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Tipover Stability Enhancement of Wheeled Mobile Manipulators Using an Adaptive Neuro-Fuzzy Inference Controller System

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***Abstract*—**In this paper an algorithm based on the adaptive neuro-fuzzy controller is provided to enhance the tipover stability of mobile manipulators when they are subjected to predefined trajectories for the end-effector and the vehicle. The controller creates proper configurations for the manipulator to prevent the robot from being overturned. The optimal configuration and thus the most favorable control are obtained through soft computing approaches including a combination of genetic algorithm, neural networks, and fuzzy logic. The proposed algorithm, in this paper, is that a look-up table is designed by employing the obtained values from the genetic algorithm in order to minimize the performance index and by using this data base, rule bases are designed for the ANFIS controller and will be exerted on the actuators to enhance the tipover stability of the mobile manipulator. A numerical example is presented to demonstrate the effectiveness of the proposed algorithm.

***Keywords*—**Mobile Manipulator, Tipover Stability Enhancement, Adaptive Neuro-Fuzzy Inference Controller System, Soft Computing.

I. Introduction

MANY investigations are done in the fields related to mobile manipulation systems such as path planning, motion planning, trajectory tracking, obstacle avoidance, etc. The subject of optimal stability has a significant role in autonomous robot systems. In this case, an interface between the manipulator and the vehicle plays a vital role in the stability investigation. The effect of dynamic interaction on the coordinated control of mobile manipulators has been studied in [1]. This effect is examined on the tracking of a mobile manipulator. A nonlinear feedback controller is designed that is capable of fully compensating the dynamic interactions. Stability analysis of mobile manipulators is considered in [2, 3]. The stability degree and the valid stable regions based on the Zero Moment Point (ZMP) criterion are derived. Then a method is presented for coordinating vehicle motion planning and manipulator motion planning considering platform stability.

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Planning mobile manipulator motions considering vehicle dynamic stability constraints is studied by Dubowsky *et al.* [4]. A planning method is presented which insures that dynamic disturbances do not exceed the capabilities of a vehicle, and comprises its stability, while permitting a mobile manipulator to perform its tasks quickly.

A trajectory planning method for a mobile manipulator with the end-effector's specified path is presented in [5]. The planning problem is formulated as an optimal control strategy. A gradient-based iterative algorithm which synthesizes the gradient function in a hierarchical manner based on the order of priority is used.

Das *et al.* [6] introduced a simple adaptive fuzzy logic based controller for tracking control of wheeled mobile robots. A Fuzzy Logic System (FLS) is used to estimate the nonlinear robot functions with no knowledge of the robot parameters. In the proposed controller approach, only measuring the position is required.

In the autonomous mobile robot for the purpose of trajectory tracking an adaptive dynamic controller is designed by Martins *et al.* [7]. They have considered a dynamic model which their input commands are velocities instead of torques used in most of the works. A σ-modification term is implemented to make the adaptive controller robust.

Some works are done on the field of dynamics and kinematics design of the wheeled mobile robots [8, 9]. Neuro-fuzzy control of a mobile robot is investigated by approximation of two nonlinear functions in [10]. The test is carried out with a standard RBF network and with the fuzzy system using both Gaussian and triangular membership function. Their learning capabilities are compared and discussed. The navigation of Khepera mobile robot is also obtained.

Some other investigations have been examined in designing fuzzy logic controllers. Fuzzy logic control of dynamic systems: from modeling to design is one of these subjects [11]. Chiou *et al.* [12] presented an adaptive fuzzy controller for robot manipulators. A model reference adaptive fuzzy sliding controller (MRAFSC) is proposed to control a five degree-of-freedom robot. MRAFSC drives the system state variables to hit a user-defined sliding surface and then slide

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along it to approach a reference model and finally parameters of the fuzzy control can be initialized to zero.

