

Passive Adaptive Network Fuzzy Inference Controller Based wheeled Mobile Robot

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Abstract: Passive adaptive network fuzzy inference controller by teleoperation based wheeled mobile robot navigation and wheel slippage has been envisaged in this paper. A passivity controller mode is employed to render the obstacle avoidance for wheeled mobile robot thereby ensuring incident-free navigation particularly unlimited workspace and surface slippage of coordination of master robot position and slave robot velocity. In order to achieve system stability, effective control strategies have been formulated. These strategies bypass robot slippage and skidding due to soft computing. Perfect position tracking of the master/slave robot with Simpson 1/3 rule based adaptive neural network fuzzy inference system is reducing the error in terms of unavoidable and acceptable forces, which is confirmed by passivity. We demonstrated theoretically, the system's stability is shown via its passivity hybrid system in that force felt by the human operator is approximately equal to the force applied by the environment force and sensor predictor of slave robot, which is a satisfactory performance outcome. Simulation results verify the effectiveness of the proposed scheme for teleoperation under passivity controller.

Key-Words: Autonomous wheeled mobile robot, Passivity, adaptive network fuzzy inference system, Simpson's 1/3 rule, teleoperation system.

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1. Introduction

Wheeled mobile robot (WMR) is travelling on a wheel slippage surfaces (or) soft surface, due to obstacles is a challenging task. The perfect and pure rolling of wheels. This wheel slippage and obstacles affect the WMR's dynamic models, creating challenges for control. Teleoperation based WMR is more useful when robot tracking can enhance the navigation and control capability, in this paper we consider the problem of WMRs unlimited workspace and surface slippage of coordination of master robot position q_m and slave robot velocity \dot{q}_s , ideal assumption of pure rolling (zero slippage) in case of two-wheeled mobile robot that travels forward/backward with free motion at any rotation/directions. We present that owing to the WMR compensate for designing the control system, the visual feedback from the lacking slave robot prediction, is added to teleoperation architecture. It is response to the operators commands using while the operator can regulate his/him commands effectively. In particular, the master robot interacts with human operator and slave robot is predicting wheel slippage/pure rolling as based on Simp-

sons 1/3 rule base adaptive network fuzzy inference system (SANFIS) and interacting with its own environment.

In wheeled mobile robot teleoperation there are two kinematics-related challenges not often experienced, which is (i) the workspace of the master robot is limited, visa versa the slave robot is often much bigger and (ii) the WMR with non-holonomic constraints are considered to move in any direction but they are not introduced any variable for direction in the scope of interlink wheel slippage and skid-steering effects [1][2]. The coordination between master and slave robot position and velocity employing bilateral tele-drive of WMRs with unlimited workspace. However, WMR on loose soil, disaster exploration and scientific expedition always require workspace mismatch and surface slippage at the time of actuated mobile robot position and desired angular velocity. These kinds of subjects are still open and remain challenges to achieve workspace mismatch and surface slippage, i.e. collision-free path while moving

towards goal.

The time delay power network method was introduced in [5] to present the mobile robot with teleoperation tracking navigations. This system is force feedback of delayed network with passivity and also obstacle based force feedback which directly relates the distance between the mobile robot and obstacles. It may be noted that the force calculation is not often in slave mode controls, which are interacting with environment forces. The time domain passivity network approach is introduced in [6], in order to restore zero velocity of the mobile robot. This type of force feedback has two important roles: (i) A human-operator facilitating sensor data communication thereby increasing velocity of slave robot; (ii) Restoring data position of the master device during stopping causes longitudinal slippage. If the slave velocity is too fast and if direction changes occur frequently, robots may fall down. Here velocity controller of slave robot cannot proceed due to existing external disturbances.

In [11]-[17] rich theory developed owing to WMRs achieve a passivity within unlimited workspace, Cartesian coordinates with non-holonomic constraints and semi-autonomous control strategy. However, WMRs kinematic model with embedded controller ensuring tracking desired angular velocity invertible errors between desired and actual linear angular velocity. The case of wheel slippage, the WMRs velocity level controller assumed as $s_1 = \frac{\gamma\omega_1}{v_1}$, $s_2 = \frac{\gamma\omega_2}{v_2}$, where s_1 is the left wheel slippage, s_2 is right wheel slippage, r is radius of the wheels, wheels actual linear velocity $v_1(left)$, $v_2(right)$ and wheel desired angular velocity $\omega_1(left)$, and $\omega_2(right)$. In this paper, synchronized joint position error: master robot desired angular velocity minus slave robot actual angular velocity does not reconnected to the real system. And also does not given any mathematical proof as well as stability proof, because most of time predictor error will give more convenient perfect tracking. In

this respect the reference [13]-[15] is lacking. We should fulfilling the gap, we considered the concept of passivity controller as per Simpson's 1/3 rule based adaptive network fuzzy influence with teleoperation system. This method shows wheel moving energy, velocity and angular velocity reallocate direct to target point, then the robot moves in forward on straight line of target from obstacles and investigate environment effect.

The presented article is prepared as follows: Section II gives the preliminary formulation of problem. In Section III, the design of control section IV gives stability analysis of dynamical system. The proposed controllers are implemented in simulation results for path planning in Section V. The conclusion is given in Section VI.

Notation : In this paper, \mathcal{R} denotes the real numbers and \mathcal{C} denotes the complex numbers, C^1 is continuous differentiable on some closed time interval. For any $X - Y$ direction the robot can move freely with different environment effects. The desired angle with respect of initial linear velocity V and initial angular velocity U at target point with respect to vehicles absolute positions and measure.

2. Problem Formulation and Preliminaries

In this paper, we consider two-wheeled mobile robot type, the back two wheels are driving wheels and front wheel is free. Thus, WMR can rotate at any direction with respect of up and down of steering wheels. Then bloc diagram of path following strategy is showing in Fig.1.

2.1 Dynamic model of mobile robot

In order to describe position of wheeled mobile robots, two different coordinates are needed.

