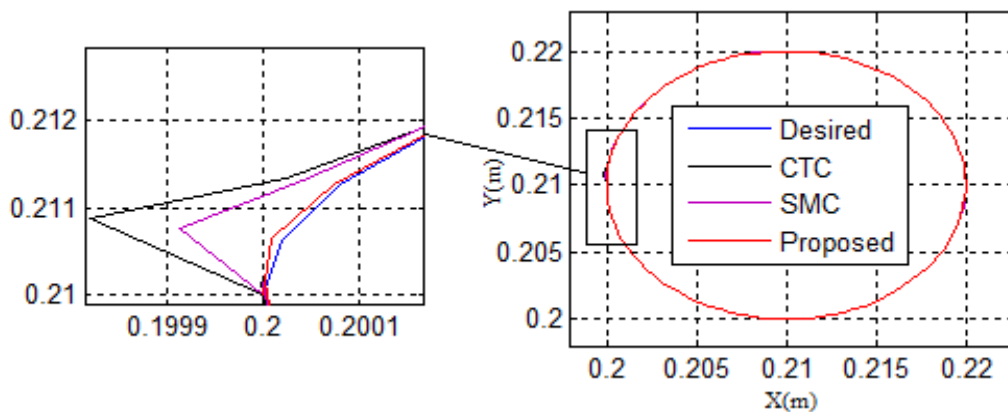


Figure 4: Trajectory tracking of the end-effector without external disturbances

Figure 5 shows the tracking errors at the active joints of the mechanism and it is found that in all the joints on average the percentage error is less than one for the proposed control scheme. Figure 6 shows the corresponding updating gains. Figure 7 shows the required control torques for the manipulator to follow the trajectory with CTC and Hybrid SMC schemes.