Neural-network control of mobile manipulators is studied in [13]. A neural network (NN)-based methodology is developed for the motion control of mobile manipulators subject to kinematic constraints. An online fuzzy logic (FL) self-motion planner and a robust adaptive controller are presented in [14] to prevent a three-wheeled robot from tipover without affecting the end-effector's motion tasks. Intelligent mobile manipulator navigation using adaptive neuro-fuzzy systems is considered in [15]. This work deals with the problem of autonomous and intelligent navigation of mobile manipulator, where there is not a complete mathematical model of robot systems and certainty of sensor data. A modular fuzzy navigation method in changing and dynamic unstructured environments has been developed. In addition, an integration of robust controller and Modified Elman Neural Network (MENN) is presented in order to deal with uncertainties.

In this paper, the formulation of a mobile manipulator with given paths for the end-effector and the vehicle is first presented. In order to make it convenient to design a dynamic system with an optimal stability index, it is then proposed that the manipulator be of a redundant form. For real-time control, a neural network with multilayer perceptron has been proposed, where its data base is generated by using the genetic algorithm in order to minimize a performance index (a criterion for measuring the tipover stability (i.e. stability against overturning) of the mobile manipulator). In this trained neural network, the rule bases for the ANFIS controller are designed and exerted on the actuators such that by planning the dynamic compensation manipulator motions, a condition for the system is created that increases the tipover stability of the mobile manipulator. Finally, a numerical example for considering the validity of the proposed algorithm is presented.

II. Modeling the Mobile Manipulator

The kinematic equations of a 3 degree-of-freedom mobile manipulator may be calculated by using the Denavit-Hartenberg notation, Table I, [16], and the general transformation matrix, Eq. (1).

Fig. 1 displays a scheme of a redundant 3 degree-of-freedom planar manipulator. Each joint is assumed a revolute one and the center of gravity for each link is assumed at the end of that link.

A general transformation matrix is a matrix which defines the frame $\{i\}$ with respect to the frame $\{i-1\}$. Eq. (1) shows the form of such matrix:

$$ {}^{i-1}_{i}T = \begin{bmatrix} c\theta_i & -s\theta_i & 0 & a_{i-1} \\ s\theta_i c\alpha_{i-1} & c\theta_i c\alpha_{i-1} & -s\alpha_{i-1} & -s\alpha_{i-1} d_i \\ s\theta_i s\alpha_{i-1} & c\theta_i s\alpha_{i-1} & c\alpha_{i-1} & c\alpha_{i-1} d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1) $$

The index i denotes the number of the appropriate link and terms "c" and "s" are extenuating of cosine and sine, respectively.

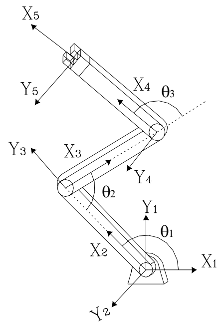

Fig. 1 Schematic diagram of a 3 degrees-of-freedom planar manipulator with coordinates attached to the joints

TABLE I
Denavit-Hartenberg Parameters and Variables

i	α_{i-1}	a_{i-1}	d_i	θ_{i-1}
1	0	a	0	0
2	0	0	0	θ_1
3	0	L_1	0	θ_2
4	0	L_2	0	θ_3
5	0	L_3	0	0

After forming transformation matrices and multiplying them to each other, the kinematics equation can be extracted in the following form:

$$ P_x = a + L_1\cos(\theta_1) + L_2\cos(\theta_1+\theta_2) + L_3\cos(\theta_1+\theta_2+\theta_3) \quad (2) $$

$$ P_y = L_1\sin(\theta_1) + L_2\sin(\theta_1+\theta_2) + L_3\sin(\theta_1+\theta_2+\theta_3) \quad (3) $$

Equations for velocities and accelerations are derived by differentiating equations (2) and (3) with respect to time. Obviously, there are 9 unknown variables while 6 equations are available. Out of these nine unknown variables, three of them can be presumed as inputs to a genetic algorithm and can be calculated such that a performance index (that a measure for determining the tipover stability of the robot and will be described afterward) becomes minimum.

A free body diagram for the vehicle is shown in Fig. 2. The vehicle has 4 wheels; two wheels at rear and the two others in front. The forces and moments from the manipulator act on the first joint attached to the vehicle. The stability depends on the difference between the upward forces of tires. It is desired that the absolute value of this force be equal to zero [17].