The master robot (or) reference frame of wheeled

mobile robot dynamical system is

$$\begin{aligned} M_m(q_m)\ddot{q}_m + C_m(q_m, \dot{q}_m)\dot{q}_m + g_m(q_m) + \tau_{dm} \\ = \tau_m + \tau_h, \end{aligned} \quad (1)$$

where $q_m, \dot{q}_m, \ddot{q}_m$ are master robot (or) reference frame position, velocity and acceleration respectively. $M_m \in R^m \times R^m$ be inertial matrices of reference frame, $C_m(q_m, \dot{q}_m) \in R^m \times R^m$ be coriolis and centrifugal effects, $\tau_{dm} \in R^m$ is desired future predicted input of master frame(i.e. error response of slave robot + master robot new control command), $g_m(q_m) \in R^m$ is gravitational forces, $\tau_h \in R^m$ is fixed environment effect, $\tau_m \in R^m$ is control signal reference frame.

The slave robot (or) local frame of wheeled mobile robot dynamical system is

$$\begin{aligned} M_s(q_s)\ddot{q}_s + C_s(q_s, \dot{q}_s)\dot{q}_s + g_s(q_s) + \tau_{ds} \\ = \tau_s - A^T(q_s)\lambda - \tau_e, \end{aligned} \quad (2)$$

where $q_s, \dot{q}_s, \ddot{q}_s$ are robot wheel skid-steering position, wheel velocity and acceleration respectively. $M_s \in R^n \times R^n$ be entire wheel inertial matrices after skidding, $C_s(q_s, \dot{q}_s) \in R^n \times R^n$ be coriolis and centrifugal effects with skidded-steering condition, $g_s(q_s) \in R^n$ is gravitational at skidded-steering condition, $\tau_{sd} \in R^n$ is desired future predicted input of slave robot (i.e. error response of master robot + camera capture slave robot new control command), λ is unknown parameter, $\tau_e \in R^n$ is environmental forces and $\tau_s \in R^n$ is control signal at skid-steering vehicle and thus moving with respect of master control reference frame within it.

2.2 WMR ssynchronized model with actual robot linear velocity and desired angle

The Fig.1 shows forward direction of WMR x-axis position where Θ_c is equal to camera capture of desired angular velocity minis predicted angular velocity, Θ_d is equal to desired linear velocity minis actual linear velocity. While A is center point of wheel mobile robot and commented angle of right/left wheel is

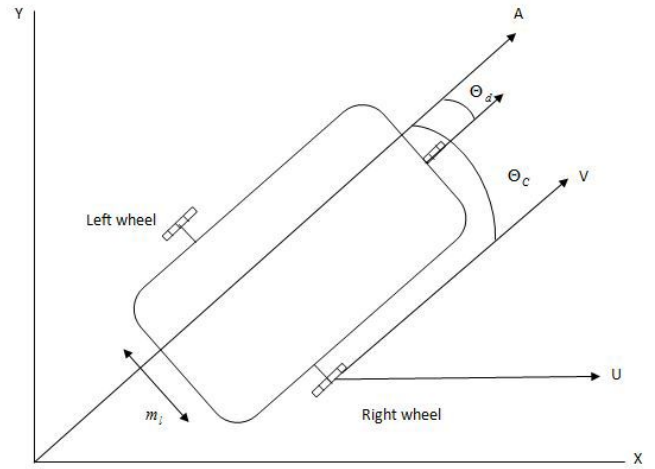


Fig. 1. Path following strategy.

$\theta = \Theta_d - \Theta_c$ which is interlinking predictor velocity of slave robot with respect of wheel radius r and width m_i .

Remark 1 If Θ_c is equal to Θ_d , then θ is equal to zero and therefore wheels get pure rolling with respect of wheel radius r . The difficulty is obtaining the exact position and wheel slippage, in [15] the position is not directly used in computer error feedback loop controller, so it is expected that the trajectory tracking performance will not be affected too much.

However, we coupled the WMR slippage with environment affect and slave robot response. Define sensor detected at right/left wheel is $\dot{\theta} = \dot{\Theta}_i + \tau_i$, $i = m, s$, where Θ_i is defined later and actual wheel slippage is not decided by states of WMR, it also depends on external environment. On behalf of we consider control input $\tau_i = \hat{\tau}_i - \bar{\tau}_i$, $i = m, s$ where $\bar{\tau}_i, i = m, s$ predicted state input vectors of master/slave robot, $\hat{\tau}_i$ is regulated out, it means that our error coming from WMR response. Define the future prediction control input $\tau_{d_i} = f(\dot{\Theta}_i, \dot{\theta}, \tau_i)$ and error between future prediction position and WMR actual position is denoted as $e_i \in R^o$. In this case we consider future prediction position will be used in Hybrid system $\mathcal{H}_{\tau_{d_i}}$, then $\mathcal{H}_{\tau_{d_i}}$ can be written in the

suggestive from:

$$\begin{aligned} \tau_{d_i} &= f(\theta, \Theta_i, \tau_i), \quad \forall \\ (\tau_{d_i}, \theta, \Theta_i, \tau_i) &\in R^{l_j} \times R^{m+1 \times n+1} \\ &\times R^{m \times n} \times R^i, \quad j = m, n, i = m, s. \end{aligned}$$

with output

$$\theta = \Theta_i + \tau_i,$$

$f : C_{m \times n} \times D_{m \times n} \rightarrow R$ is semi continuous and locally bounded on the compact intervals of \mathcal{B} , the inputs τ_m, τ_s and $\tau_{d_i}, i = m, s$ exists in f and without restrictions on the initial state and non zero restriction on the input and with linear asymptotic gain satisfies the Lipschitz condition, then stabilizer of the WMR is taken linear as

$$\dot{f}(\theta, \Theta_i, \tau_i) = \frac{\partial f(\theta, \Theta_i, \tau_i)}{\partial \theta} + \frac{\partial f(\theta, \Theta_i, \tau_i)}{\partial \Theta_i} \quad (3)$$

and

$$\mathcal{B} = \{(\tau_{d_i}, \theta) \in (C_{m \times n} \times D_{m \times n}) : \tau_{d_i} = \theta\},$$

where $C_{m \times n} \subset R^{m+1 \times n+1} \times R^m, D_{m \times n} \subset R^{m+1 \times n+1} \times R^n$.

3. Design of Control System

Definition:(Passivity) The unlimited workspace of the WMR, the coordination of master/slave robot position, velocity is related to linear combination of angular velocity and designed angle $\Theta_i, i = m, s$, then

$$\begin{aligned} \Theta_m(t) &= \dot{q}_m + \Gamma q_s, \quad \Theta_s(t) = \dot{q}_s + \Gamma q_m \quad (4) \\ \dot{\Theta}_m(t) &= \ddot{q}_m + \Gamma \dot{q}_s, \quad \dot{\Theta}_s(t) = \ddot{q}_s + \Gamma \dot{q}_m, \end{aligned}$$

where $\Gamma = \text{diag}(\Gamma_1, \Gamma_2, \dots, \Gamma_n) \in R^{m \times n}$ is control gain positive definite matrix.

