Simpsons 1/3 base fuzzy neural network with passive controller of wheeled mobile robot system

K. Suganya and V. Arulmozhi

Department of Research-Ph.D Computer Science, Tiruppur Kumaran College for Women, Tiruppur, India

ABSTRACT

The paper investigates Passivity of Simpson 1/3 rule fuzzy neural network controller by tele-operation-based wheeled mobile robot navigation and wheel slippage. To render the obstacle avoidance for wheeled mobile robot and ensuring incident-free navigation particularly unlimited workspace and surface slippage of coordination for master robot position and slave robot velocity, a passivity controller mode is employed. Effective control strategies are formulated to achieve system stability in which soft-computing methodology is accessed to bypass robot wheel slippage and skidding. Soft-computing based fuzzy neural network system is framed through Simpson 1/3 rule for reducing master/slave robot position error on behalf of unavoidable and acceptable forces, which is confirmed by teleoperation system. We concluded mathematically, the system stability which has been shown via its passivity of the fuzzy neural network controller. The forces which can be handled by the human operator are approximately equal to the forces applied by the environmental force and sensor predictor of slave robot whichever comes under the unlimited workspace. Simulation results are verified with the effect of the proposed controller.

Index Terms: Autonomous wheeled mobile robot, Passivity, adaptive network fuzzy inference system, Simpson’s 1/3 rule, teleoperation system.

1. Introduction

In wheeled mobile robot (WMR) navigating over obstacles, such as rocky terrain, sharp surfaces, or areas with low frictions are happen frequently. It is very important to know the number and type of wheels in the robot to model the kinematics and dynamics, which are challenging issues in reconfiguration features that can over cross the obstacles and climb on a slope. WMR when moving on uneven terrain is presented, the relation between the contact path of wheel and terrain, obstacle height is one of the most important in robot control designs. Generally, wheeled vehicles are simpler, more efficient, and faster than other robots with the assumption of rolling without slipping of wheels are considered in nonholonomic systems phenomenon.

The dynamic model of wheel slippage and obstacles affect are consider in the controller for velocity loss and desired inputs. A Teleoperation based WMR is more useful when robot tracking can enhance navigation and wheel slippage. In many scenarios, a human partner can control the mobile robots through a teleoperation interface to perform a collaborative task (Choi & Jung, 2020; Cooke, 2006; Tunc, 2010; Tunc & Tunc, 2011; 2017). In particular, teleoperation is utilized for workspace mismatch; a matching process is carried out between the master and the slave robot wheel velocity.

In other words, mobile robots passively cooperate with the human partner. For improving the performance of human-robot interaction, it is essential to make the mobile robots actively cooperate with the human partner according to human’s control intention. In this paper, we consider the problem of WMRs unlimited workspace and surface slippage of coordination of master robot position and slave robot velocity with an ideal assumption of pure rolling (zero slippage) is carried out in Simpson 1/3 rule fuzzy neural network system (SFNNS). The fuzzy logic controller has been effectively applied in this research to control the position and orientation of mobile robots in the environment. We have designed an SFNNS to solve the navigation problem of the wheeled mobile robot in an unknown and changing environment. SFNNS are motivated by human calculation, which works based on observation. The visual feedback from the host computer (human operator) and slave robot predicted wheel slippery/pure rolling can be interconnected in
Simpsons 1/3 rule base fuzzy neural network system (SFNNS).

In (Li et al., 2017; Liang, Wang, Chen, Guo, & Liu, 2015; Luo, Lin, Li, & Yang, 2019; Shing and Jang, 1993; Wu Wang & Dang, 2014; Yamchi & Esfanjani, 2017; Yoo & Park, 2018) rich theory developed owing to the passivity of WMR with unlimited workspace, a Cartesian coordinate of non-holonomic constraints, and a semi-autonomous control strategy. The WMR kinematic model with the embedded controller was introduced to ensuring the tracking desired angular velocity, invertible errors between desired and actual velocity. The synchronized of position error: master robot desired angular velocity minimize the slave robot angular velocity, in (Li et al., 2017; Liang et al., 2015; Luo et al., 2019) does not give this kind of information and unlimited workspace. And also does not give any mathematical proof as well as stability proof, because most of the time predictor error will give more convenient perfect tracking. In this respect the reference (Li et al., 2017; Liang et al., 2015; Luo et al., 2019; Shing and Jang, 1993; Wu Wang & Dang, 2014; Yamchi & Esfanjani, 2017; Yoo & Park, 2018) is lacking.

