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Neural Network Nonlinearity Compensation for a Mobile Manipulator

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Abstract: ***A control structure that makes possible the integration of a linear controller and a neural network (NN) compensator for a mobile manipulator is presented. The stability of the closed loop system and the boundedness of tracking errors are proved using Lyapunov theory. The NN compensation scheme proposed in this work can deal with unmodeled bounded nonlinearity and/or unstructured unmodeled dynamics in the mobile manipulator. On-line NN parameter tuning algorithms do no require off-line learning yet guarantee small tracking errors and bounded control signals are utilized.***

Keywords: Mobile manipulator, Neural network, Compensation, Stability, Nonlinearity

1. Introduction

Mobile manipulators have been introduced as a way of expanding the effective workspace of robot manipulators. Robots with moving vehicle such as macro-micro manipulators, space manipulators, and underwater robotic vehicles can be used for extending the workspace in repair and maintenance, inspection, welding, cleaning, and machining operation. Mobile manipulators possess strongly coupled dynamics of mobile vehicles and manipulators. With the assumption of known dynamics, much research has been carried out. Wei et al. [1] addressed the dynamic modeling of mobile manipulator based on floating like base. Li and Song [2] proposed the kinematic analysis of the mobile robotic arm, the Cartesian spatial planning of the robotic arm and the design of the mobile robotic arm control system. In [3], a low cost mobile manipulator for autonomous localization and grasping is deigned.

Most approaches require the precise knowledge of dynamics of the mobile manipulator, or, they simplify the dynamical model by ignoring dynamics issues, such as vehicle dynamics, payload dynamics, dynamics interactions between the vehicle and the arm, and unknown disturbances such as the dynamic effect caused by terrain irregularity. To handle unknown dynamics of mechanical systems, robust, and adaptive controls have been extensive investigated for robot manipulators and dynamic nonholonomic systems. Sugiyamaet al. [4] developed the picking and assembling system with mobile manipulator. In [5], adaptive robust output feedback motion/force control strategies were proposed for mobile manipulators under both holonomic and nonholonomic constraints in the presence of uncertainties and disturbances. Impedance control of flexible base mobile manipulator using singular perturbation method and sliding mode control law was presented in [6]. Because of the difficulty in dynamic modeling, adaptive neural network control has been studied for different classes of systems, such as robotic manipulators [7] and mobile robots [8]. In [9], adaptive neural network controls have been developed for the motion control of mobile manipulators subject to kinematic constraint. In [10], the neural network-based control of wheeled mobile manipulators with unknown kinematic models is proposed. In these schemes, the controls are designed at kinematic level with velocity as input or dynamic level with torque as input, but the actuator dynamics are ignored. Therefore, the actuator nonlinearity deteriorates the system performance. The actuator nonlinearity compensation techniques are published in [11] for saturation, in [12] for friction, and in [13] for hysteresis.

In this paper, an NN-based compensation scheme is proposed for the joint space position control of a mobile manipulator. Two NN-based proposed controllers are developed to control the arm and the vehicle, independently. Each controller output comprises a linear control term and an NN compensation term. The NN compensation term is used for on line estimation of unknown nonlinear dynamics caused by parameter uncertainty and disturbances. No preliminary learning stage is required for the NN weights. The tracking stability of the closed loop system, the convergence of the NN learning process and the boundedness of NN weight estimation errors are all rigorously proven using Lyapunov synthesis. This paper is as follows. Section 2 provides the mobile manipulator. The neural network is derived in Section 3. The proposed NN-based compensation scheme is developed in Section 4. Simulation results of the NN-based proposed controller are given in Section 5. Finally, conclusions are included in Section 6.

2. Mobile manipulator

Consider a mobile manipulator mounted on nonholonomic mobile platform, as shown in Fig. 1. The dynamics of a mobile manipulator subject to kinematics can be obtained using Lagrangian approach in the form [1]

$$\mathrm{M}(\mathrm{q})\ddot{q} + C(q,\dot{q}) + F(\dot{q}) + G(q) + \tau_d = B(q)A^T(q)\lambda \quad (1)$$

where kinematic constraints are described by

$$\mathrm{A}(\mathrm{q})\dot{q} = 0 \quad (2)$$

and $\mathrm{q} \in R^p$ is the generalized coordinates, $\mathrm{M(q)} \in R^{p\times p}$ is a symmetric and positive definite inertia matrix, $\mathrm{C}(\mathrm{q},) \in \dot{R}^{p\times p}\mathrm{C}(\mathrm{q},\dot{q}) \in R^{p\times p}$ s the centripetal and Coriolis matrix, $\mathrm{F}(\dot{q}) \in R^p$ denotes the surface friction, $\mathrm{G(q)} \in R^p$ is the gravitational vector, τ_d denotes the bounded unknown disturbances including unstructured unmodeled dynamics,

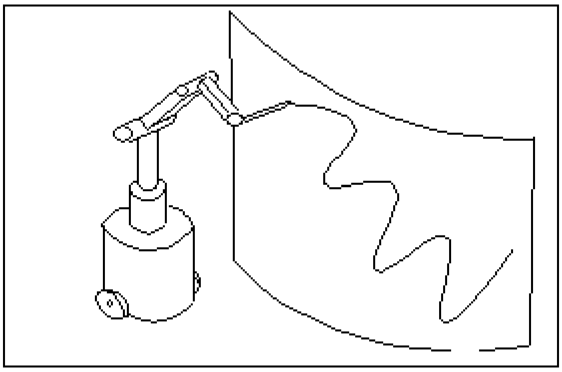


Figure 1: Trajectory tracking of a mobile manipulator

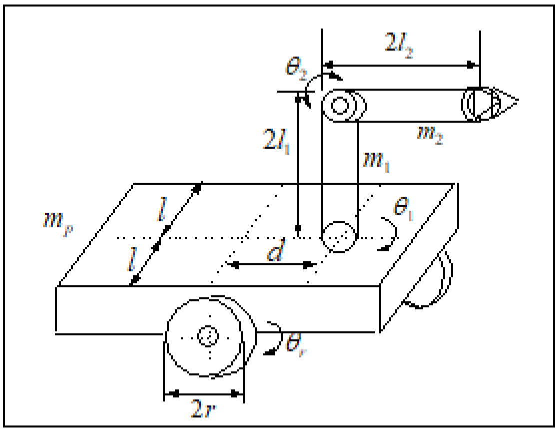


Figure 2: Two – DOF manipulator mounted on a mobile manipulator.

$B(q) \in R^{p\times(p-r)}$ is the input transformation matrix, $\tau \in R^{p-r}$ is the input vector, $A(q) \in R^{r\times p}$ is the matrix associated with the constraints, and $\lambda \in R^{r}$ is the vector of constraint forces.

In (1), the following properties hold [14].

Property 1 (Skew Symmetricity)

$$\dot{M} - 2C = -(\dot{M} - 2C)^T$$
$$\dot{M} = C + C^T. \quad (3)$$

The generalized coordinates q may be separated into two sets $q = [q_v q_r]^T$ with $q_v \in R^m$ describes the generalized coordinates appearing in the constraint equations (2), and $q_r \in R^n$ are the free generalized coordinates; $p = m + n$. Therefore, (2) can be simplifed to

$$A_v(q_v)\dot{q}_v = 0. \quad (4)$$

with.$A(q_v) \in R^{r\times m}$ Assume that the robot is fully actuated, then (1) can be further rewritten as

$$\begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix}\begin{bmatrix} \ddot{q}_v \\ \ddot{q}_r \end{bmatrix} + \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix}\begin{bmatrix} \dot{q}_v \\ \dot{q}_r \end{bmatrix} + \begin{bmatrix} F_1 \\ F_2 \end{bmatrix} + \begin{bmatrix} G_1 \\ G_2 \end{bmatrix} = \begin{bmatrix} B_{v\tau_v} \\ \tau_r \end{bmatrix} - \begin{bmatrix} A_v^T\lambda \\ 0 \end{bmatrix} (5)$$

where $\tau_v \in R^{m-r}$ represents the actual torque vector of the constrained coordinates, those related to the constrained motion of the wheels, the joints, and the end effector. For simplicity in the theoretical derivation, hereafter we consider only the case where the vehicle motion is constrained. However, the proposed theory can be easily extended to include joint and/or end-effector constraints. $B_v \in R^{m\times(m-r))}$ represents the input transfomation matrix; $\tau_r \in R^n$ the actuating torque vector of the free coordinates; $\tau_{d1}$and τ_{d2} are disturbance torques bounded by $\|\tau_{d1}\| < \tau_{1N}$ and $\|\tau_{d2}\| < \tau_{2N}$, with τ_{1N} and τ_{2N} some positive constants.