If system exists with above inputs and satisfies the following condition such that (1)-(2) is said to be passive:

$$\int_0^t \Theta_i^T(t) \hat{\tau}_i(t) dt \geq -\gamma, i = m, s, \quad (5)$$

where $\tau_m = \hat{\tau}_m - \tilde{\tau}_m, \tau_s = \hat{\tau}_s - \tilde{\tau}_s$ and γ is some

generic constant.

Assumption 1: The master robot controller τ_m , slave robot controller τ_s and $M_m \in R^{m \times m}, M_s \in R^{n \times n}$ are exists in fixed environment and constant wheel skid-steering is happen, if there exists a constant $C_\gamma > 0$ such that

$$|2M_m M_s \tau_m \tau_s| \leq C_\gamma$$

Assumption 2: If human operator with disturbance of master robot linear velocity and slave robot desired angle with fixed environment effect is happen and error angle $\theta = 0$, then

$$\int_0^t \tau_h(t) \Theta_d(t) dt \geq 0$$

and

$$-\int_0^t \tau_e(t) \Theta_c(t) dt \geq 0$$

where $\Theta_d \in R^{m \times 1}, \Theta_c \in R^{n \times 1}$.

3.1 Feedback passivation

The master and slave inputs can be defined as

$$\begin{aligned} \bar{\tau}_m(t) &= -M_m(q_m) \Gamma \ddot{q}_m - C_m \Gamma(q_m, \dot{q}_m) q_m \\ &+ \hat{\tau}_m - \tau_{d_m} + \tau_h \\ \bar{\tau}_s(t) &= -M_s(q_s) \Gamma \ddot{q}_s - C_s \Gamma(q_s, \dot{q}_s) q_s \quad (6) \\ &+ \hat{\tau}_s - \tau_{d_s} - \tau_e, \end{aligned}$$

where $\Gamma = \text{diag}(\Gamma_1, \Gamma_2, \dots, \Gamma_n) \in R^{m \times n}$ is control gain positive definite matrix and $\bar{\tau}_m, \bar{\tau}_s$ are master/slave new state input vectors.

More specifically, there exists a locally Lipschitz function $V : R^{l_j} \times R^{m+1 \times n+1} \times R^{m \times n} \times R^j \rightarrow R$ such that the following lemma holds.

Lemma 1: Suppose θ is close to desired input controller τ_{d_m}, τ_{d_s} , then equation (4)-(5) are satisfied, if there exists a constant γ_1 such that system (1)-(2) is passive with respect of controller (6) as the following condition hold:

$$\int_0^t \theta^T \bar{\tau}_i(t) dt \geq -\gamma_1, i = m, s. \quad (7)$$

Proof: Consider the kinetic energy of Lyapunov func-

tion

$$V(t) = \frac{1}{2}\dot{\Theta}_i^2(t) + \frac{1}{2}\theta^T B(q_i)\theta, \quad i = m, s, \quad (8)$$

where $B(q_i)$ is $R^{o \times o}$ matrix and $\dot{\theta} = \dot{\Theta}_i - \tau_i$, $i = m, s$.

Differentiating (10) w.r.t, t, we get

$$\begin{aligned} \dot{V}(t) &= \Theta_i \dot{\Theta}_i(t) + \theta^T B(q_i) \dot{\theta} \\ &= \Theta_i [\ddot{q}_i(t) + \Gamma \dot{q}_i(t)] + \theta^T B(q_i) [\dot{\Theta}_i - \tau_i] \\ &= \Theta_i [\ddot{q}_i(t) + \Gamma \dot{q}_i(t)] + \theta^T B(q_i) [\ddot{q}_m(t) \\ &+ \Gamma \dot{q}_s(t) + \ddot{q}_s(t) + \Gamma \dot{q}_m(t) - [-M_m \Gamma \dot{q}_m(t) \\ &- C_m \Gamma q_m(t) + \bar{\tau}_m] - M_s \Gamma \dot{q}_s(t) - C_m \Gamma q_m(t) \\ &+ \bar{\tau}_m - M_s \Gamma \dot{q}_s(t) - C_s \Gamma q_s(t) + \bar{\tau}_s \\ &= [\dot{q}_m(t) + \Gamma q_s(t) + \dot{q}(t) + \Gamma q_m(t)] \\ &\times [\ddot{q}_m(t) + \Gamma \dot{q}_s(t) + \ddot{q}_s(t) + \Gamma \dot{q}_m(t)] \\ &- B(q_i) [\dot{q}_m(t) + \Gamma q_s(t) + \dot{q}_s(t) + \Gamma q_m(t)] \\ &\times [\ddot{q}_m(t) + \Gamma \dot{q}_s(t) + \ddot{q}_s(t) + \Gamma \dot{q}_m(t) \\ &+ M_m \Gamma \dot{q}_m(t) + C_m \Gamma q_m(t) + \bar{\tau}_m + M_s \Gamma \dot{q}_s(t) \\ &+ C_s \Gamma q_s(t) + \bar{\tau}_s] \\ &= -B(q_i) [\ddot{q}_m \bar{\tau}_m + \ddot{q}_m \bar{\tau}_s + 2q_m C_m \Gamma^2 q_s \\ &+ 2q_s \Gamma \bar{\tau}_m + q_s^2 \Gamma^2 C_s + 2q_s \Gamma \bar{\tau}_s + \ddot{q}_s \bar{\tau}_m + \ddot{q}_s \bar{\tau}_s]. \end{aligned}$$

By using the inequality $2ab \leq a^2\epsilon + \frac{b^2}{\epsilon}$, we get

$$\begin{aligned} \dot{V}(t) &\geq -B(q) [M_m \dot{q}_m^2 + \frac{1}{2M_m} \bar{\tau}_m^2 + M_m \dot{q}_m^2 \\ &+ \frac{1}{2M_m} \bar{\tau}_s^2 + C_m \Gamma q_m^2 + C_m \Gamma q_s^2 + C_m \Gamma q_s^2 \\ &+ \frac{\Gamma}{C_m} \bar{\tau}_m + C_s \Gamma q_s^2 + C_s \Gamma q_s^2 + \frac{1}{C_s \Gamma} \bar{\tau}_s^2 \\ &+ M_s \dot{q}_s^2 + \frac{1}{2M_s} \bar{\tau}_m^2 + M_s \dot{q}_s^2 + \frac{1}{2M_s} \bar{\tau}_m^2] \\ &\geq -B(q_i) [\frac{1}{M_m} \tau_m + \frac{1}{M_s} \tau_s] \\ &\geq -B(q_i) [2M_m M_s \tau_m \tau_s]. \end{aligned}$$

As per Assumption 1 $B(q_i)C_\gamma \leq \gamma$, the above lemma is passive.