The time-domain passivity network approach was introduced in (Lee, Martinez-Palafox, & Spong, 2006), to restore the zero-velocity of the mobile robot. This type of force feedback has two important roles: (i) A human-operator facilitating sensor data communication to increasing the velocity of slave robot; (ii) Restoring data position of the master device is interfering with longitudinal slippage: in both case, if slave velocity is too fast, robots may fall. However (Li et al., 2017; Luo et al., 2019), teleoperation system with two kinematics-related challenges are experienced, which is (i) the workspace of the master robot is limited, vice verse the slave robot is often much bigger, and (ii) the WMR with non-holonomic constraints are considered to move in any direction. But in that article has not introduced any variable for direction concerning wheel slippage and skid-steering effects. The coordination between master and slave robot position and velocity employing bilateral tele-drive of WMRs with unlimited workspace, which is commonly considered (Lee et al., 2006; Lee & Xu, 2006; Suganya & Arulmozhi, 2016; 2017; Tipsuwan & Chow, 2004). Indeed WMR is travelling 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. In this manner, this kind of objective is still open and remains a challenge to achieve workspace mismatch and surface slippage, i.e., collision-free path while moving towards a goal.

The wave variables-based teleoperation control and neural network system (NNS) has been presented mobile robot collision-free path in (Yang, Wang, Li, Li, & Su, 2017). Indeed in (Sun, Naghdy, & Du, 2017), the passivity-based neural network control system is used for teleoperation system and teleoperation delay of mobile manipulator system is evaluated internet-based human loop system (Santiago, Slawinski, & Mut, 2017). In this paper haptic control is used in teleoperation system: the master robot should be equipped with a haptic device that can be reacted the force feedback from the slave robot. The force reflection in the slave robot should be regulated and transferred to the master side to maintain stability, which is solved by the backstepping control method. In (Choi & Jung, 2020) discussed neural network learning technique is applied in position-based force controller in the framework of a haptic device. The mobile robot contact force is made by a haptic device of bilateral transparency system: the contact force of the slave robot is controlled by the position-based master robot through force feedback. These systems are making communication errors when a hard force of the master robot/sequence of obstacles might be happening due to unlimited workspace.

In this paper, we consider obstacle avoidance of master/slave robots and communication errors are considered through SFNNS, which resolving incident navigation and particularly unlimited workspace. For surface slippage of coordination for master robot position and slave robot velocity, a passivity controller mode is employed. Effective control strategies are formulated to achieve system stability in which soft-computing methodology is accessed to bypass robot slippage and skidding. Soft-computing based neural network system is framed through Simpson 1/3 rule for reducing master/slave robot position error on behalf of unavoidable and acceptable forces, which is confirmed by passivity.

The presented article is prepared as follows: In Section 2 preliminary formulation of the problem is discussed. Section 3, presents the design of the control section, while Section 4 provides stability analysis of a dynamical system. The proposed controllers are implemented in simulation results for path planning in Section 5. The conclusion of the results is presented in Section 6.

Notations: In this paper, R denotes the real numbers and C is the complex numbers, C’ is continuously differentiable on some closed time interval. In any direction, the robot can move freely with different environmental effects. The angle Θ_2 is interlinking with initial linear velocity V and initial angular U at target point A and Θ_d is desired angle.
2. Problem formulation and preliminaries

In this paper, we consider a two-wheeled mobile robot system, the back two wheels are driving wheels and the front wheel is free. Thus, WMR can rotate in any direction to the up and down of steering wheels. The block diagram of the path strategy is showing in Figure 1.

2.1. Dynamic model of mobile robot

To describe the position of wheeled mobile robots, two different coordinates are needed.

The master robot (or) reference frame of wheeled mobile robot dynamical system is

\[ M_m(q_m) \ddot{q}_m + C_m(q_m, \dot{q}_m)q_m + g_m(q_m) + \tau_{d_m} = \tau_m + \tau_h, \]

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

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

\[ M_s(q_s) \ddot{q}_s + C_s(q_s, \dot{q}_s)q_s + g_s(q_s) + \tau_{d_s} = \tau_s - A^T(q_s)\lambda - \tau_e, \]

where \( q_s, \dot{q}_s, \ddot{q}_s \) are robot wheel skid-steering wheel position, velocity and acceleration. \( M_s \in \mathbb{R}^n \times \mathbb{R}^n \) is entire wheel inertial matrices of slave robot, \( C_s(q_s, \dot{q}_s) \in \mathbb{R}^n \times \mathbb{R}^n \) is coriolis and centrifugal effects with skidded-steering condition, \( g_s(q_s) \in \mathbb{R}^n \) is gravitational at skidded-steering condition, \( \tau_{d_s} \in \mathbb{R}^n \) is desired input of slave robot (i.e., error response of master robot + camera capture slave robot desired command), \( \lambda \) is unknown parameter, \( \tau_e \in \mathbb{R}^n \) is environmental forces and \( \tau_s \in \mathbb{R}^n \) is control signal at the skid-steering vehicle with camera capture of slave control reference frame respectively.