It is straightforward to show that the following properties hold.

Property 2 :

$$\dot{M}_{21} = C_{21} + C_{12}^T$$
$$M_{12} = M_{12}^T. \quad (6)$$

Let $S_v(q_v) \in R^{m\times(m-r)}$ be a full rank matrix formed by a set of smooth and linearly independent vector fields in the null space of$A_v(q_v)$, i.e,

$$S^T(q_v)A_v^T(q_v) = 0. \quad (7)$$

According to (7) , it is possible to find an auxiliary vector time function $v(t) \in R^{m-r}$such that, for all t

$$\dot{q}_v = S(q_v)v(t) \quad (8)$$

and its derivative is

$$.\ \ddot{q}_v = S(q_v)\dot{v} + \dot{S}(q_v)v. \quad (9)$$

Equation (8) is called the steering system. v(t)can be regarded as a velocity input vector steering the state vector qin state space.

Let us consider the first m -equations of (5)

$$M_{11}q_v + M_{12}\ddot{q}_r + \ddot{C}_{11}\dot{q}_v + C_{12}\dot{q}_r + F_1 + G_1 + \tau_{d1} = B_v\tau_v - A_v^T\lambda. \quad (10)$$

Multiplying both sides of (10) by$S^T$and using (7) to eliminate the constraint force we obtain

$$S^T M_{11}\ddot{q}_v + S^T M_{12}\ddot{q}_r + S^T C_{11}\dot{q}_v + S^T C_{12}\dot{q}_r + S^T F_1 + S^T G_1 + S^T\tau_{d1} = S^T B_v\tau_v. (11)$$

Substituting (8) and (9) into (11) yields

$$S^T M_{11}S\dot{v} + S^T M_{11}\dot{S}v + S^T M_{12}\ddot{q}_r + S^T C_{11}Sv + S^T C_{12}\dot{q}_r + S^T F_1 + S^T G_1 + S^T\tau_{d1} = S^T B_v\tau_v\,. \quad (12)$$

Let us rewrite (12) in a compact form as

$$\bar{M}_{11}\dot{v} + \bar{C}_{11}v + f_1 + \bar{\tau}_{d1} = \bar{\tau}_{d1} (13)$$

where $\bar{M}_{11} = S^T M_{11}S$, $\bar{C}_{11} = S^T C_{11}S + S^T M_{11}\dot{S}$, $\bar{\tau}_{d1} = S^T\tau_{d1}$;$\|\bar{\tau}_{d1}\| \le \bar{\tau}_{1N}$ with $\bar{\tau}_{1N}$ some positive constant, and

$$\bar{\tau}_v = S^T B_v\tau_v = \bar{B}_v\tau_v \quad (14)$$
$$f_1 = S^T(M_{12}\ddot{q}_r + C_{12}\dot{q}_r + F_1 + G_1). (15)$$

f_1 consists of the gravitational and friction force, the disturbances on the vehicle base, and the dynamic interaction with the mounted manipulator arm which has been shown to have significant effect on the base motion, thus it needs to be compensated for [15]

Property 3: $\dot{\bar{M}} - 2\bar{C}_{11}$ is skew-symmetric.

Proof:

$$\dot{\bar{M}} - 2\bar{C}_{11} = 2\acute{S}^T M_{11}\dot{S} + S^T\dot{M}_{11}S - 2S^T M_{11}\dot{S} - 2S^T C_{11}S = S^T(\dot{M}_{11} - 2C_{11})S. \quad (16)$$

Since $\dot{M} - 2C_{11}$ is skew-symmetric, therefore, $\dot{\bar{M}} - 2\bar{C}_{11}$ is also skew-symmetric.

Let us consider the last n-equations of (5)

$$M_{21}\ddot{q}_r + M_{22}\ddot{q}_r + C_{21}\dot{q}_v + C_{22}\dot{q}_r + F_2 + G_2 + \tau_{d2} = \tau. \quad (17)$$

Rearrange (17) as follows:

$$M_{22}\ddot{q}_r + C_{22}\dot{q}_r + (M_{21}\ddot{q}_v + C_{21}\dot{q}_v + F_2 + G_2 + \tau_{d2} = \tau. \quad (18)$$

Equation (18) represents the dynamic equation of the mounted manipulator arm. The terms in the brackets consist of the dynamic interaction term$(M_{21}\ddot{q}_v + C_{21}\dot{q}_v)$, the gravitational and friction force vector, and the disturbance on the manipulator. Equation (8), (13), and (18) form the complete dynamic model of the mobile manipulator subject to kinematic constraints.

The Lagrange formulism is used to derived the dynamic equation of the mobile manipulator. The dynamical equations of the mobile manipulator in Fig. 2 can be expressed in the matrix form where

$$q_v = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix}, q_r = \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix},$$

$$M_{11} = \begin{bmatrix} m_{p12} + \frac{2I_w sin^2\theta}{r^2} & -\frac{2I_w sin\theta cos\theta}{r^2} & m_{12}dsin\theta \\ -\frac{2I_w sin\theta cos\theta}{r^2} & m_{p12} + \frac{2I_w cos^2\theta}{r^2} & -m_{12}dcos\theta \\ m_{12}dsin\theta & -m_{12}dcos\theta & I_p + I_{12} + m_{12}d^2 + 2I_w\frac{l^2}{r^2} \end{bmatrix}$$

$$M_{12} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ I_{12} & 0 \end{bmatrix}, M_{21} = \begin{bmatrix} 0 & 0 & I_{12} \\ 0 & 0 & 0 \end{bmatrix}, M_{22} = \begin{bmatrix} I_{12} & 0 \\ 0 & I_{12} \end{bmatrix},$$

$$M_{p12} = m_p + m_{12}, m_{12} = m_1 + m_2, I_{12} = I_1 + I_2$$

$$C_{11} = \begin{bmatrix} \frac{2I_w \dot{\theta} sin\dot{\theta}cos\theta}{r^2} & \frac{2I_w\dot{\theta}sin^2\theta}{r^2} & m_{12}d\dot{\theta}cos\theta \\ \frac{2I_w\dot{\theta}cos\theta}{r^2} & -\frac{2I_w\dot{\theta}sin\dot{\theta}cos\theta}{r^2} & m_{12}d\dot{\theta}sin\theta \\ 0 & 0 & 0 \end{bmatrix}$$

$$C_{12} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, C_{12} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, C_{22} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$G_1 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, G_2 = \begin{bmatrix} 0 \\ 0 \\ m_2 g l_2 sin\theta_2 \end{bmatrix}, \tau_v = \begin{bmatrix} \tau_R \\ \tau_L \end{bmatrix}, \tau_v = \begin{bmatrix} \tau_1 \\ \tau_v \end{bmatrix}$$

$$A_v^T = \begin{bmatrix} -sin\theta \\ cos\theta \\ -d \end{bmatrix}, B_v = \frac{1}{r}\begin{bmatrix} cos\theta & cos\theta \\ sin\theta & sin\theta \\ -l & -l \end{bmatrix},$$

$$\lambda = -m_{p12}(\dot{x}cos\theta + \dot{y}sin\theta)\dot{\theta}. \quad (19)$$

Similar dynamical models have been reported in the literature, for instance in [1] the mass and inertia of the driving wheels and manipulator are considered explicitly.

3. Neural Networks

NN have been used extensively in feedback control systems [16, 17]. Most applications are ad hoc with no demonstrations of stability. The stability proofs that do exist rely almost invariably on the universal approximation property for NN.

The three layers NN in Fig. 3 consists of an input layer, a hidden layer, and an output layer. The hidden layer has L neurons, and the output layer has m neurons. The multi-layer NN is a nonlinear mapping from input space R^n into output spaceR^m.

The NN output yis a vector with m components that are determined in terms of the n components of the input vector x by the equation

$$y_i = \sum_{k=1}^{L}[w_{ik}\sigma(\sum_{j=1}^{n} v_{kj}x_j + v_{k0}) + w_{i0}];\ i = 1,2, \dots, m \quad (20)$$

where $\sigma(.)$ is the hyperbolic tangent function, v_{kj}, the interconnection weights from input to hidden layer, w_{ik}, interconnection weights from hidden to output layer. The

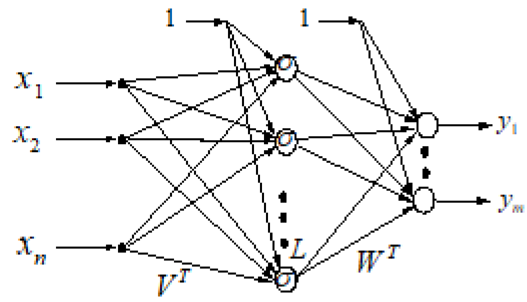


Figure 3: Neural networks.