3.2 Wheeled mobile robot error dynamical model

If θ close to future predicted input τ_{d_i} , $i = m, s$ then $\tau_{d_i} = \theta - \tau_i$, $i = m, s$. Let WMR is moving

on smooth plane, then τ_{d_i} is constant (i.e. no skid-steering on wheel) and $\theta = \Theta + c$. However, if skid-steering is happen, the future prediction τ_{d_i} is not constant but derivation of τ_{d_i} is bounded, i.e. $|\dot{\tau}_{d_i}| \leq k_\alpha$, $k_\alpha > 0$. If future input is depending wheel slippage as well as communication error e_i , $i = m, s$. For this we assume error e_i , $i = m, s$ is difference between future prediction position and as well as current position with respect of skid-steering effect frame respectively.

In above situation, the error e_i , $i = m, s$ can be established corresponding to (4) and $|\dot{\tau}_{d_i}|$ is unbounded, then e_m and e_s can be accumulated as

$$\begin{aligned} e_m &= \Theta_m - \int_0^t \tau_{d_m}(t) dt \\ e_s &= \Theta_s - \int_0^t \tau_{d_s}(t) dt \end{aligned} \quad (9)$$

Fig.2 shows two different framers connecting in Tele-operation task, having clear environment information rather than local information and more effective commands within unlimited workspace of slave robot mapping and limited workspace of human operator to assess the WMRs position, i.e. master robot

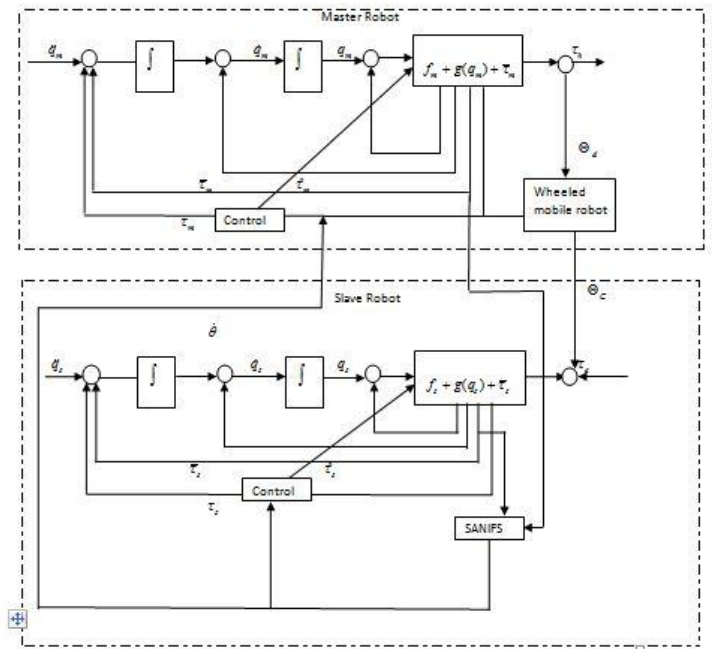


Fig. 2. Control structure of dynamic stabilizer.

Remark 2 In this case $\ddot{\Theta}$ and higher derivatives

are zero because our system is second order differential system, if you go behind the limit this methodology not support.

4. Stability Analysis

In this section stability analysis of system (1)-(2) with implementing hybrid passivity error feedback controller described as follows:

4.1 Synchronization of master/slave robot error dynamical system

The important issue that needs is smooth tracking without wheel slippage; hence two dynamical system errors must be synchronized. In this situation as based on equation (7) the coordination $q_i, i = m, s$ reflexed to error vector e_i , then system (9) can be written as

$$\begin{aligned} M_m(e_m)\ddot{e}_m(t) + C_m(e_m, \dot{e}_m)e_m + g(q_m) + \tau_{d_m} \\ = \tau_h + \hat{\tau}_m \end{aligned} \quad (10)$$

$$\begin{aligned} M_s(e_s)\ddot{e}_m(t) + C_s(e_s, \dot{e}_s)e_s + g(q_s) + \tau_{d_s} \\ = -\tau_e + \hat{\tau}_s, \end{aligned}$$

where $\tau_{d_m}, \tau_{d_s}, \tau_h, \tau_e$ are same as equation (1)-(2) and $\hat{\tau}_m, \hat{\tau}_s$ are defined later.

4.2 Passivity control design of master/slave robot error dynamical system

The important issue that needs is smooth tracking without wheel slippage; hence two dynamical system errors must be synchronized. For this we assume $e_i, i = m, s$ can be utilized in hybrid system dynamics. In this case we consider error input e_i can be written in the suggestive form

$$\begin{aligned} \dot{\tau}_{d_i} + e_i &\in f_1(\theta, \dot{\theta}_i, \tau_i) \\ e_i &= f_1(\theta, \dot{\theta}_i, \tau_i) - \dot{\tau}_{d_i} \\ (\dot{\tau}_{d_i}, e_i, \theta, \dot{\theta}_i, \tau_i) &\in R^{l_j} \times R^o \\ &\times R^{m+1 \times n+1} \times R^{m \times n} \times R^j, \quad j = m, s \end{aligned}$$

with output

$$e_i - \dot{\theta} = \tau_i - \dot{\tau}_{d_i}.$$

$f_1 : C_{m \times n} \times D_{m \times n} \rightarrow R$ is semi continuous and locally bounded on the compact intervals of \mathcal{D} , the inputs τ_m, τ_s, e_i and $\tau_{d_i}, i = m, s$ exists in f_1 and satisfies (3) then

$$\mathcal{D} = \{(\dot{\tau}_{d_i} + e_i, \dot{\theta}) \in (C_{m \times n} \times D_{m \times n}) : \dot{\tau}_{d_i} + e_i = \dot{\theta}\},$$

where $C_{m \times n} \subset R^{m+1 \times n+1} \times R^m, D_{m \times n} \subset R^{m+1 \times n+1} \times R^n$.