2.2. WMRs synchronized model with actual robot linear velocity and desired angle

Figure 1 shows the forward direction of WMR x-axis position, where \( \Theta_c \) is equal to camera capture of desired angular velocity, \( \Theta_d \) is equal to desired linear velocity minus actual linear velocity. The point \( A \) is centre a point of wheel mobile robot with respect to right/left wheel commented angles. Then \( \theta = \Theta_d - \Theta_c \) which is inter-linking velocity of slave robot, wheel radius \( r \) and width \( m \).

Remark 1. If \( \Theta_c \) is equal to \( \Theta_d \), then \( \theta \) is equal to zero, that is wheels getting pure rolling to wheel radius \( r \). If \( \Theta_c \) is not equal to \( \Theta_d \), then \( \theta \) is not equal to zero, that is difficult to obtain to get exact position and without wheel slippage. In (Tipsuwan & Chow, 2004) the position is directly used in the feedback control loop, it is very difficult to predict the exact trajectory tracking performance through the host computer.

In this paper, the WMR slippage with environment effect of slave robot response is defined in sensor detected at right/left wheels, that is \( \dot{\theta} = \Theta_i - \dot{\tau}_i \), \( i = m, s \), where \( \Theta_i \) is actual wheel slippage, which is depending on external environment(soil). On behalf of we consider control input \( \tau_i = \dot{\tau}_i - \dot{\tau}_i = m, s \) where \( \dot{\tau}_i, i = m, s \) is predicted state input vectors of master/slave robot, \( \dot{\tau}_i \) is regulated output, that is cumulative output error coming from WMR response.

Then future prediction control input is \( \tau_{d_i} = f(\Theta_i, \dot{\theta}, \dot{\tau}_i) \) and error future prediction position and WMR actual position is denoted as \( e_i \in \mathbb{R}^n \). In this case, future prediction position is used in Hybrid system \( \mathcal{H}_{i}, \mathcal{H}_{i} \), then \( \mathcal{H}_{i} \) can be written in the suggestive from:

\[ \tau_{d_i} = f(\dot{\theta}, \Theta_i, \dot{\tau}_i) \]

\[ (\tau_{d_i}, \dot{\theta}, \dot{\tau}_i) \in \mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R}^n, \]

with output

\[ \dot{\theta} = \Theta_d - \Theta_c. \]

If \( f : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R} \) is semi continuous and locally bounded in a compact set \( \mathcal{B} \), then inputs \( \tau_{m,i} \) and \( \tau_{d,i} \) are exists in \( f \), which are satisfies the Lipschitz condition, then stabilization of WMR is

\[ f(\dot{\theta}, \Theta_i, \dot{\tau}_i) = \frac{\partial f(\dot{\theta}, \Theta_i, \dot{\tau}_i)}{\partial \dot{\theta}} + \frac{\partial f(\dot{\theta}, \Theta_i, \dot{\tau}_i)}{\partial \Theta_i} \]

and
3. Design of control system

In this section we proved master/slave robot can have an unlimited workspace with passivation.

3.1. Feedback passivation

The unlimited workspace of the WMR, the coordination of master/slave robot position, velocity is related to a linear combination of angular velocity and designed angle \(\Theta_2 = \Sigma m, s\), then

\[
\begin{align*}
\Theta_1(t) &= \dot{q}_m + \Gamma q_m, \Theta_2(t) = \ddot{q}_s + \Gamma q_m \\
\dot{\Theta}_1(t) &= \ddot{q}_m + \Gamma \dot{q}_m, \dot{\Theta}_2(t) = \ddot{q}_s + \Gamma \dot{q}_m,
\end{align*}
\]

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

The system (1)-(2) is said to passive if there exists \(\theta = \Theta_2 - \Theta_1\) with (4) such that the following conditions hold

\[
\begin{align*}
\int_0^t \Theta_2^2 \, dt + \frac{1}{2} \int_0^t \dot{B}(q_i) \, \theta \, dt &\geq -2 \gamma_i, i = m, s,
\end{align*}
\]

where \(B(q_i) \in \mathbb{R}^{m \times m}\) is asymmetric and positive definite matrix and \(\gamma\) is some generic constant.