Threshold offsets are denoted by v_{k0}, w_{i0}.

By collecting all the NN weights v_{kj}, w_{ik} into matrices V_T,W_T, the NN equation may be written in terms of vectors as

$$y = W^T\sigma(V^Tx). \quad (21)$$

The threshold are included as the first column of the weight matrices W^T,V^T; to accommodate this, the vector x and $\sigma(.)$need to be augmented by placing a '1' as their first element(e.g. $x = [1\, x_1\, x_2 \dots x_n]^T$). In this equation, to represent (20) one has sufficient generality if $\sigma(.)$is taken as a diagonal function from R^L to R^L, that is $\sigma(z) = diag\{\sigma(z_k)\}$for a vectorz $= [z_1 z_2 \dots z_L]^T \in R^L$.

Many well-known results say that any sufficiently smooth function $\bar{y}$can be approximated arbitrary closely on a compact set using a three-layer NN with appropriate weights, i.e.

$$\bar{y} = W^T\sigma(V^Tx) + \varepsilon(x) \quad (22)$$

where $\varepsilon(x)$ is the NN approximation error, and $\|\varepsilon(x)\| \le \epsilon_N$ on a compact setS [18]. The first layer weights Vare selected randomly and will not be tuned. The second layer weights W are tunable. It is shown [19] that for such NN, termed random variable functional link(RVFL) NN, the approximation property holds. The approximating weights W are ideal target weights, and it is assumed that they are bounded such that $\|W\| \le W_M$.

4. Neural network compensation of a mobile manipulator

In this section, NN based control laws and NN weighting laws will be derived for the stable joint space tracking of a mobile manipulator described by (8), (13), and (18). The mobile manipulator dynamics is redefined as an error dynamics based on a set of carefully chosen Lyapunov functions. NN on-line estimators are constructed and new learning laws are proposed. New control laws for the manipulator arm and vehicle are derived by taking into account the dynamic coupling between two. A proof on the tracking stability of the overall closed loop system and the boundedness on NN weight estimation errors are provided. The proposed control structure is shown in Fig. 4.

Consider the vehicle dynamics represented by (8) and (13). Tracking control of the steering system (8) has been extensively addressed in the literature [4]. For example, for a wheeled mobile robot with two independent actuated wheels, the kinematic parameters in (8) are defined as

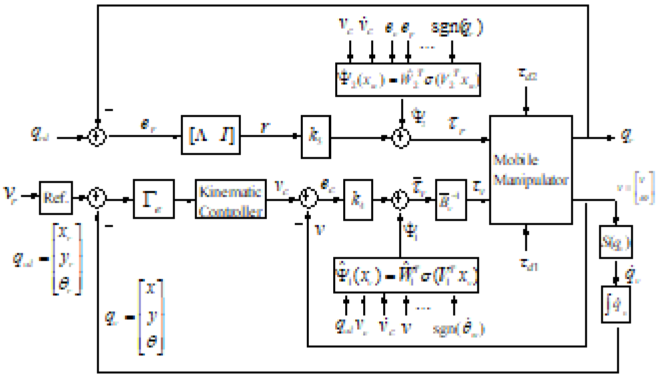


Figure 4: The proposed NN compensation of a mobile manipulator

$$S(q_v) = \begin{bmatrix} cos\theta & -dsin\theta \\ sin\theta & dcos\theta \\ 0 & 1 \end{bmatrix}, v = \begin{bmatrix} v \\ w \end{bmatrix} \text{ and } q_v = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} \quad (23)$$

where (x, y) represents the Cartesian coordinates of the cart, θ its orientation, v and w its linear and angular velocities, respectively. Let the reference motion of the vehicle be prescribed as

$$\begin{bmatrix} \dot{x}_r \\ \dot{y}_r \\ \dot{\theta}_r \end{bmatrix} = \begin{bmatrix} cos\theta & 0 \\ sin\theta & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v_r \\ w_r \end{bmatrix} \quad (24)$$

where $v_r > 0$ and w_r are reference linear and angular velocities, respectively. Stable linear and nonlinear velocity feedback laws for (23) can be found in [20] to achieve the asymptotic tracking. For instance, the following feedback velocity input guarantees that the position tracking of (24) is asymptotically stable [14]:

$$v_c = \begin{bmatrix} v_c \\ w_c \end{bmatrix} = \begin{bmatrix} v_r cose_3 + k_1 e_1 \\ w_r + k_2 v_r e_2 + k_3 v_r sine_3 \end{bmatrix} \quad (25)$$

where positive constant k_1, k_2 and k_3 are control gains, and the position tracking errors are defined as

$$e = \Gamma_e(q_{vd} - q_v)$$

$$\begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix} = \begin{bmatrix} cos\theta & sin\theta & 0 \\ -sin\theta & cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_r - x \\ y_r - y \\ \theta_r - \theta \end{bmatrix}. \quad (26)$$

Choosing the following Lyapunov function can prove the stability tracking system

$$V_1 = k_1(e_1^2 + e_1^2) + 2k_3 v_r (1 - cose_3) \quad (27)$$

Differentiating yields

$$\dot{V}_1 = 2k_1(e_1\dot{e}_1 + e_2\dot{e}_2) + 2k_3 v_r \dot{e}_3 sine_3. \quad (28)$$

Given the desired velocity, $v_c(t)$ define now the auxiliary velocity tracking error as

$$e_c = v_c - v. \quad (29)$$

The velocity tracking error is

$$e_c = \begin{bmatrix} e_4 \\ e_5 \end{bmatrix} = \begin{bmatrix} v_c - v \\ w_c - w \end{bmatrix} = \begin{bmatrix} v_r cose_3 + k_1 e_1 - v \\ w_r + k_2 v_r e_2 + k_3 v_r sine_3 - w \end{bmatrix} \quad (30)$$

where k_1, k_2, k_3 are positive constants.

Substituting the derivative of the position error in (28), we obtain

$$\dot{V}_1 = 2k_1 e_1(v_2 e_2 - v_1 + v_r cose_3) + 2k_1 e_2(-v_2 e_1 + v_r sine_3) + 2k_3 v_r(\omega_r - v_2) sine_3 \quad (31)$$

Using (30) and defining $k_2 = (\frac{k_1}{k_3 v_r})$ yield

$$\dot{V}_1 = -k_1^2 e_1^2 - k_3^2 v_r^2 sin^2 e_3 - (k_1 e_1 - e_4)^2 - (k_5 v sine_3 - e_5)^2. \quad (32)$$

Differentiating (29), multiplying both sides by M_{11} and substituting (13) into it yields

$$\bar{M}_{11}\dot{e}_c = -\bar{C}_{11} e_c + f_1 + \bar{\tau}_{d1} + \bar{M}_{11}\dot{v}_c + \bar{C}_{11} v_c - \bar{\tau}_v. \quad (33)$$

Equation (33) represents the vehicle dynamics in terms of tracking errors.

Let us choose the Lyapunov function as

$$V_2 = \frac{1}{2} e_c^T \bar{M}_{11} e_c. \quad (34)$$

Differentiating (34) yields

$$\dot{V}_2 = e_c^T \bar{M}_{11}\dot{e}_c + \frac{1}{2} e_c^T \dot{\bar{M}}_{11} e_c \quad (35)$$

Substituting (33) into (35) we obtain

$$\dot{V}_2 = e_c^T\{f_1 + \bar{\tau}_{d1} + \bar{M}_{11}\dot{v}_c + \bar{C}_{11} v_c - \bar{\tau}_v\} + \frac{1}{2} e_c^T(\dot{\bar{M}}_{11} - 2\bar{C}_{11}) e_c$$
$$= e_c^T\{f_1 + \bar{M}_{11}\dot{v}_c + \bar{C}_{11} v_c + \bar{\tau}_{d1} - \bar{\tau}_v\} \quad (36)$$

Now consider the arm dynamics (18). Let us define the arm error as

$$e_r = q_{rd} - q_r \quad (37)$$

and the tracking error as

$$r = \dot{e}_r + \Lambda e_r \quad (38)$$

where $k = k^T > 0$. In (38), tracking error r can be regarded as an input to a linear dynamics system with state variable e_r. Therefore, when $r \to 0$, it can guarantee that $e_r \to 0$ [14].