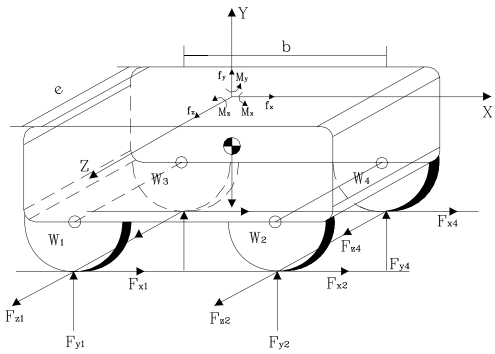

Fig. 2 Free body diagram of the vehicle

Considering the interaction between the vehicle and the manipulator, the forces and moments from the manipulator will exert on the vehicle and consequently affect the tires upward forces. Using the Newton's formulation, the governing equation will be derived as follows:

$$F_{y1}+F_{y2}+F_{y3}+F_{y4}+f_y-Mg=ma_y \tag{4}$$

$$b(F_{y2}+F_{y4})+(-Mg+f_y+ma_y)\frac{b}{2}-hf_x+M_z-\frac{h}{2}ma_x=0 \tag{5}$$

It is assumed that the tracking velocity of the vehicle is constant; therefore:

$$a_x=a_y=a_z=0 \tag{6}$$

The tracking velocity of the end-effector is also constant and its trajectory is predefined for some special tasks.

III. Applying Soft Computing Approach for Tipover Stability

In order to enhance the tipover stability of the mobile robot, in this paper, the genetic algorithm is used as a useful optimization tool to minimize a performance index. The performance index, J, is defined as the absolute value of the moment in the z direction, M_z, acting on the vehicle from the manipulator.

$$J=|M_z| \tag{7}$$

Noting that this equation denotes tires upward forces are affected by M_z. In Eq. (7), $M_z=\tau_1$ is the torque from the manipulator and is calculated in the form of:

$$\begin{aligned}\tau_1 &= m_1L^2_1\ddot{\theta}_1+m_2L^2_1\ddot{\theta}_1+m_2L^2_2(\ddot{\theta}_1+\ddot{\theta}_2)+2m_2L_1L_2c_2\ddot{\theta}_1+m_2L_1L_2c_2\ddot{\theta}_2+m_3L^2_1\ddot{\theta}_1\\ &+m_3L^2_2(\ddot{\theta}_1+\ddot{\theta}_2)+m_3L^2_3(\ddot{\theta}_1+\ddot{\theta}_2+\ddot{\theta}_3)+2m_3L_1L_2c_2\ddot{\theta}_1+m_3L_1L_2c_2\ddot{\theta}_2+2m_3L_1L_3\\ &c_{23}\ddot{\theta}_1+m_3L_1L_3c_{23}\ddot{\theta}_2+m_3L_1L_3c_{23}\ddot{\theta}_3+2m_3L_2L_3c_3\ddot{\theta}_1+2m_3L_2L_3c_3\ddot{\theta}_2+m_3L_2L_3c_3\ddot{\theta}_3\\ &-2m_3L_1L_2s_2\dot{\theta}_1\dot{\theta}_2-m_3L_1L_2s_2\dot{\theta}_1^2-2m_3L_1L_3s_{23}\dot{\theta}_1(\dot{\theta}_2+\dot{\theta}_3)-m_3L_1L_3s_{23}\dot{\theta}_2(\dot{\theta}_2+\\ &\dot{\theta}_3)-m_3L_1L_3s_{23}\dot{\theta}_3(\dot{\theta}_2+\dot{\theta}_3)-2m_3L_2L_3s_3\dot{\theta}_1\dot{\theta}_3-2m_3L_2L_3s_3\dot{\theta}_2\dot{\theta}_3-m_3L_2L_3s_3\dot{\theta}_3^2\\ &+m_1gL_1c_1+m_2gL_1c_1+m_2gL_2c_{12}+m_3gL_2c_{12}+m_3gL_2c_{12}+m_3gL_3c_{123}-2m_2L_1\\ &L_2s_2\dot{\theta}_1\dot{\theta}_2-m_2L_1L_2s_2\dot{\theta}_2^2\end{aligned} \tag{8}$$

The values of $\theta_1,\dot{\theta}_1,\ddot{\theta}_1$ are assumed as inputs to the genetic algorithm and minimizing the performance index J is its output.