The master and slave inputs can be defined as

\[
\begin{align*}
\ddot{q}_m(t) &= -M_m(q_m) \Gamma \dot{q}_m - C_m \Gamma q_m \dot{q}_m + \ddot{\tau}_n + \tau_h \\
\ddot{q}_s(t) &= -M_s(q_s) \Gamma \dot{q}_s - C_s \Gamma q_s \dot{q}_s + \ddot{\tau}_e + \tau_e,
\end{align*}
\]

where \(\Gamma = \text{diag}(\Gamma_1, \Gamma_2, \ldots, \Gamma_n) \in \mathbb{R}^{m \times m}\) is control gain positive definite matrix and \(\ddot{\tau}_m, \ddot{\tau}_e\) are master/slave robot predicted state input vectors.

More specifically, there exists a locally Lipschitz function \(V : \mathbb{R}^t \times \mathbb{R}^{m \times m} \times \mathbb{R}^{m \times m} \times \mathbb{R}^t \rightarrow \mathbb{R}\) such that the following lemma holds.

**Lemma 1:** Suppose \(\theta\) is close to desired input controller \(\ddot{\tau}_m, \ddot{\tau}_e\), and the equation (4)-(5) are satisfied, if there exist constants \(\gamma_1, \gamma_2, \gamma_3\), then system (1)-(2) is passive with respect of controller (6) such that the following conditions hold:

\[
\begin{align*}
\int_0^t \dot{\theta} \, \theta \, dt &\geq -\gamma_1, \\
\int_0^t \dot{\theta} \, \theta \, dt &\geq -\gamma_2, \\
\int_0^t \dot{\theta} \, \theta \, dt &\geq -\gamma_3, i = m, s.
\end{align*}
\]

**Proof:** Consider the kinetic energy of positive definite Lyapunov function

\[
V(t) = \frac{1}{2} \Theta_2^2(t) + \frac{1}{2} \dot{B}(q_i) \, \theta, i = m, s.
\]
If \( 2ab \geq -\epsilon \|a\|^2 - \frac{1}{\epsilon} \|b\|^2, \epsilon = 6, 4, \) and apply this condition on (9), we get

\[
\dot{V}(t) \geq -\frac{12}{5} q_i t_d - 6 \oint t_i ds
\]

Integrating (10) on \((0,t)\), we get

\[
V(t) \geq V(0) - \frac{12}{5} \oint q_i t_d ds
- 6 \oint t_i ds
- 2t \oint t_i ds
\]

If \( \gamma = \max \{ V(0), \frac{12}{5} \gamma_1, \frac{6}{5} \gamma_2, 2 \gamma_3 \} \), then

\[
\Theta_i^2 + \frac{1}{2} (B(q_i)) \dot{\Theta} \geq -2 \gamma
\]

therefore the above lemma is passive.

### 3.2. Wheeled mobile robot error dynamical model

If \( \dot{\theta} \) is close to future prediction input \( \tau_d, i = m, s \) and \( \tau_d = \tau_i - \Theta_i, i = m, s \), is constant then WMR is moving on smooth plane (i.e., There is no skid-steering on wheel). However, if skid-steering is happen, the future prediction \( \tau_d \) is not constant, therefore derivation of \( \tau_d \) is bounded, i.e., \( |\dot{\tau}_d| \leq k_s, k_s > 0 \). Then future input is depending on wheel slippage as well as communication error \( e_i, i = m, s \), such that error \( e_i, i = m, s \) is differentiable with respect of future prediction position and as well as current position and skid-steering.

In above situation, the error \( e_i, i = m, s \) can be established corresponding to (4) and \( |\dot{\tau}_d| \) is unbounded, then

\[
\dot{e}_m = \Theta_m - \int_0^t \tau_d(t') dt'
\]

\[
\dot{e}_s = \dot{\Theta}_s - \int_0^t \tau_d(t') dt'
\]

Figure 2 shows two different framers connecting in Teleoperation task, having clear environment information rather than local information and more effective commands within the unlimited workspace of slave robot mapping and a limited workspace of a human operator to assess the WMRs position.