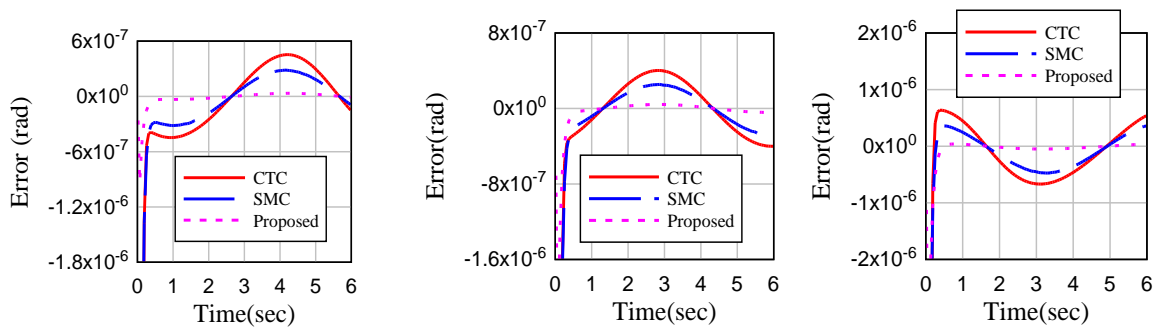


Figure 5: Tracking Errors at the Actuated joints

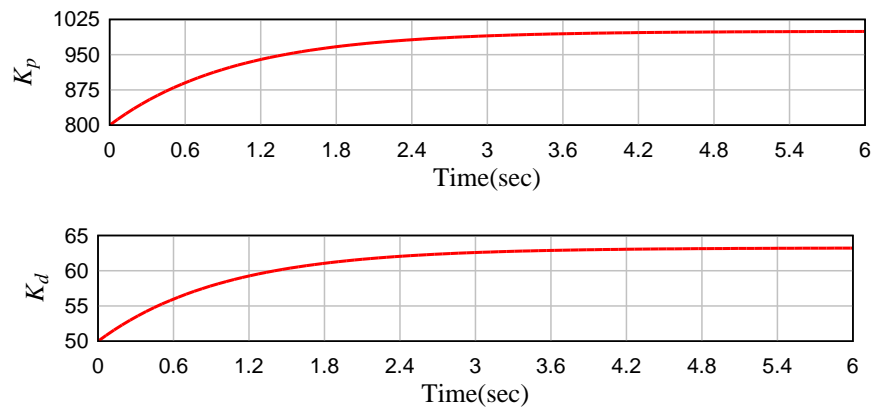


Figure 6: Intelligent tuning method gains

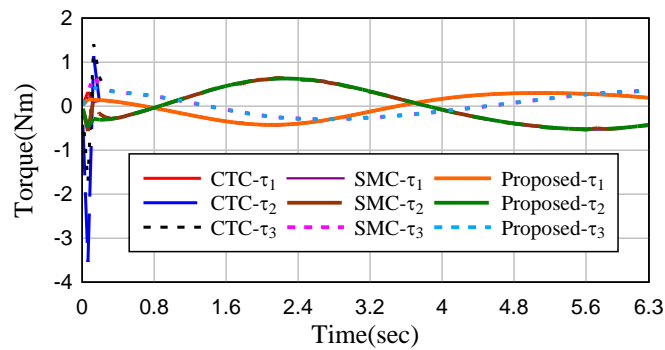


Figure 7: Control Torques at the Actuated joints

4.2. Tracking Control with External Disturbances

In this simulation the external disturbances at the actuated joints are introduced randomly as a time-domain Gaussian noise signals (*i.e.*, $\Delta\tau_a \leq 1$). All other parameters remain same as in the normal tracking conditions. The results of the simulation for all three controllers are shown in figure 8. Here, the proposed intelligent gain tuning technique has better computational time than conventional CTC and Hybrid SMC controllers. This shows that the proposed controller has a fast response time on X86-based PC with 4 GB RAM and 3.10GHz dual core Intel processor and demonstrates its effectiveness in compensating for external disturbances. The tracking errors of the three actuated joints are shown in figure 9. From these figures, it is clear that the error of each actuated joint (in radian) is rapidly converging to zero and the proposed controller convergence rate is more compared with conventional CTC and Hybrid SMC.

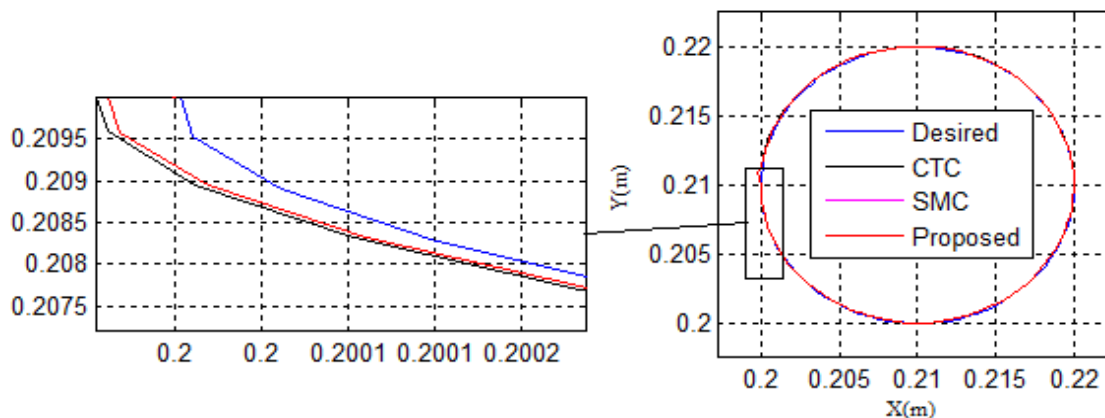


Figure 8: Trajectory tracking of the end-effector with external disturbances

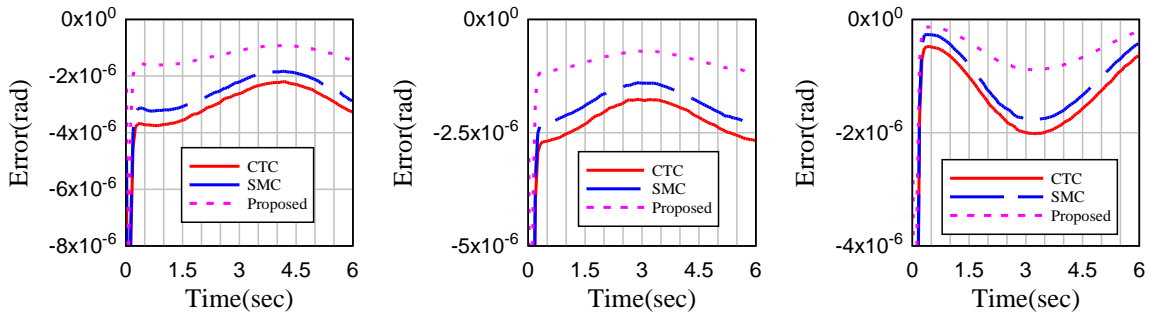


Figure 9: Tracking Errors at the Actuated joints

Figure 10 shows the updated gain history. In Figure 11 the required torques for each actuated joint by the three controllers, i.e. conventional CTC, Hybrid SMC and intelligent gain tuning are illustrated and compared in the presence of external disturbances. From these, it can be concluded that the torques applied to each actuator by the conventional CTC and Hybrid SMC to reject disturbances are initially higher in magnitude than in the intelligent gain tuning technique, and may cause saturation in the actuators. Therefore, it is obvious that intelligent gain tuning technique performance is same as conventional control schemes under the same conditions, without increasing the maximum torques of the actuated joints.