Differentiating (38) yields

$$\dot{r} = \ddot{e}_r + \Lambda\dot{e}_r = \ddot{q}_{rd} - \ddot{q}_r + \Lambda\dot{e}_r. \quad (39)$$

Therefore, we have

$$\dot{q}_r = \dot{q}_{rd} = (r - \Lambda e_r) \quad (40)$$

$$\ddot{q}_r = \ddot{q}_{rd} - \dot{r} + \Lambda(r - \Lambda e_r) \quad (41)$$

The manipulator dynamics (18) can be formulated in terms of the tracking error as

$$M_{22}\dot{r} = -C_{22} r + f_2 + \tau_{d2} - \tau_r \quad (42)$$

where the nonlinear manipulator function is

$$f_2 = M_{22}(\ddot{q}_{rd} + \Lambda\dot{e}_r) + C_{22}(\dot{q}_{rd} + \Lambda e_r) + M_{21}\ddot{q}_v + C_{21}\dot{q}_v + F_2 + G_2. \quad (43)$$

The nonlinear manipulator function f_2 consists of the manipulator dynamics $(M_{22}(\ddot{q}_{rd} + \Lambda\dot{e}_r) + C_{22}(\dot{q}_{rd} + \Lambda e_r) + F_2 + G_2)$ and the dynamics of interaction with the vehicle base $(M_{21}\ddot{q}_v + C_{21}\dot{q}_v)$.

To design the manipulator torque input, we choose the Lyapunov function as

$$V_3 = \frac{1}{2} r^T M_{22} r. \quad (44)$$

Notice that M_{22} is a symmetric positive definite matrix. Differentiating (44) yields

$$\dot{V}_3 = r^T M_{22}\dot{r} + \frac{1}{2} r^T \dot{M}_{22} r$$
$$= r^T(-C_{22} r - \tau_r + f_2 + \tau_{d2}) + \frac{1}{2} r^T \dot{M}_{22} r$$

$$= r^T(-\tau_r + f_2 + \tau_{d2}) + \frac{1}{2}r^T(\dot{M}_{22} - 2C_{22})r = r^T(-\tau_r + f_2 + \tau_{d2}). \quad (45)$$

Let us consider the overall dynamics (5) that combines both the arm and vehicle dynamics. Consider the Lyapunov function as

$$V_4 = V_1 + \frac{1}{2}\begin{bmatrix} Se_c \\ r \end{bmatrix} M \begin{bmatrix} Se_c \\ r \end{bmatrix}. \quad (46)$$

In the proposed LyapunovfunctionV_4, $V_1$is used to account for the nonholonomic steering system (8), and the second term accounts for the vehicle base and manipulator arm dynamics, as well as the dynamic couplings between two.

From (46) we have

$$V_4 = V_1 + \frac{1}{2}\begin{bmatrix} Se_c \\ r \end{bmatrix}\begin{bmatrix} M_{11} & M_{12} \\ M_{12}^T & M_{22} \end{bmatrix}\begin{bmatrix} Se_c \\ r \end{bmatrix}$$
$$= V_1 + \frac{1}{2}(Se_c)^T M_{11}(Se_c) + \frac{1}{2}r^T M_{12}^T(Se_c) + \frac{1}{2}(Se_c)^T M_{12} r + \frac{1}{2}r^T M_{22} r$$
$$= V_1 + \frac{1}{2}e_c^T(S^T M_{11} S)e_c + r^T M_{12}^T(Se_c) + \frac{1}{2}r^T M_{22} r$$
$$= V_1 + \frac{1}{2}e_c^T \bar{M}_{11} e_c + r^T M_{12}^T(Se_c) + \frac{1}{2}r^T M_{22} r$$
$$= V_1 + V_2 + V_3 + r^T M_{12}^T(Se_c). \quad (47)$$

Differentiating (47) yields

$$\dot{V}_4 = \dot{V}_1 + \dot{V}_2 + \dot{V}_3 + \frac{d}{dt}\{r^T M_{21}(Se_c)\}. \quad (48)$$

Substituting (32), (36), and (45) into (48) yields

$$\dot{V}_4 \le e_c^T(-\bar{\tau}_v + f_1 + \bar{M}_{11}\dot{v}_c + \bar{C}_{11}v_c + \bar{\tau}_{d1} + r^T(-\tau_r + f_2 + \tau_{d2}) + \frac{d}{dt}\{r^T M_{21}(Se_c)\} \quad (49)$$

where the four terms in (32) are negative.

From the definition of f_1 in (15) and (40), (41) we have

$$f_1 = S^T(M_{12}\ddot{q}_r + C_{12}\dot{q}_r + F_1 + G_1)$$
$$= S^T\{M_{12}(\ddot{q}_{rd} - \dot{r} + \Lambda(r - \Lambda e_r) + C_{12}(\dot{q}_{rd} - (r - \Lambda e_r)) + F_1 + G_1\}$$
$$= -S^T\{M_{12}\dot{r} + (C_{12} - M_{12}\Lambda)(r - \Lambda e_r)\} + \bar{f}_1 \quad (50)$$

where $\bar{f}_1 = S^T(M_{12}\ddot{q}_{rd} + C_{12}\dot{q}_{rd} + F_1 + G_1)$.

From the definition off_2 in (9) and (43) we have

$$f_2 = M_{21}(\acute{S}_v + S\dot{v}) + C_{21}Sv + \{M_{22}(\ddot{q}_{rd} + \Lambda\dot{e}_r) + C_{22}(\dot{q}_{rd} + \Lambda e_r) + F_2 + G_2$$
$$= -S^T\{M_{12}\dot{r} + (C_{12} - M_{12}\Lambda)(r - \Lambda e_r)\} + \bar{f}_1 \quad (51)$$

where $\bar{f}_2 = M_{22}(\ddot{q}_{rd} + \Lambda\dot{e}_r) + C_{22}(\dot{q}_{rd} + \Lambda e_r) + F_2 + G_2$.

Substituting (50) and (51) into (49) and after some collections of them we have

$$\dot{V}_4 \le e_c^T(-\bar{\tau}_v + \bar{M}_{11}\dot{v}_c + \bar{C}_{11}v_c) - r^T\tau_r + e_c^T f_1 + r^T f_2 + f_2\bar{\tau}_{d1} + r^T\tau_{d2}. \quad (52)$$

First of all, we carry out the following derivation

$$e_c^T f_1 + r^T f_2 + \frac{d}{dt}\{r^T M_{21}(Se_c)\}$$
$$= e_c^T\bar{f}_1 + r^T\bar{f}_2 - (Se_c)^T\{M_{12}\dot{r} + (C_{12} - M_{12}\Lambda - \Lambda e_r)\} + r^T(M_{21}S\dot{v}_c - M_{21}S\dot{e}_c + M_{21}\dot{S}v_c - M_{21}\dot{S}e_c + C_{21}Sv_c - C_{21}Se_c + \dot{r}^T M_{21}Se_c + r^T\dot{M}_{21}Se_c + r^T M_{21}\dot{S}e_c + r^T M_{21}Se_c$$
$$= e_c^T\bar{f}_1 + r^T\bar{f}_2 - (Se_c)^T\{(C_{12} - M_{12}\Lambda)(r - \Lambda e_r)\} + r^T(M_{21}S\dot{v}_c + M_{21}\dot{S}v_c + C_{21}Sv_c + C_{12}Se_c)$$
$$= e_c^T\bar{f}_1 + r^T\bar{f}_2 - (Se_c)^T\{-C_{12}\Lambda e_r - M_{12}\Lambda(r - \Lambda e_r)\} + r^T(M_{21}S\dot{v}_c + M_{21}\dot{S}v_c + C_{21}Sv_c) \quad (53)$$

where Properties 2 and 3 have been used in the previous derivations.