Remark 2 In this case, the third derivative of \( \Theta \) and higher derivatives are zero because our system is gaining to perform a second-order differential system.

### 4. Stability analysis

In this section stability analysis of system (1)-(2) with error feedback control is described as follows:

#### 4.1. Synchronization of master/slave robot error dynamical system

The important issue that needs is smooth tracking that is without wheel slippage; two dynamic system
errors must be synchronized. In this situation based on equation (7) the coordination \( q_s, i = m, s \) can be refixed to error vector \( e_i \), then

\[
\begin{align*}
M_m(e_m)\dot{e}_m(t) + C_m(e_m, \dot{e}_m)e_m + g(q_m) + \tau_{du} &= \tau_h + \tau_m \\
M_i(e_i)\dot{e}_i(t) + C_i(e_i, \dot{e}_i)e_i + g(q_s) + \tau_d &= -\tau e + \tau s,
\end{align*}
\]

where \( \tau_{du}, \tau_d, \tau_h, \tau_e \) are same as equation (1)-(2) and \( \dot{\tau}_m, \dot{\tau}_s \) are defined later.

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

In this case we consider error input \( e_i \) can be written in the suggestive form;

\[
\begin{align*}
\dot{e}_i &= f_i(\dot{\theta}, \theta_i, \tau_i) \\
(\dot{\tau}_d + e_i, \dot{\theta}, \theta_i, \tau_i) &\in R^n \times R^0 \\
\times R^{m+1 \times n+1} \times R^m \times R^q, j = m, s
\end{align*}
\]

with output coordination of

\[
e_i = \hat{\theta} - \hat{\theta}_i = \dot{\theta} - \dot{\theta}_i.
\]

\( f_1: C_{m \times n} \times D_{m \times n} \rightarrow R \) is semi continuous and locally bounded in a compact set \( D \), the inputs \( \tau_m, \tau_s, e_i \) and \( \tau_d, i = m, s \) exists in \( f_1 \) and satisfies (3) then

\[
\mathcal{D} = (\{ (\tau_d + e, \theta, \theta_i) \in (C_{m \times n} \times D_{m \times n}) : \dot{\tau}_d + e_i = \dot{\theta} = \dot{\theta}_i \},
\]

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

If \( e_i, i = m, s \) is utilized in regulated output controller, then

\[
\begin{align*}
\dot{\tau}_m &= -M_m(e_m)\dot{e}_m - C_m(e_m, \dot{e}_m)e_m - g(q_m) - \tau_h - \int_0^t \tau_{du} \, dt \\
= -M_m(e_m)\dot{e}_m - C_m(e_m, \dot{e}_m)e_m - g(q_m) - \tau_h + \int_0^t \tau_{du} \, dt \\
\dot{\tau}_s &= -M_i(e_i)\dot{e}_i - C_i(e_i, \dot{e}_i)e_i - g(q_s) + \tau_e - \int_0^t \tau_d \, dt.
\end{align*}
\]

Using Lemma 1, we can analyze the passivity as follows:

**Theorem 1:** Suppose \( \dot{\theta} \) is close to desired input controller(11), under Lemma 1, the proposed tracking wheeled mobile robot system (1)-(2) is stable in terms of \( q_m \rightarrow q_s \) as \( t \rightarrow \infty \).

**Proof:** Consider the semi positive definite function

\[
V_s = \frac{1}{2} \int_0^t e_i^T k_m q_m ds + \frac{1}{2} \int_0^t e_i^T k_e e_i ds
\]

where \( k_m, k_e \) are algebraic constant of master/slave robots.
If \( \triangle C_s = \max \left\{ \int_0^t e_m^T k_m q_m ds + \frac{1}{2} \int_0^t e_k^T k_s q_k ds \right\} \), then

\[
\frac{1}{2} \int_0^t e_m^T k_m q_m ds + \frac{1}{2} \int_0^t e_k^T k_s q_k ds
\]

\[
- C_s e_m^T k_m e_m - C_s e_k^T k_s e_s
\]

\[
\leq C_s + C_s \left\{ - e_m^T k_m e_m - e_k^T k_s e_s + \int_0^t \int_0^t e_m^T k_m q_m ds \right\}
\]

\[
+ \int_0^t e_k^T k_s q_k ds \right) ds
\]

Using Grownall’s inequality

\[
\int_0^t e_m^T k_m q_m ds + \frac{1}{2} \int_0^t e_k^T k_s q_k ds
\]

\[
\leq 2C_s t \exp \left( \int_0^t e_m^T k_m q_m ds \right)
\]

\[
+ \int_0^t e_k^T k_s q_k ds \right) \right) ds
\]

If \( q_m \rightarrow q_s \) as \( t \rightarrow \infty \), therefore

\[
\int_0^t e_m^T k_m q_m ds = \int_0^t e_k^T k_s q_k ds
\]

therefore the system (1)-(2) is stable.