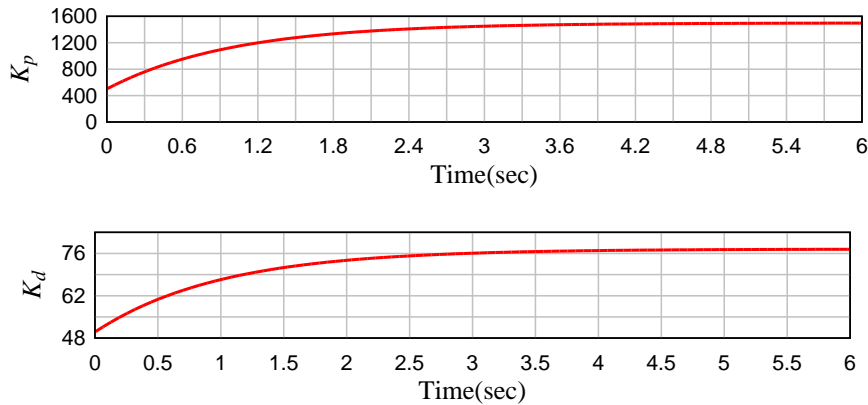


Figure 10: Intelligent tuning method gains

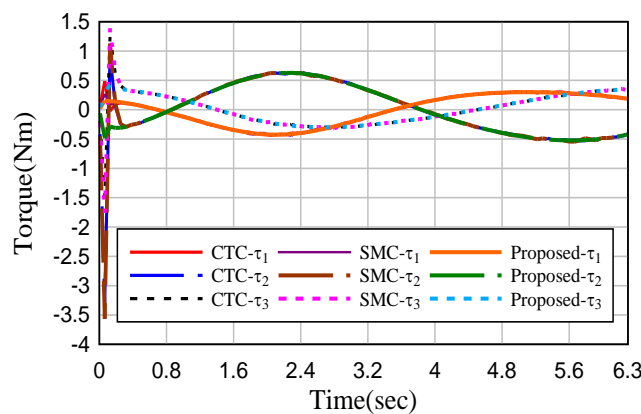


Figure 11: Control Torques at the Actuated joints

4.3. Experimental Results

The experimental results for without disturbance is carried out for a scaled prototype having three servos as shown in figure 12. A straight-line trajectory between points P1(17.5,10.10) cm and P2 (21.5,10.10) cm has been considered for the simulation. The prototype is connected to the Arduino

UNO board and the desired joint angles are supplied to the prototype through Arduino program at a constant speed of 10 rpm for each servo. The results of the simulations are presented in figure 13 and the corresponding joint angles and the desired joint angles are shown in figure 14. Obviously, this controller in open-loop mode has a very rough trajectory in the Cartesian space. By using updated joint angles and their velocities, a computed torque will be supplied in every step of the trajectory. The work is under progress.

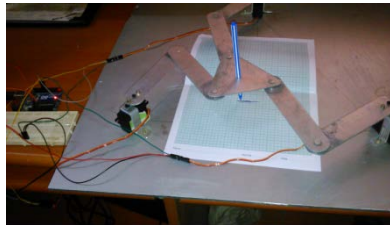


Figure 12: Scaled Prototype

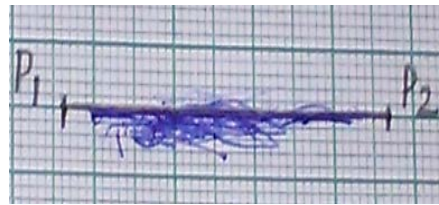


Figure 13: Simulation results

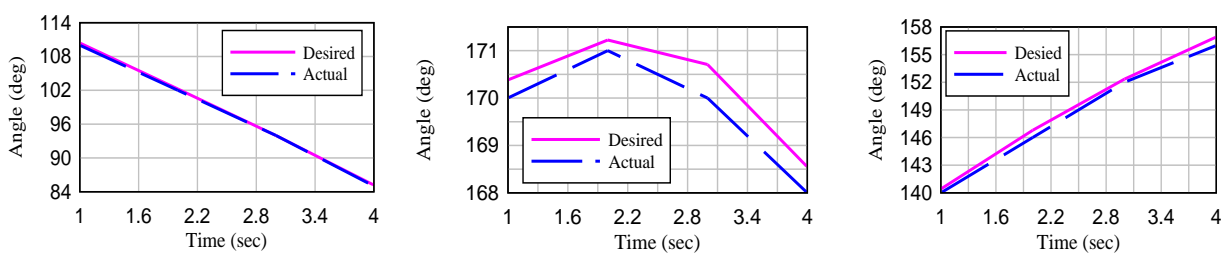


Figure 14: Experimental and theoretical actuated joint angles

Conclusions

This paper presented trajectory tracking performance improvements of planar parallel manipulators with an intelligent gain-tuning approach based on a single layer neural network model. Based on CTC as a nominal controller, an intelligent gain tuning technique using neural network was proposed. Simulation results for a 3-RRR planar parallel manipulator show the effectiveness of the proposed controller for a given trajectory. It has been shown that the proposed controller with online gain tuning using neural network brings about the smallest tracking error and quicker convergence rate compared with conventional CTC and hybrid SMC controllers. The stability of the proposed controller was verified with Lyapunov stability theorem to guarantee the tracking performance of the manipulator. The main advantages of the proposed controller in comparison with the existing conventional CTC and Hybrid SMC methods are: (1) It can compensate the huge amount nonlinear uncertainties and external disturbances as seen from error histories (2) The proposed controller does not require the upper limits of uncertainties and approximation errors. Future work could include implementation of proposed gain tuning for control of scaled model and design of disturbance rejection observer to the model operating in highly disturbed environments.

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