Although genetic algorithm is a strong optimization tool, it is a time-consuming approach such that it is not recommended to be applied in real-time control. To overcome this drawback, a neural network is implemented.

In applying a neural network, first, one should determine which variables vary and then define the range of their variations. By applying the genetic algorithm and changing the variables for about all possible configurations of the mobile manipulator, a look-up table is obtained containing the optimal values of $\theta_1,\dot{\theta}_1,\ddot{\theta}_1$. Now, a neural network is trained with these inputs and their proper outputs.

IV. Numerical Example

For some reason the task of the mobile manipulator may be defined as painting a surface or carrying a light load from one point to another point in space while there are some obstacles on the ground that the vehicle is ought to avoid of contact while in motion. This matter may enforce both the end-effector and the vehicle to follow some predefined trajectories. A numerical example is presented to show the validity of the proposed optimal stability algorithm. Furthermore, it is assumed that the vehicle and the end-effector must track a predefined trajectory with a constant speed. The specifications of the mobile manipulator are given in Table II.

TABLE II
Specifications of a Mobile Manipulator

Parameter	Value
Base Mass	10 (Kg)
Link 1 Mass	1 (Kg)
Link 2 Mass	1 (Kg)
Link 3 Mass	1 (Kg)
L_1	0.7 (m)
L_2	0.7 (m)
L_3	0.7 (m)
b	0.5 (m)
α	0.5 (rad)
Base velocity	1 (m/s)
End-effector tracking velocity	1/14 (m/s)

The trajectory of the end-effector is assumed as an inclined line with a constant slope α as shown in Fig. 3.

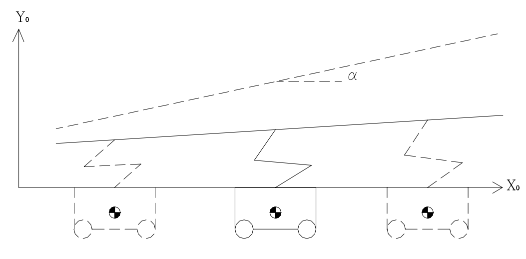

Fig. 3 The end-effector and the vehicle trajectories

Parameters in Table III are inputs to the neural network and optimal values of $\theta_1,\dot{\theta}_1,\ddot{\theta}_1$ are outputs of that network that must minimize the performance index J. The look-up table consists of 2,352 data. This table shows the quantities for velocity v of the vehicle, angle α, vertical distance b, and vertical position of the end-effector P_y, respectively.

TABLE III
VARIABLE INCREMENT FOR TRAINING

Variables	Variation Range	Increment
$v(m/s)$	0.5 – 1.4	0.15
$\alpha(rad)$	0.1 – 1.1	0.2
$b(m)$	0 – 0.6	0.1
$P_y(m)$	0 – 2.1	0.3

The specifications of the neural network after 800 epochs are shown in Table IV.

TABLE IV
SPECIFICATIONS OF THE TRAINED NEURAL NETWORK

Network Type	Feed-Forward Back-Propagation
Adaptation learning function	Gradient Descent with Momentum (learngdm)
Performance function	Mean Square Error (MSE)
Number of Layers	3
Layer 1	25 neurons, Transfer function: Tansig
Layer 2	20 neurons, Transfer function: Tansig
Layer 3	3 neurons, Transfer function: Purelin
Epochs	800

The purpose of using the genetic algorithm here is to evolving a solution to satisfy a set of criteria after several generations [18, 19, and 20]. By manipulation a pool of individuals through a set of operators (reproduction, crossover, and mutation) a solution for a specific problem will be found. Each individual is represented by a chromosome which contains the characteristics of that individual and after every generation each individual creates variables that are the corresponding solution of the problem. The three principle operations in the evolution are reproduction, crossover and mutation. Reproduction options manage how the genetic algorithm produces the next generation. Crossover rules merge two parents (from the individuals) to form children for the next generation while mutation rate utilizes casual changes to form children for the new generation.