If $e_i, i = m, s$ is utilized in dynamical system, then regulated output controller

$$\begin{aligned} \hat{\tau}_m &= -M_m(e_m)\ddot{e}_m - C_m(e_m, \dot{e}_m)e_m - g(q_m) \\ &\quad - \tau_h - \int_0^t \tau_{d_m} dt \end{aligned} \quad (11)$$

$$\begin{aligned} \hat{\tau}_s &= -M_m(e_s)\ddot{e}_s - C_s(e_s, \dot{e}_s)e_s - g(q_s) \\ &\quad + \tau_e - \int_0^t \tau_{d_s} dt. \end{aligned}$$

Using the Lemma 1, we can analyze the passivity of the proposed controllers is per the following theorem.

Theorem 1: Suppose $\dot{\theta}$ is close to desired input controller(11), equation (4)-(7) are satisfied, under Assumption 1 and 2, the proposed tracking wheeled mobile robot system (1)-(2) is stable in terms of $q_s \rightarrow e_s, q_m \rightarrow e_m$ as $t \rightarrow \infty$.

Proof: Consider the semi-definite function

$$\begin{aligned} V_s &= \frac{1}{2} e_m^T k_m e_m + \frac{1}{2} e_s^T k_s e_s \end{aligned} \quad (12)$$

$$+ \int_0^t e_m^T k_m e_m ds + \int_0^t e_s^T k_s e_s ds.$$

Differentiating (14) w.r.t, t

$$\begin{aligned} \dot{V}_s &= e_m^T k_m (\dot{e}_m + e_s^T k_s \dot{e}_s + e_m^T k_m e_m + e_s^T k_s e_s) \\ &= e_m^T k_m (\dot{e}_m + e_m) + e_s^T k_s (\dot{e}_s + e_s) \\ &= e_m^T k_m (\tau_h + e_m - c_m e_m - \tau_{d_m} + \dot{\theta}_m \\ &\quad - \int_0^t \tau_{d_m} ds) + e_s^T k_s (-\tau_e + e_s - c_s e_s \\ &\quad - \tau_{d_s} + \dot{\theta}_s - \int_0^t \tau_{d_s} ds) \\ &= e_m^T k_m [\tau_h + e_m - c_m e_m - \tau_{d_m} + \ddot{q}_m(t) \\ &\quad + \Gamma \dot{q}_s(t) - \int_0^t \tau_{d_m} ds] + e_s^T k_s [-\tau_e + e_s \\ &\quad - c_s e_s - \tau_{d_s} + \ddot{q}_s(t) + \Gamma \dot{q}_m(t) - \int_0^t \tau_{d_s} ds] \end{aligned}$$

$$\begin{aligned}
 \dot{V}_s &= e_m^T k_m \{ \tau_h + \bar{e}_m - c_m e_m - \tau_{d_m} \\
 &+ \frac{1}{M_m} (-c_m q_m - \tau_{d_m} + \tau_m + \tau_h) + \Gamma \dot{q}_s \\
 &- \int_0^t \tau_{d_m} ds \} + e_s^T k_s \{ -\tau_e + \bar{e}_s - c_s e_s \\
 &- \tau_{d_s} + \frac{1}{M_s} (-c_s q_s - \tau_{d_s} - \tau_e + \tau_s) \\
 &+ \Gamma \dot{q}_m - \int_0^t \tau_{d_s} ds \} \\
 &= e_m^T k_m \{ \tau_h + \bar{e}_m - c_m (q_m - q_{m_d} + \tau_m \\
 &- \tau_{m_d}) - \tau_{d_m} + \frac{1}{M_m} (-c_m q_m - \tau_{d_m} \\
 &+ \tau_m + \tau_h) + \Gamma \dot{q}_s - \int_0^t \tau_{d_m} ds \} \\
 &+ e_s^T k_s \{ -\tau_e + \bar{e}_s - c_s (q_s - q_{s_d} + \tau_s - \tau_{s_d}) \\
 &- \tau_{d_s} + \frac{1}{M_s} (-c_s q_s - \tau_{d_s} - \tau_e + \tau_s) \\
 &+ \Gamma \dot{q}_m - \int_0^t \tau_{d_s} ds \}.
 \end{aligned}$$

If $M_m \geq 1$, $M_s \geq 1$, $c_m \geq 1$, c_s , $\Gamma \geq 1$, then

$$\begin{aligned}
 \dot{V}_s &\leq e_m^T k_m \{ \bar{e}_m - \tau_{d_m} + \Gamma \dot{q}_s - \int_0^t \tau_{d_m} ds \} \\
 &+ e_s^T k_s \{ \bar{e}_s - \tau_{d_s} + \Gamma \dot{q}_m - \int_0^t \tau_{d_s} ds \} \\
 &\leq e_m^T k_m \{ \bar{e}_m + \frac{1}{\Gamma} e_m - q_s - \tau_{d_m} \} \quad (13) \\
 &+ e_s^T k_s \{ \bar{e}_s + \frac{1}{\Gamma} e_s - q_m - \tau_{d_s} \} \\
 &\leq -e_m^T k_m q_s - e_m^T k_m \tau_{d_m} - e_s^T k_s q_m \\
 &- e_s^T k_s \tau_{d_s}.
 \end{aligned}$$

Integration (15) on $(0, t)$, we get

$$\begin{aligned}
 V_s(t) - V_s(0) &\leq - \int_0^t e_m^T k_m q_s ds - \int_0^t e_m^T k_m \tau_{d_m} ds \\
 &- \int_0^t e_s^T k_s q_m ds - \int_0^t e_s^T k_s \tau_{d_s} ds \quad (14)
 \end{aligned}$$

We know that $\int_0^t \Theta_i^T \hat{\tau}_i(t) dt \geq -\gamma_1$ and apply this condition in (16), we get

$$\begin{aligned}
 V_s(t) - V_s(0) &\leq 2\gamma_1 - \int_0^t e_m^T k_m q_s ds \quad (15) \\
 &- \int_0^t e_s^T k_s q_m ds.
 \end{aligned}$$

Using Gronwall's inequality for (17), we get

$$V_s(t) \leq e^{-(e_m^T k_m q_s + e_s^T k_s q_m)} \quad (16)$$

If $q_s \rightarrow e_m$, $q_m \rightarrow e_s$ as $t \rightarrow \infty$, therefore the

system (1)-(2) is stable.