Substituting (53) into (52) we obtain

$$\dot{V}_4 \le e_c^T(-\bar{\tau}_v + \bar{M}_{11}\dot{v}_c + \bar{C}_{11}v_c) - r^T\tau_r + e_c^T\bar{f}_1 + r^T\bar{f}_2 + (Se_c)^T\{C_{12}\Lambda e_r + M_{12}\Lambda(r - \Lambda e_r)\} + r^T(M_{21}S\dot{v}_c + M_{21}\dot{S}v_c + M_{21}\dot{S}v_c + C_{21}Sv_c) + e_c^T\bar{\tau}_{d1} + r^T\tau_{d2}$$
$$= e_c^T[-\bar{\tau}_v + \bar{M}_{11}\dot{v}_c + \bar{C}_{11}v_c + \bar{f}_1 + S^T\{C_{12}\Lambda e_r + M_{12}\Lambda(r - \Lambda e_r)\}] + r^T(-\tau_r + \bar{f}_2 + M_{21}S\dot{v}_c + M_{21}\dot{S}v_c + C_{21}Sv_c) + e_c^T\bar{\tau}_{d1} + r^T\tau_{d2}. \quad (54)$$

Therefore

$$\dot{V}_4 \le e_c^T(-\bar{\tau}_v + \Psi_1) + r^T(-\tau_r + \Psi_2) + e_c^T\bar{\tau}_{d1} + r^T\tau_{d2} \quad (55)$$

with unknown nonlinear terms

$$\Psi_1 = \bar{M}_{11}\dot{v}_c + \bar{C}_{11}v_c + f_1 + S^T\{C_{12}\Lambda e_r + M_{12}\Lambda(r - \Lambda e_r)\} \quad (56)$$

$$\Psi_2 = \bar{f}_2 + M_{21}S\dot{v}_c + M_{21}\dot{S}v_c + C_{21}Sv_c. \quad (57)$$

The nonlinear terms Ψ_1 and Ψ_2 are to be identified on-line using NN estimators. In light of the universal approximation ability of the NN,Ψ_1 and Ψ_2 may be identified using NN with sufficiently high number of hidden-layer neurons such that

$$\Psi_1 = W_1^T\sigma(V_1^T x) + \varepsilon_1(x)$$
$$\Psi_2 = W_2^T\sigma(V_2^T x) + \varepsilon_2(x) \quad (58)$$

where x is input pattern to the NN defined as

$$x \equiv [q_{vd}^T v_c^T \dot{v}_c^T e_c^T e_r^T r^T q_{rd}^T \dot{q}_{rd}^T \dot{q}_{rd}^T]^T. \quad (59)$$

W_1 and W_2 are ideal and unknown weights, respectively, which are assumed to be constant and bounded by

$$\|W_1\|_F \le W_{1M},\ \|W_2\|_F \le W_{2M} \quad (60)$$

with W_{1M} and W_{2M} some known positive constants. The approximation error ε_1 and ϵ_2 are bounded by $\|\varepsilon_1\| \le \varepsilon_{1N}$ and $\|\varepsilon_2\| \le \varepsilon_{2N}$, with ε_{1N} and ϵ_{2N} two positive constants.

The NN estimates ofΨ_1 andΨ_2 are given by

$$\hat{\Psi}_1 = \hat{W}_1^T\sigma(V_1^T x)$$
$$\hat{\Psi}_2 = \hat{W}_2^T\sigma(V_2^T x). \quad (61)$$

Thus, the main objective is to design proper control laws and stable NN learning laws such that the unknown robot dynamics can be largely compensated for the NN estimators, and the stability of the robot error dynamics and the boundedness on the NN estimation weights can be guaranteed.

We will use an NN to approximate Ψ_1 and$\Psi_2$for computing the control law. The control input then becomes

$$\bar{\tau}_v = k_4 e_c + \hat{W}_1^T\sigma(V_1^T x)$$
$$\bar{\tau}_r = k_5 r + \hat{W}_2^T\sigma(V_2^T x) \quad (62)$$

where $k_4$and k_5 are positive constants.

Substituting (62) and (58) into (55) yields

$$\dot{V}_4 \le e_c^T\left\{-\left(k_4 e_c + \hat{W}_1^T\sigma(V_1^T x)\right) + W_1^T\sigma(V_1^T x) + \varepsilon_1\right\} + r^T\{-(k_5 r + \hat{W}_2^T\sigma(V_2^T x) + W_2^T\sigma(V_2^T x) + \varepsilon_2\} + e_c^T\bar{\tau}_{d1} + r^T\tau_{d2}$$
$$= -e_c^T k_4 e_c - r^T k_5 r + e_c^T\tilde{W}_1\sigma(V_1^T x) + r^T\tilde{W}_2\sigma(V_2^T x) + e_c^T\varepsilon_1 + r^T\varepsilon_2 + e_c^T\bar{\tau}_{d1} + r^T\tau_{d2} \quad (63)$$

where $\tilde{W}_1 = W_1 - \hat{W}_1$, $\tilde{W}_2 = W_2 - \hat{W}_2$,.

Let us define

$$\varepsilon = \begin{bmatrix}\varepsilon_1\\ \varepsilon_2\end{bmatrix},\ \tau_D = \begin{bmatrix}\bar{\tau}_{d1}\\ \tau_{d2}\end{bmatrix} \text{ and } W = \begin{bmatrix}W_1 & 0\\ 0 & W_2\end{bmatrix}.$$

Based on the bounds of every element of the vectors and matrices defined above, we may show that the following properties hold:

$$\|\varepsilon\| \le \|\varepsilon_1\| + \|\varepsilon_2\| \le \varepsilon_{1N} + \varepsilon_{2N} \equiv \varepsilon_N$$
$$\|\tau_D\| \le \|\bar{\tau}_{d1}\| + \|\tau_{d2}\| \le \tau_{1N} + \tau_{2N} \equiv \tau_N$$
$$\|W\|_F \le \|W_1\|_F + \|W_2\|_F \le W_{1M} + W_{2M} \equiv W_M. \tag{64}$$

It remains to show how to the NN tuning algorithms for NNs, so that tracking performance are guaranteed.

Theorem 1: Given the system (13) and (18), select the control law as (62). Let the NN parameter tuning be provided by

$$\dot{\widehat{W}}_1 = \sigma(V_1^T x)e_c^T - k_6\|E\|\widehat{W}_1 \tag{65}$$
$$\dot{\widehat{W}}_2 = \sigma(V_2^T x)r^T - k_6\|E\|\widehat{W}_2 \tag{66}$$

where $E = (e_c^T, r^T)$ and k_6 are positive definite design parameter. By properly choosing the control gain and design parameter, tracking errors of error dynamics described by (8), (33), (42) and the NN estimation weights $\widehat{W}_1$ and $\widehat{W}_2$ are evolves practical bounds by the right hand sides of (73) and (74)

Proof) Select the Lyapunov function candidate as

$$V = V_4 + \frac{1}{2}tr\left(\widetilde{W}_1^T\widetilde{W}_1\right) + \frac{1}{2}tr(\widetilde{W}_2^T W_2). \tag{67}$$

Differentiating yields

$$\dot{V} = \dot{V}_4 + tr\left(\widetilde{W}_1^T\dot{\widetilde{W}}_1\right) + tr(\widetilde{W}_2^T\dot{\widetilde{W}}_2). \tag{68}$$

Let $\bar{k} = \min(k_4, k_5)$. From (63) and (64) it follows that

$$\dot{V}_4 \le -E^T\bar{k}E + e_c^T\widetilde{W}_1^T\sigma(V_1^Tx) + r^T(\widetilde{W}_2^T\sigma(V_2^Tx) + \|E\|(\epsilon_N + \tau_N)$$
$$\le -\bar{k}\|E\|^2 + e_c^T\widetilde{W}_1^T\sigma(V_1^Tx) + r^T(\widetilde{W}_2^T\sigma(V_2^Tx) + \|E\|(\epsilon_N + \tau_N) \tag{69}$$

Using (69), we obtain

$$\dot{V} \le -\bar{k}\|E\|^2 + e_c^T\widetilde{W}_1^T\sigma(V_1^Tx) + r^T(\widetilde{W}_2^T\sigma(V_2^Tx) + \|E\|(\epsilon_N + \tau_N) + tr\left(\widetilde{W}_1^T\dot{\widetilde{W}}_1\right) + tr(\widetilde{W}_2^T\dot{\widetilde{W}}_2). \tag{70}$$

Applying the tuning laws (65) and (66), one has

$$\dot{V} \le -\bar{k}\|E\|^2 + \|E\|(\epsilon_N + \tau_N) + tr\left(\widetilde{W}_1^T\left(\dot{\widetilde{W}}_1 + e_c^T\sigma(V_1^Tx)\right)\right) + tr(\widetilde{W}_2^T\left(\dot{\widetilde{W}}_2 + r^T\sigma(V_2^Tx)\right)).$$
$$= -\bar{k}\|E\|^2 + \|E\|(\epsilon_N + \tau_N) + k_6\|E\|tr\left(\widetilde{W}_1^T\widehat{W}_1\right) + k_6\|E\|tr(\widetilde{W}_2^T\widehat{W}_2).$$
$$= -\bar{k}\|E\|^2 + \|E\|(\epsilon_N + \tau_N) + k_6\|E\|tr\{\widetilde{W}^T\widehat{W}\} \tag{71}$$

where $\dot{\widetilde{W}}_1 = -\dot{\widehat{W}}_1$ and $\dot{\widetilde{W}}_2 = -\dot{\widehat{W}}_2$.