### 4.3. Passivity of neural network controller

The robot is moving towards an unknown target location with an obstacle path. The objective of this control structure is to avoid collision and how to get acquire information from a sensor within an obstacle’s environment. Therefore, the necessary control is

\[
\tau_m = f_m(q_m, q_s, q_m, \Theta_m, \Theta_s, e_s)
\]

\[
+ g(q_m) + \tau_{m_t} + \tau_m
\]

\[
\tau_s = f_s(q_i, q_i, \Theta_i, \Theta_s, e_m)
\]

\[
+ g(q_i) + \tau_{s_t} + \tau_s
\]

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

### 4.4. Simpson 1/3 rule fuzzy neural network system (SFNNS)

The neural network system (NNS) with the weighted average method is briefly explained (Enayati, Ferrigno, & De Momi, 2018; Luo et al., 2019; Santiago et al., 2017). In this section, \( e_s, i = m, s \) is accords to Simpson 1/3 rule, that is Simpson 1/3 rule fuzzy neural network system (SFNNS) is interlinking the following fuzzy rules;

Rules: If \( e_s, i = m, s \) is \( \tau_m \) THEN \( X_n = M_m q_m + N_m a_m + O_m q_m + P_m \Theta_m + Q_m \Theta_s + W_m e_s \), where \( M_i \) is \( q_m, N_i \) is \( q_s, O_i \) is \( q_m, P_i \) is \( \Theta_m, Q_i \) is \( \Theta_s \) and \( W_i \) is \( e_s, i = m, s \).

\[
\tau_m = q_m \cdot M_m \cdot q_m + q_s \cdot N_m + q_s \cdot O_m + P_m \Theta_m + Q_m \Theta_s + W_m e_s.
\]

(17)

Based on (16)-(17), if output membership functions are related to errors \( e_s, i = m, s \), then SFNNS has five layers which are performed as follows;

**Layer 1:** In this layer, the outputs are depending on control action, where the controls are followed by Simpson’s 1/3, Simpson’s 3/8, and trapezoidal rule. In this paper, we followed Simpson 1/3 rule, which is

\[
\tau_m = \frac{h}{3} \left[ (\text{sensor detected angle at right wheel})^2
\right.
\]

\[
- \text{desired position at right wheel})^2
\]

\[
+ 3(\text{sensor detected angle at left wheel})^2
\]

\[
+ \text{desired position at left wheel})^2
\]

\[
+ (\text{commented angle right}
\]

\[
- \text{robot right wheel angle})^2
\]

\[
+ (\text{commented angle left}
\]

\[
- \text{robot left wheel angle})^2
\]

\[
+ (\text{future point error at master robot}
\]

\[
- \text{current position left/right wheel})^2
\]

\[
+ g(q_m)
\]

\[
\tau_s = \frac{h}{3} \left[ (\text{sensor detected error angle at right wheel})^2
\right.
\]

\[
- \text{sensor detected error angle at left wheel})^2
\]

\[
+ 3(\text{commented right wheel angle}
\]

\[
- \text{right wheel velocity/left wheel acceleration})^2
\]

\[
+ (\text{commented left wheel angle}
\]

\[
- \text{left wheel velocity/ right wheel acceleration})^2
\]

\[
+ (\text{sensor detected error angle at right/left}
\]

\[
- \text{future point error at slave robot})^2
\]

\[
+ g(q_s)
\]
Here, $X_n$ and $Y_n$ are truth value of output mesh point.

Layer 3: This layer is a normalization layer, it could be rearranged all outputs in SFNNS. Therefore

$$X_n = \frac{X_n}{X_n - \tau_{dn}}, \quad Y_n = \frac{Y_n}{Y_n - \tau_{ds}}$$

Layer 4: This layer is called the output node layer whose output is a 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

$$\frac{X_n}{X_n - \tau_{dn}} + g(q_m) + \tau_{dn} + \bar{\tau}_m = \dot{X}_n(q_m \cdot M_m)$$

Layer 5: This layer is fixed, the sum of determines of output defuzzification is equivalent to overall system output with steering angles, that is

$$\sum_{i=m, s} X_n \cdot \Theta_i + g(q_m) + \tau_{dn} + \bar{\tau}_m = \frac{\sum_{i=m, s} X_n \cdot \Theta_i + g(q_m) + \tau_{dn} + \bar{\tau}_m}{\sum_{i=m, s} Y_n \cdot \Theta_i + g(q_m) + \tau_{ds} + \bar{\tau}_s}$$

To train the learning process of safe navigation, the actual coordinate sensor data and desired angle data set is used SFNNS 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.