4.3 Passivity of adaptive network fuzzy inference controller

The robot is moving towards unknown target location with obstacles path. The objective of this control structure is to avoid collision and how to get acquire information form sensor within obstacles environment. Therefore, the necessary control

$$\begin{aligned}
 \tau_m &= f_m(q_m, \dot{q}_m, \ddot{q}_m, \Theta_m, \dot{\Theta}_m, e_s) \\
 &+ g(q_m) + \tau_{d_m} + \bar{\tau}_m \quad (17) \\
 \tau_s &= f_s(q_s, \dot{q}_s, \ddot{q}_s, \Theta_s, \dot{\Theta}_s, e_m) \\
 &+ g(q_s) + \tau_{d_s} + \bar{\tau}_s
 \end{aligned}$$

guarantees perfect sensor detection of robot system (1)-(2). This controller is directly related to distance between the mobile robot and obstacles with worst environment. It is running based on obstacle information and prevents of mobile robot collisions. The master device causes changing in its velocity and changing the position to suit desired velocity occur $e_i, i = m, s$ that is error between desired velocity and actual position. The slave robot is interacting the environment force with force feedback and suit is desert distance between sensor visual to area around the obstacle error e_s .

4.4 Simpsons 1/3 rule based adaptive network fuzzy inference system

In this section adaptive network fuzzy inference system (ANFIS) with weighted average method is briefly explained [5][6][11]. This proposed Simpsons 1/3 rule based adaptive network fuzzy inference system (SANFIS) control is interlinking the following fuzzy rules

Rules: IF $e_i, i = m, s$ is τ_m THEN $X_n = M_m q_m + N_m \dot{q}_m + O_m \ddot{q}_m + P_m \Theta_m + Q_m \dot{\Theta}_m + W_m e_s$, where M_i is q_i , N_i is \dot{q}_i , O_i is \ddot{q}_i , P_i is Θ_i , Q_i is $\dot{\Theta}_i$ and W_i is $e_i, i = m, s$.

IF $e_i, i = m, s$ is τ_s THEN $Y_n = M_s q_s + N_s \dot{q}_s + O_s \ddot{q}_s + P_s \Theta_s + Q_s \dot{\Theta}_s + W_s e_m$, where M_i is q_i , N_i is \dot{q}_i , O_i is \ddot{q}_i , P_i is Θ_i , Q_i is $\dot{\Theta}_i$ and W_i is $e_i, i = m, s$.

$$\begin{aligned} \tau_m &= q_m \cdot M_m^* + \dot{q}_m \cdot N_m + \ddot{q}_m \cdot O_m \\ &+ \Theta_m \cdot P_m + \dot{\Theta}_m \cdot Q_m = W_m \cdot e_s \quad (18) \\ &+ g(q_m) + \tau_{d_m} + \bar{\tau}_m \\ \tau_s &= q_s \cdot M_s^* + \dot{q}_s \cdot N_s + \ddot{q}_s \cdot O_s \\ &+ \Theta_s \cdot P_s + \dot{\Theta}_s \cdot Q_s = W_s \cdot e_m \\ &+ g(q_s) + \tau_{d_s} + \bar{\tau}_s. \end{aligned}$$

Based on (19)-(20), if output membership functions are related to errors $e_i, i = m, s$, then SANFIS has five layers which are performed as follows;

Layer1 : In this layer the outputs are depending on control action, where the controls are followed Simpson's 1/3, Simpson's 3/8 and trapezoidal rule. In this paper we followed Simpson 1/3 rule, that is

$$\begin{aligned} \tau_m &= \frac{h}{3} \left[(\text{sensor detected angle at right wheel} \right. \\ &\quad \left. - \text{desired position at right wheel})^2 \right. \\ &+ 3((\text{sensor detected angle at left wheel} \\ &\quad \left. - \text{desired position at left wheel})^2 \right. \\ &+ (\text{commented angle right} \\ &\quad \left. - \text{robot right wheel angle})^2 \right. \\ &+ (\text{commented angle left} \\ &\quad \left. - \text{robot left wheel angle})^2 \right. \\ &+ \text{future point error at master robot} \\ &\quad \left. - \text{current position left/right wheel})^2 \right] \\ &+ g(q_m) \\ \tau_s &= \frac{h}{3} \left[(\text{sensor detected error angle at right wheel} \right. \\ &\quad \left. - \text{sensor detected error angle at left wheel})^2 \right. \\ &+ 3((\text{commented right wheel angle} \\ &\quad \left. - \text{right wheel velocity/left wheel acceleration})^2 \right. \\ &+ (\text{commented left wheel angle} \\ &\quad \left. - \text{left wheel velocity/ right wheel acceleration})^2 \right. \\ &+ (\text{sensor detected error angle at right/left} \end{aligned}$$

–future point error at slave robot)²)]
+ $g(q_s)$

Layer2 : In this layer the controller is received the outputs as multiplication of inputs to each other.

Therefore

$$\begin{aligned} \tau_m &= q_m \cdot M_m + \dot{q}_m \cdot N_m + \ddot{q}_m \cdot O_m \\ &+ \Theta_m \cdot P_m + \dot{\Theta}_m \cdot Q_m + W_m \cdot e_s \quad (20) \\ &+ g(q_m) + \tau_{d_m} + \bar{\tau}_m = X_n \\ \tau_s &= q_s \cdot M_s^* + \dot{q}_s \cdot N_s + \ddot{q}_s \cdot O_s \\ &+ \Theta_s \cdot P_s + \dot{\Theta}_s \cdot Q_s + W_s \cdot e_m \\ &+ g(q_s) + \tau_{d_s} + \bar{\tau}_s = Y_n. \end{aligned}$$

Here X_n and Y_n are truth value of output mesh point.