Using the matrix theory [14], we have

$$\dot{V} \le -\bar{k}\|E\|^2 + \|E\|(\epsilon_N + \tau_N) + k_6\|E\|tr\{\widetilde{W}(W - \widetilde{W})\}$$
$$\le -\bar{k}\|E\|^2 + \|E\|(\epsilon_N + \tau_N) + k_6\|E\|\|\widetilde{W}\|(W_M - \|\widetilde{W}\|)$$
$$\le -\|E\|\{\bar{k}\|E\| - (\epsilon_N + \tau_N) - k_6\|\widetilde{W}\|W_M + k\|\widetilde{W}\|^2\}$$
$$\le -\|E\|\{\bar{k}\|E\| - (\epsilon_N + \tau_N) - k_6(\|\widetilde{W}\| - \frac{W_M}{2})^2 - \frac{k_6W_M^2}{4}\} \tag{72}$$

which has guaranteed to be negative as long as

$$\|E\| \ge \frac{\frac{1}{4}k_6W_M^2 + \varepsilon_N + \tau_N}{\bar{k}} \tag{73}$$

or

$$\|\widetilde{W}\| \ge \frac{\sqrt{\frac{1}{4}k_6W_M^2 + \varepsilon_N + \tau_N}}{\bar{k}} + \frac{1}{2}W_M. \tag{74}$$

◊

Note that stability radius may be decreased any amount by increasing the gain $\bar{k}$. It is noted that conventional controller does not posses this property when system nonlinearity is present in mobile manipulators. Moreover, it is difficult to guarantee the stability of such highly nonlinear system using only a conventional controller. Using the NN nonlinearity compensation, stability of the system is proven, and the tracking errors $\|E\| = (e_c, r)$ can be kept arbitrary small by increasing the gain $\bar{k}$. The NN weight errors are fundamentally bounded in terms of W_M. The initial weights V are selected randomly, while the initial weights W are to set zero. Then the control loop in Fig. 4 holds the system stable until the NN begins to learn.

5. Simulation and Experimental Results

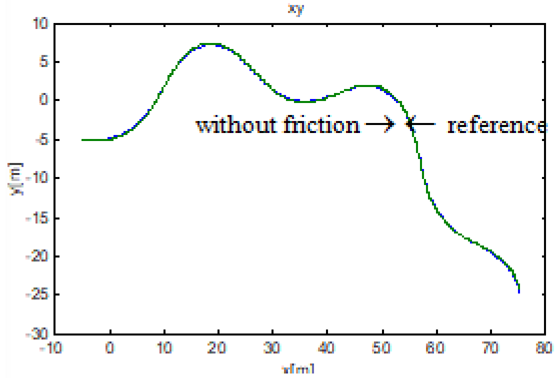
In this section, we illustrates the effectiveness of a proposed NN compenation for a mobile manipulator. For computer simulations, we took the vehicle and arm parameters as $m_p = 10[Kg]$, $m_1 = 1[Kg]$, $m_2 = 1[Kg]$, $I_1 = I_2 = I_w = 1[Kg.m^2]$, $I_p = 5[Kg.m^2]$, $l_1 = l_2 = 0.051[m]$, $2l = 0.35[m]$, and $r = 0.05[m]$, $d = 0.001[m]$. The controller gains were chosen so that the closed loop system exhibits a critical damping behavior $k_1 = 10$, $k_2 = 5$, $k_3 = 5$, $k_4 = diag\{40, 40\}$, $k_5 = diag\{10,10\}$, $k_6 = 1$, $\Lambda = diag\{5,5\}$. The reference points are constructed by using the kinematic model (24) and the following velocities, as follows:

$$v_r = 1.0[\frac{m}{sec}]$$
$$\omega_r = -1 + 6\sin(0.0139t)[\frac{deg}{sec}]. \tag{75}$$

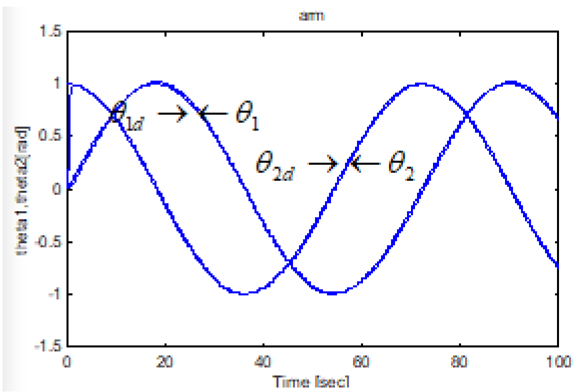
The reference trajectory to the arm are $\theta_{1d}(t) = \sin(0.698t)$ and $\theta_{2d}(t) = \cos(0.698t)$. The departure posture vector is $(-5, -5, 0°)$ and the goal is trajectory following. Fig. 5 shows the reference trajectory response of a mobile manipulator. In Fig. 6, the friction nonlinearity is included in the mobile manipulator, the response with a feedback controller exhibits a steady state error. The friction nonlinearity [12] is as follows: $f_{vehicle} = \alpha_0 sgn(\dot{\theta}_w) + \alpha_1 e^{-\alpha_2|\dot{\theta}_w|}sgn(\dot{\theta}_w)$ with constant $\alpha_0 = 0.2$, $\alpha_1 = 0.02$ and $\alpha_2 = 0.01$. θ_w is angular position of the driving wheel. For arm friction, $f_{arm} = \alpha_0 sgn(\dot{q}_r) + \alpha_1 e^{-\alpha_2|\dot{q}_r|}sgn(\dot{q}_r)$ with constant $\alpha_0 = 0.2$, $\alpha_1 = 0.02$ and $\alpha_2 = 0.01$. q_r is angular position of the arm. Some preprocessing of signals yields amore advantageous choice for $x(t)$ than (59) that already contains some of the nonlinearities inherent to mobile manipulator dynamics. The NN input vector x for vehicle can be taken as $x_{vehicle} \equiv [q_{vd}^T v_c^T \dot{v}_c^T e_r^T r^T \dot{r}^T \dot{q}_{rd}^T \ddot{q}_{rd}^T\ sgn(\dot{\theta}_w)^T]^T$ where the signum function is needed in the friction terms. The NN input vector x for arm is $x_{arm} \equiv [v_c^T \dot{v}_c^T e_c^T \dot{e}_c^T e_r^T \dot{e}_r^T \dot{q}_{rd}^T \ddot{q}_{rd}^T\ sgn(\dot{q}_r)^T]^T$. The number of nodes in successive layers of the NNs is 18-18-2, respectively. In Fig. 7(a)-(b), we see that the NN control scheme compensates the friction effects. The velocity eror, friction nonlinearity, and NN output are shown in Fig. 7(c)-(e).

The dynamic NN controller is implemented on a mobile robot. Fig 8(a) shows the experimental set up for a mobile manipulator. The wheels have a radius $r = 0.05[m]$ and are mounted on an axle of length$2R = 0.35[m]$. The wheels are drived by motors having rated torque $20[mN.m]$ at $3000[rpm]$ and $24[V]$rated voltage. Each motor is equipped with an incremental encoder counting $600[\frac{pulse}{turn}]$ and a gear. As shown in Fig. 8(b), the control algorithm is implemented at a $100[Hz]$ sampling rate via PC microcontroller. Wheel PWM duty cycle commands are sent to the robot and the encoders measure $\Delta\varphi_R$ and $\Delta\varphi_l$ for odometric computation. If $\Delta\varphi_R$ and $\Delta\varphi_l$be the wheel angular displacements measured during sampling time T_s by the encoders, the robot linear and angular displacements are constructed as $\Delta s = (\frac{r}{2})(\Delta\varphi_R + \Delta\varphi_l), \Delta\theta = (\frac{r}{2R})(\Delta\varphi_R - \Delta\varphi_l)$. The posture estimated at time $t_k = KT_s$ is

$$\hat{q}_k = \begin{bmatrix} \hat{x}_k \\ \hat{y}_k \\ \hat{\theta}_k \end{bmatrix} = \hat{q}_{k-1} + \begin{bmatrix} cos\bar{\theta}_k & 0 \\ sin\bar{\theta}_k & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta s \\ \Delta\theta \end{bmatrix} \quad (76)$$

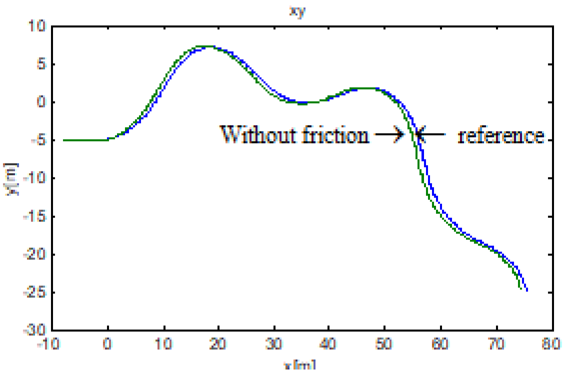


(a)

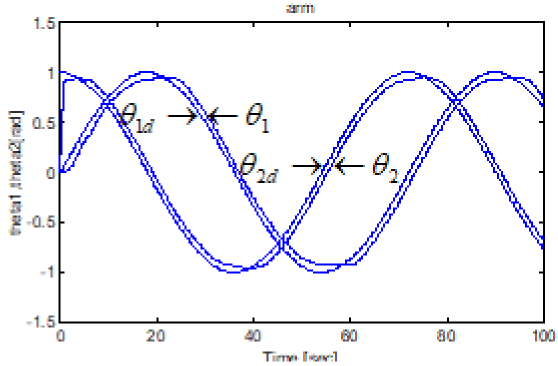


(b)

Figure 5: Response without friction nonlinearity of a mobile manipulator (a) vehicle trajectory and (b) arm position.