5. Simulation result

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 in absence of navigation with respect of sensor device response. The sensor data is working on obstacle avoidance with respect of Simpson 1/3 rule fuzzy neural network system (SFNNS). The dynamical model of the mobile robot in global coordination can be reformulated via Simpsons 1/3 rule method as $X_n = \frac{t_m}{t_{me}}$, where $\dot{q}_{rwr}, \dot{q}_{rol}$ right wheel velocity and left wheel position of master robot and $m_i$ is distance between two wheels and $X_n = \frac{t_m}{t_{me}}$, left wheel velocity and right wheel position of master robot respectively. Similarly $Y_n = \frac{t_s}{t_{se}}$, where $\dot{q}_{sr}, \dot{q}_{sd}$ right wheel velocity and left wheel position of slave robot and $m_i$ is distance between two wheels and $Y_n = \frac{t_s}{t_{se}}$ is left wheel velocity and right wheel position of slave robot (Figure 3).

Forward and backward movements will be interpreted to the moving position of a control device and negative direction of $Y$-axis/$X$-axis. Consequently, the mobile robot right hand coordinated is observed by $\tau_m$ concerning position and wheel slippage, that is moving of right hand is
Movement of mobile robot left hand positive to the decided point is controlled by $\tau_{s}$ with respect of negative direction on the $X -$ axis/$Y -$ axis. The simulation results of NNS and SFNNS models with path segments of master/slave position and velocity profiles are given in Figures 4 and 5. It shows that the mobile robot can follow the path as stable to minimum error.

6. Comparison of the two approaches

To demonstrate the feasibility of different control algorithms were carried out: neural network system (NNS) and Simpson 1/3 rule fuzzy neural network system (SFNNS). The trained network shown in Figure 3, is implemented into the vehicle model of real-time MATLAB experiments. The adaptive technology that is SFNNS delivers the best result from
the data set, the results are shown in Figures 4 and 5 and right/left wheel error angle response is shown in Figures 6 and 7.

Indeed, MATLAB-Simulink with SFNNS simulation trajectories are almost converge within 15 seconds. In this sense, SFNNS is the best approach, and performance measures are tabulated in Tables 1–3.

7. Conclusions

The Simpson 1/3 rule fuzzy neural network system (SFNNS) is efficient in fast and minimizes the error convergence of wheeled mobile robot system. The control is constructed under teleoperation with passivity to achieve system stability in which the soft-computing methodology discloses the robot wheel slippage and skidding. Soft-computing based Simpson 1/3 rule fuzzy neural network system (SFNNS) is calculating the received/communicated signals from master/slave robot, for reducing the unavoidable and acceptable forces, which is confirmed by passivity. From this analysis, the method shows that the force felt by the human operator is almost equal to the force applied by the predictor environment and sensor slave robot data, which resolves incident navigation and particularly unlimited workspace, surface slippage of coordination for master robot position, and slave robot velocity. The feasibility of different control algorithms: neural network system (NNS) and Simpson 1/3 rule fuzzy neural network system (SFNNS) are showed in this article. Among that Simpson 1/3 rule, fuzzy neural network system (SFNNS) simulation trajectories are almost converging within 15 seconds. The results are shown in Figures 4 and 5 and the right/left wheel error angle response is showed in Figures 6 and 7. In this sense, SFNNS is the best approach, and performance measures are tabulated in Tables 1–3.

Acknowledgments

The work of the authors are supported by National Research Foundation (NRF) funded by the Korean government (MSIT) (No.NRF-2017M3C7A1044815).

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

Choi, H., & Jung, S. (2020). Teleoperation control of a position-based impedance force controlled mobile robot by neural network learning: Experimental Studies. Asian Journal of Control, 22(1), 92–103. doi:10.1002/asjc.1909

Cooke, N. J. (2006). Human factors of remotely operated vehicles. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 50(1), 166–169. SAGE Publications Sage CA: Los Angeles, CA, doi: 10.1177/154193120605000135

Enayati, N., Ferrigno, G., & De Momi, E. (2018). Skill-based human robot cooperation in tele-operated path tracking. Autonomous Robots, 42(5), 997–1009. doi:10.1007/s10514-017-9675-4

Lee, D., & Xu, D. (2006). Feedback r– passivity of Lagrangian systems for mobile robot teleoperation, In Proc. of the IEEE Int. Conf. on Robotics and Automation, Shanghai, China.