Layer3 : This layer is normalization layer, it could be rearranged all outputs in SANFIS. Therefore

$$\bar{X}_n = \frac{X_n}{X_n - \tau_{d_m}}, \quad \bar{Y}_n = \frac{Y_n}{Y_n - \tau_{d_s}} \quad (21)$$

Layer4 : This layer is called adaptive output node whose output is product of normalized firing strength. A defuzzification node determines the weighted consequence of the output and connection between input and output, which is written as

$$\begin{aligned} (19) \quad \frac{X_n}{X_n - \tau_{d_m}} + g(q_m) + \tau_{d_m} + \bar{\tau}_m &= \bar{X}_n (q_m \cdot M_m \\ &+ \dot{q}_m \cdot N_m + \ddot{q}_m \cdot O_m + \Theta_m \cdot P_m + \dot{\Theta}_m \cdot Q_m \\ &+ W_m e_s + g(q_m) + \tau_{d_m} + \bar{\tau}_m) \\ \frac{Y_n}{Y_n - \tau_{d_s}} + g(q_s) + \tau_{d_s} + \bar{\tau}_s &= \bar{Y}_n (q_s \cdot M_s \\ &+ \dot{q}_s \cdot N_s + \ddot{q}_s \cdot O_s + \Theta_s \cdot P_s + \dot{\Theta}_s \cdot Q_s \\ &+ W_s e_m + g(q_s) + \tau_{d_s} + \bar{\tau}_s) \end{aligned} \quad (22)$$

Layer5 : This node is fixed node and sum of determines of output defuzzification is equivalent to overall system output with steering angles, that is

$$\begin{aligned} \sum_{i=m,s} \bar{X}_n \cdot \Theta_i + g(q_m) + \tau_{d_m} + \bar{\tau}_m &= \frac{\sum_{i=m,s} \bar{X}_n \cdot \Theta_i}{\sum_{i=s,m} \bar{X}_n \cdot \Theta_i} \\ &+ g(q_m) + \tau_{d_m} + \bar{\tau}_m, \\ \sum_{i=m,s} \bar{Y}_n \cdot f_r + g(q_s) + \tau_{d_s} + \bar{\tau}_s &= \frac{\sum_{i=m,s} \bar{Y}_n \cdot \Theta_i}{\sum_{i=s,m} \bar{Y}_n \cdot \Theta_i} \end{aligned} \quad (23)$$

$$+g(q_s) + \tau_{d_s} + \bar{\tau}_s.$$

To train the learning process of safe navigation, the actual coordinate sensor data and desired angle data set is used SANFIS while the testing dataset is verifying Simpson'1/3 rule due to accuracy and effectiveness. The specification of the proposed control structure is demonstrated in simulation.

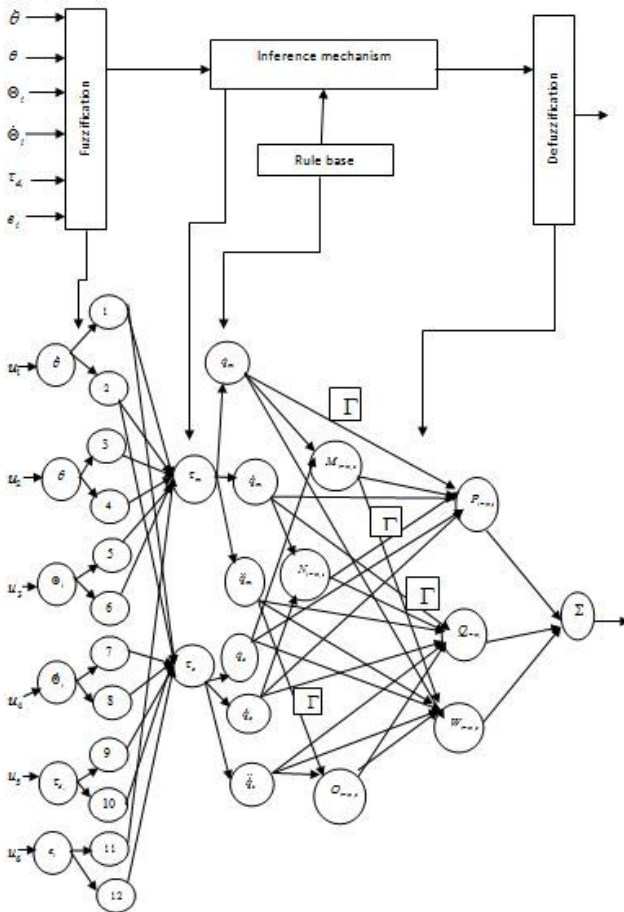


Fig. 3. The proposed SANFIS structure: in this figure 1.sensor detected angle at right wheel, 2.sensor detected angle at right wheel, 3. commented right wheel angle, 4. commented left wheel angle, 5. current position of right wheel/desired position of right wheel, 6. current position of left wheel/desired position of left wheel, 7.right wheel velocity/left wheel acceleration, 8.left wheel velocity/right wheel acceleration, 9.future point on right wheel, 10.future point on left wheel, 11.future point master robot error, 12.future point slave robot error

5. Simulation Result

In order to achieve the smooth and stable movement of wheeled mobile robot we used teleoperation system with designed controller as proposed earlier. The master robot generate the path for the mobile

robot while slave robot to follows without navigation with respect of sensor device response. The sensor data is working on obstacle avoidance with respect of Simpsons 1/3 rule based adaptive network fuzzy inference system(SANFIS). The dynamical model of the mobile robot in global coordination can be reformulated via Simpsons 1/3 rule method as $X_n = \frac{\tau_m}{q_{mr}-q_{ml}}$, where \dot{q}_{mr} , q_{ml} right wheel velocity and left wheel position of master robot and m_l is distance between two wheels and $\bar{X}_n = \frac{\tau_m}{q_{ml}-q_{mr}}$, left wheel velocity and right wheel position of master robot respectively. Similarly $Y_n = \frac{\tau_s}{q_{sl}-q_{sr}}$, where \dot{q}_{sr} , q_{sl} right wheel velocity and left wheel position of slave robot and m_l is distance between two wheels and $\bar{Y}_n = \frac{\tau_s}{q_{sl}-q_{sr}}$, left wheel velocity and right wheel position of slave robot.

Forward and backward movements will be interpreted to moving position of control device, the negative direction on Y-axis/X-axis. Consequently, mobile robot right hand coordinated is observed by τ_m with respect of position and wheel slippage, that is moving of right hand is controlled by left hand of τ_s . Movement of mobile robot left hand positive to decided point is controlled by τ_s with respect of negative direction on the X-axis/Y-axis. The simulation results of ANFIS and SANFIS models path segments with master/slave contact mode position and torque tracking profiles are given in Fig.4 and Fig.5, it shows that the mobile robot can follow the path as stable with respect of minimum error.