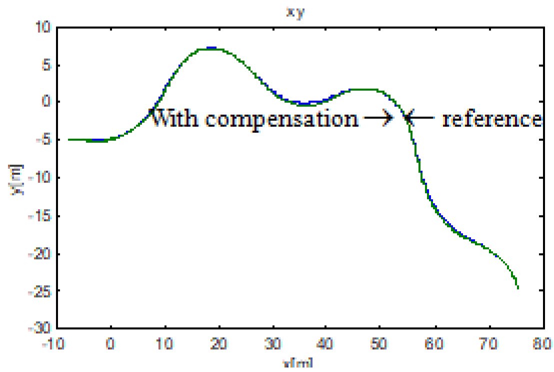


(a)

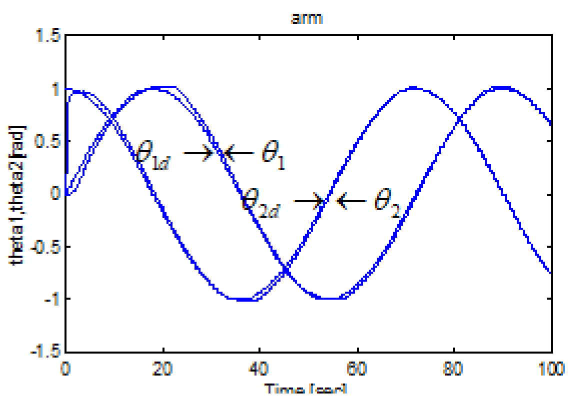


(b)

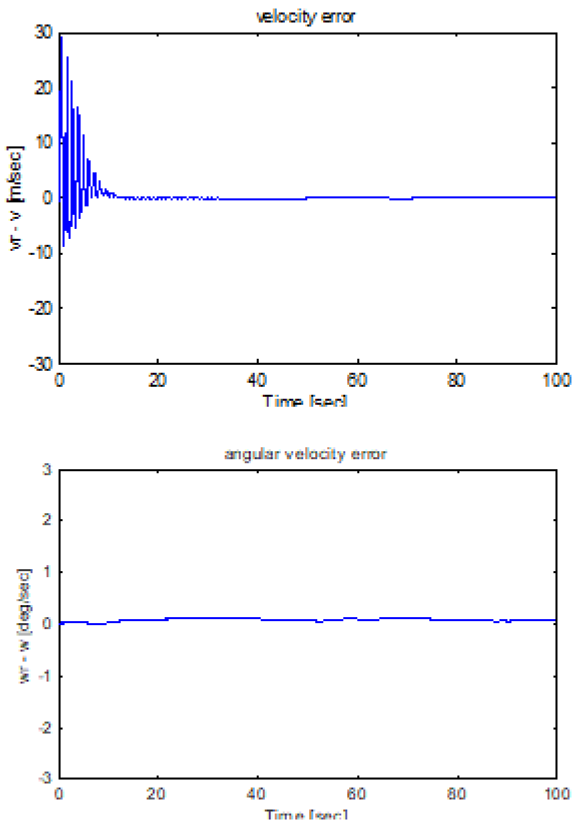
Figure 6: Response with friction nonlinearity of a mobile manipulator (a) vehicle trajectory and (b) arm position.



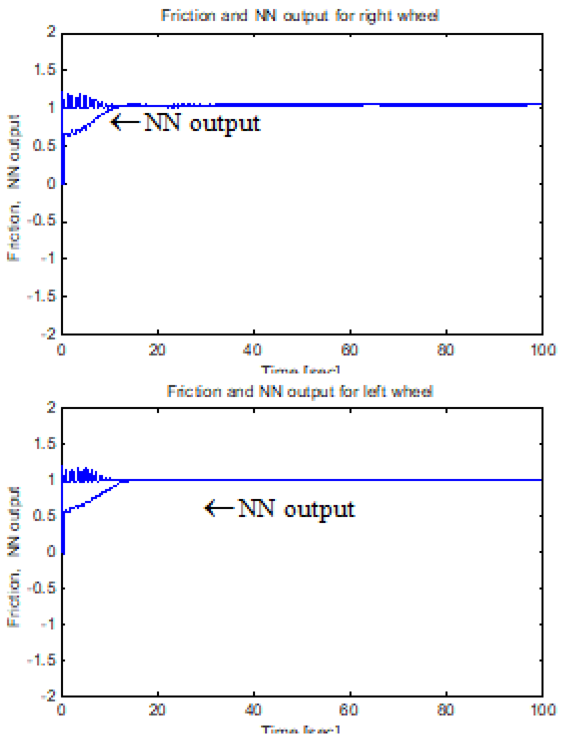
(a)

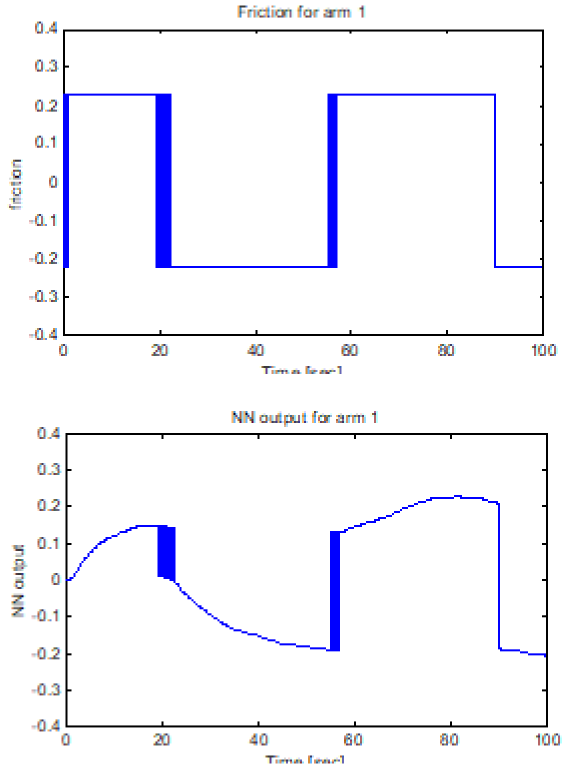


(b)

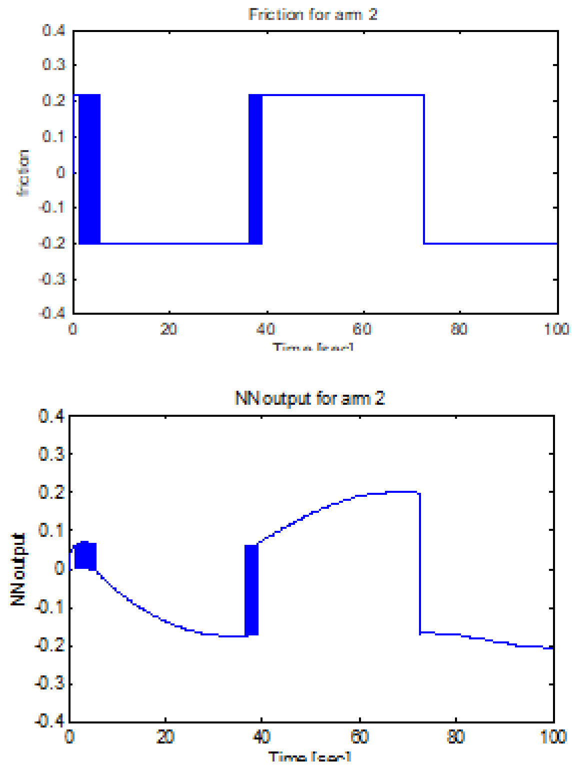


(c)