Lee, D., Martinez-Palafox, O., & Spong, M.W. (2006). Bilateral teleoperation of a wheeled mobile robot over delayed communication network. In Proc. of the IEEE Int.
Conf. on Robotics and Automation Orlando, FL (pp. 3298–3303).
Li, W., Ding, L., Liu, Z., Wang, W., Gao, H., & Tavakoli, M. (2017). Kinematic bilateral tele-driving of wheeled mobile robots coupled with slippage. *IEEE Transactions on Industrial Electronics*, 64(3), 2147–2157. doi:10.1109/TIE.2016.2619320
Liang, X., Wang, H., Chen, W., Guo, D., & Liu, T. (2015). Adaptive image-based trajectory tracking control of wheeled mobile robots with an uncalibrated fixed camera. *IEEE Transactions on Control Systems Technology*, 23(6), 2266–2282. doi:10.1109/TCST.2015.2411627
Luo, J., Lin, Z., Li, Y., & Yang, C. (2019). A teleoperation framework for mobile robots based on shared control. *IEEE Robotics and Automation Letters*, 4, 1–8.
Santiago, D.D., Slawinski, E., & Mut, V. A. (2017). Stable delayed bilateral teleoperation of mobile manipulators. *Asian Journal of Control*, 19(3), 1140–1152. doi:10.1002/asjc.1461
Shing, J., & Jang, R. (1993). ANFIS: Adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man, and Cybernetics*, 23(3), 665–685. doi:10.1109/21.256541
Suganya, K., & Arulmozhi, V. (2016). Soft computing controller based path planning wheeled mobile robot. In 2016 *IEEE International Conference on Advances in Computer Applications* (ICACA) (pp. 230–234).
Suganya, K., & Arulmozhi, V. (2017). Sliding mode control with soft computing based path planning wheeled mobile robot. In 2017 *International Conference on Advanced computing and communication system* (ICACCS), Jan 6-7, 2017.
Sun, D., Naghdy, F., & Du, H. (2017). Neural network based passivity control of teleoperation system under time-delays. *IEEE Transactions on Cybernetics*, 47(7), 1666–1679. doi:10.1109/TCYB.2016.2554630
Tipsuwan, Y., & Chow, M.Y. (2004). Gain Scheduler middleware: A methodology to enable existing controllers for networked control and teleoperation-Part II: Teloperation. *IEEE Transactions on Industrial Electronics*, 51(6), 1228–1127. doi:10.1109/TIE.2004.837865
Tunc, C. (2010). A note on boundedness of solutions to a class of non-autonomous differential equations of second order. *Applicable Analysis and Discrete Mathematics*, 4(2), 361–372.
Tunc, C., & Tunc, O. (2011). Uniformly stability and boundedness of solutions of second order nonlinear delay differential equations. *Applied and Computational Mathematics*, 10(3), 449–462.
Tunc, C., & Tunc, O. (2017). A note on the stability and boundedness of solutions to non-linear differential systems of second order. *Journal of the Association of Arab Universities for Basic and Applied Sciences*, 24, 169–175.
Wu, X. Y., & Dang, X. (2014). Robust adaptive sliding-mode control of condenser-cleaning mobile manipulator using fuzzy wavelet neural network. *Fuzzy Sets and Systems*, 235, 62–82. vol doi:10.1016/j.fss.2013.07.009
Yamchi, M.H., & Esfanjani, R.M. (2017). Distributed predictive formation control of networked mobile robots subject to communication delay. *Robotics and Autonomous Systems*, 75, 194–207.
Yang, C., Wang, X., Li, Z., Li, Y., & Su, C. (2017). Teleoperation control based on combination of wave variables and neural network. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 47(8), 2125–2135. doi:10.1109/TSMC.2016.2615061
Yoo, S. J., & Park, B. S. (2018). Connectivity-preserving approach for distributed adaptive synchronized tracking of networked uncertain nonholonomic mobile robots. *IEEE Transactions on Cybernetics*, 48(9), 2598–2608. doi:10.1109/TCYB.2017.2743690