6. Comparison of the Two Approaches

To demonstrate the characteristics of the proposed system, experiments were carried to assess both adaptive network fuzzy inference system(ANFIS) and Simpsons 1/3 rule based adaptive network fuzzy inference system(SANFIS). The adaptive techniques can be used to generate the membership function and fuzzy system delivers the best result from dataset, the results are shown in Fig.4 and Fig.5 and right/left

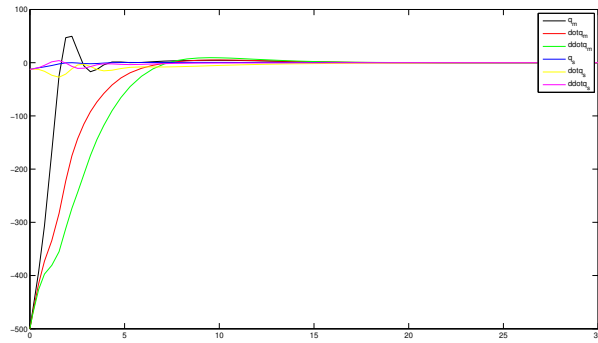


Fig. 4. The error response of right/left coordination of master/slave robot with ANFIS

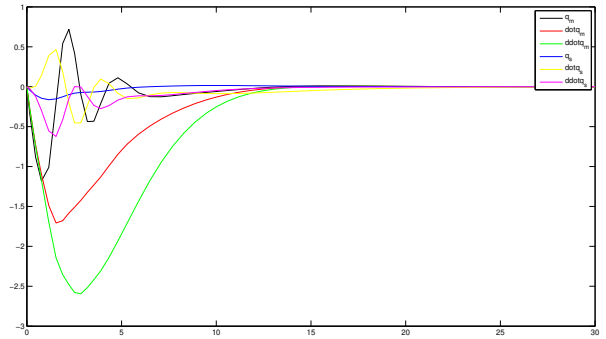


Fig. 5. The error response of right/left coordination of master/slave robot with SANFIS

wheel error angle response is shown in Fig.6 and Fig.7.

The Simpsons 1/3 with adaptive neural network fuzzy inference system (SANFIS) approach requires by far the shortest pre-training time almost within 15 seconds all the trajectories are convergent. In this sense, SANFIS is the best approach and performance measures are tabulated in Tables 1-4. In Table 1 compares another distinguishing property of the approaches namely the need for pre-training, the error bound for Master/Slave robots with left/right wheel angles are given in Table 2. Table 3 and 4 shows the Position, velocity and angular velocity of Master/Slave with right/left wheel response respectively. In this table, the SANFIS approach requires by far the minimum pre-training time. As depicted, the proposed controllers can behave correctly in all cases and this task is realized efficiently.

7. Conclusions

Robust, fast and minimal error converge control is proposed for a teleoperation based wheeled mobile robot system under passivity with hybrid system that can achieve perfect tracking and transparency. This theoretical analysis shown the force felt by the human operator is almost equal to the force applied by the predictors environment and sensor data slave robot. The control scheme is provided to perfect position tracking of the master/slave robot with sense of

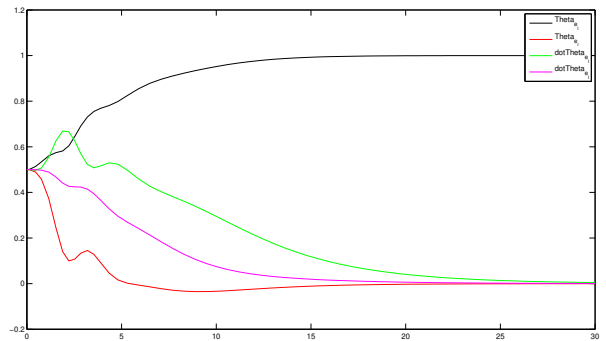


Fig. 6. The error angle response of right/left wheel with ANFIS

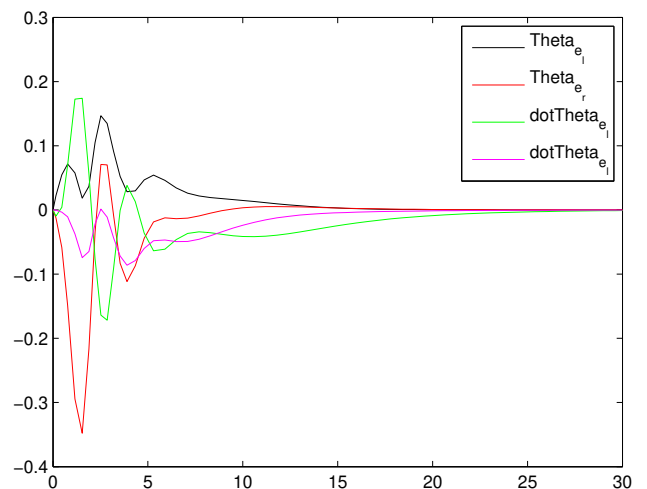


Fig. 7. The error angle response of right/left wheel with SANFIS

teleoperation in the environment. A soft-computing based adaptive network fuzzy inference system can select the suitable steering angle by Simpson's 1/3 rule to achieve collision-free path while moving to reach the goal. The ANIFS and SANFIS approaches are tested for the same command signal. For the tracking error performance, SANFIS showed the best performance. On the other hand, designed controller provided passivity to the system and stability to the wheeled mobile robot. The simulation result exhibited the efficiency of the proposed controller system. It is believed that future research in this area will also be very promising because of efficient sensor incoming/outgoing signals, demands and robustness in adaptive network fuzzy inference systems, which can benefit from four wheel mobile robot robustness and fast responsiveness of sliding mode control.

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Time(Sec)	Model
ANFIS	20-25
SANFIS	15-20

Table.1 : Comparison of pre-training time convergences.

	θ	$\dot{\theta}$
ANFIS	0.9999	0.0047
SANFIS	4.8529e-06	1.5817e-04

Table.2 : Comparison two methods ANFIS and SANFIS with left/right commented angle and sensor detected angle left/right.

	q_m	\dot{q}_m	\ddot{q}_m
ANFIS	-4.7521e-04	-0.0058	0.0064
SANFIS	-7.5854e-05	-2.1220e-05	-4.8266e-05

Table.3 : Comparison of ANFIS and SANFIS with coordination of master robot.

	q_s	\dot{q}_s	\ddot{q}_s
ANFIS	-0.0016	-0.0661	-0.0103
SANFIS	8.7194e-05	-0.0020	-3.1626e-04

Table.4 : Comparison of ANFIS and SANFIS with coordination of slave robot.

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