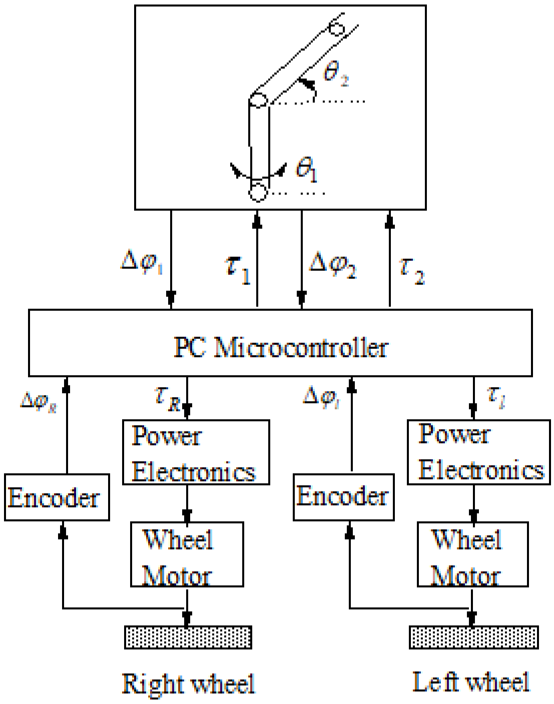
(d)



(e)

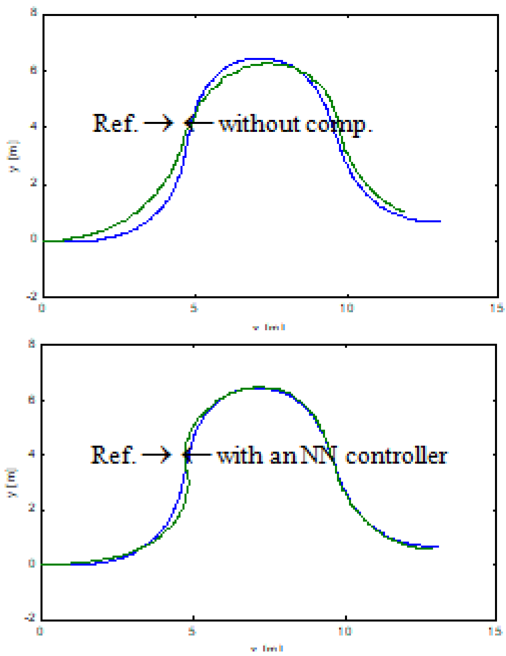
Figure 7: Response with NN compensation of a mobile manipulator: (a) vehicle trajectory, (b) arm position, (c) velocity error, friction and NN output(d) for vehicle and (e) for arm.

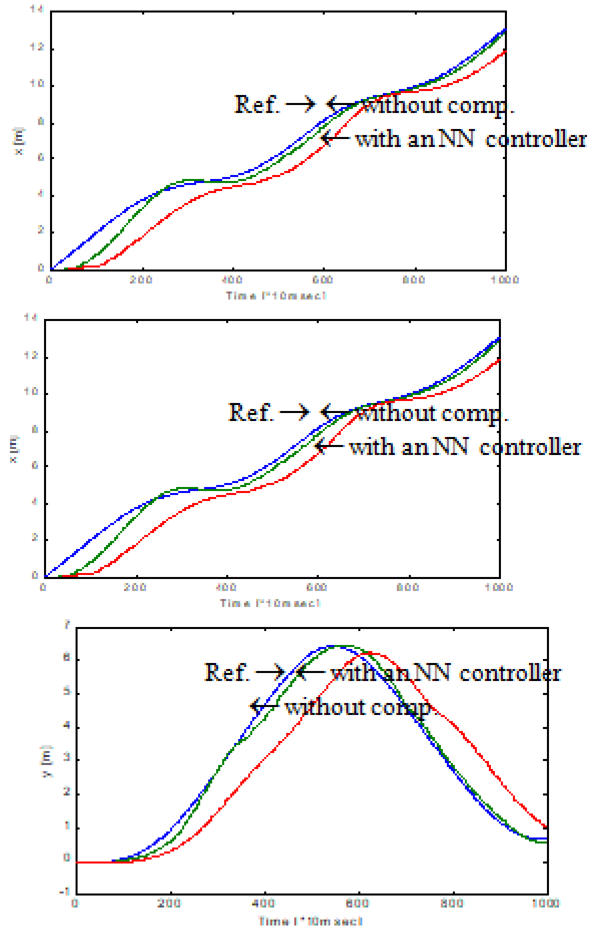
(a)



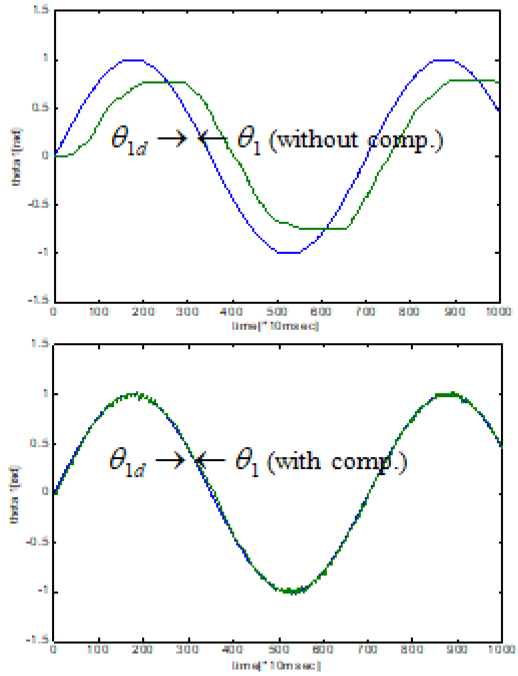
(b)

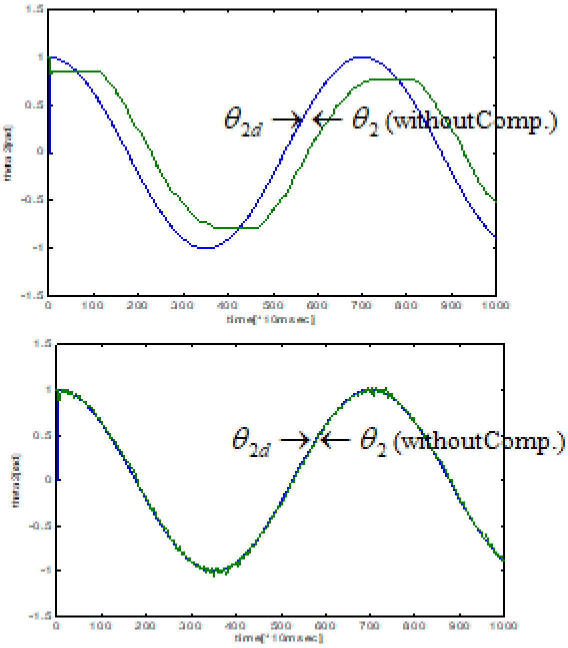
Figure 8: (a) Experimental setup for a mobile manipulator and (b) control architecture.





(a)





(b)

Figure 9: Experimental tracking response of a mobile manipulator with/without an NN compensation: (a) for the vehicle, (b) for the arm .

where $\bar{\theta}_k = \hat{\theta}_{k-1} + \Delta\theta/2$. The NN input vector x_{NN} can be taken as x $= [v_c^T \dot{v}_c^T \ sgn(\Delta\varphi) V^T]^T$. The reference trajectory is generated by the following velocities;

$$v_r = 1.1[\frac{m}{sec}]\ v_r = 1.1[m/\sec]$$

$$\omega_r = -5.7 + 28\sin(\frac{t}{2})[\frac{deg}{sec}]. \quad (77)$$

The reference trajectory to the arm are $\theta_{1d}(t) = \sin(0.698t)$ and $\theta_{2d}(t) = \cos(0.698t)$ .Fig. 9 shows the tracking response with friction nonlinearity. The performance degraded by the friction effects. However, the proposed NN controller shows an improvement in trajectory response compared with the feedback controller. The tracking response of mobile manipulator with/without for the vehicle and the arm are shown in Fig 9(a) and(b).

6. Conclusions

The NN conpensation with a linear controller for tracking of a mobile manipulators has been developed. In fact, perfect knowledge of the mobile manipulator parameters is unattainable, e.g., the friction nonlinearity is very difficult to model by conventional techniques. To confront this, an NN compensation with guaranteed performance has been derived. There is not need of a prior information of the parameters of the mobile manipulator, because the NN learns them on the fly. Also, The proposed control scheme is shown to be asymptotically stable through theoretical proof and simulation and experiment with a mobile manipulator.

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