Here are the genetic algorithm specifications;
Number of chromosomes: 100
Number of iteration: 200
Number of values: 3
Precision of the values: 20
Crossover rate: 0.8
Mutation rate: 0.01-0.05

V. STABILITY CRITERION FUNCTION FOR FLC SYSTEMS

Conventionally, the design of a fuzzy logic controller relies on the knowledge of expert operators and needs sufficient experiences. Many works have been done to help the designers how to choose proper data bases and rule bases. In reference [21] a method is presented in order to evaluate the regions of the data base and the related rules that are undesirable from the stability point of view. In order to evaluate the stability of the closed-loop fuzzy logic control system, a dual SISO linear system with linear PD-controller is first defined, where the input to the PD-controller is e and its output is u. The relation between u and e at each instant is given by:

$$u_i = k_p e_i + k_d \dot{e}_i \tag{9}$$

For each element of the I-O set, one should ask the following question in its dual linear system with linear PD-controller:
Is it possible to determine real positive parameters K_p and K_d in Eq. (9) such that for a given element of the I-O set, (i.e. $e_i, \dot{e}_i$ and $u_i = \Phi(e_i, \dot{e}_i)$) the closed loop system with linear PD-controller be stable?
If the answer is positive then it can be concluded that the given element of I-O set does not decline the stability of neither the fuzzy logic closed loop system nor its dual system. Therefore, such an element [$e_i, \dot{e}_i$, and u_i] is a "stable I-O element". Contrary to the above statement, an "unstable I-O element" is defined when the answer to the mentioned question is negative.
A function $s(e,\dot{e})$ is defined to show the stability of the fuzzy logic controller.

$$s(e,\dot{e}) = \begin{cases} 1 & if\ [e,\dot{e},u] \quad is\ a\ stable\ I-O\ element \\ 2 & if\ [e,\dot{e},u] \quad is\ an\ unstable\ I-O\ element \end{cases} \tag{10}$$

This function may be drawn with respect to $e,\dot{e}$ in a 3-dimensional coordinate. This function is called "Stability Criterion Function". By using this function, we must redesign the rule base of FLC for the undesirable regions when the stability criterion function is 2.
This approach is used in designing the rule base of the adaptive neuro-fuzzy inference controller system. There are two inputs as $e_i, \dot{e}_i$ which are the differences between the state variables at each time increment. The output is the control action $u_i = T_i$ where $i = 1,2,3$. These quantities are the proper applied torques on the joints.

A linear Sugeno fuzzy-model based controller is employed in planning the ANFIS structure with a triangular membership function. The coefficients of the fuzzy reasoning (i.e. c_{i1}, c_{i2}) in Eq. (11) are initially set equal to zero.

$$y_i = c_{i0} + c_{i1}x_1 + c_{i2}x_2 \tag{11}$$

After training, these values are adjusted to their proper quantities according to the mentioned stability criterion (i.e. the performance index J as the stability measure of the mobile manipulator is minimized). Regarding the stability criterion for the ANFIS controller (i.e. Eq. (10)), a rule base is acceptable if a pair of K_p and K_d in Eq. (9) will be found in such a way the closed-loop system with the PD-controller be stable. Based on this criterion, the rule bases are designed and are shown in Tables V, VI, and VII. A fuzzy set assumed here including 7 fuzzy variables. These linguistic descriptions are as: NVL (Negative Very Large), NL (Negative Large), Negative Small (NS), Z (Zero), PS (Positive Small), PL (Positive Large), and PVL (Positive Very Large).

Notice that an important property of the neuro-fuzzy controllers is their application to nonlinear systems, and also

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noting that these controllers are robust to both noise and parameter deteriorations.

TABLE V
RULE BASE FOR $e_1, \dot{e}_1$ AND u_1

$\dot{e}_1$	***PL***	NVL	NL	Z	PL	PVL
	PS	NVL	NL	Z	PL	PVL
	Z	NVL	NL	Z	PS	PVL
	NS	NVL	NS	Z	PL	PVL
	NL	NVL	NL	Z	PL	PVL
		NL	***NS***	***Z***	***PS***	***PL***
				e_1		

TABLE VI
RULE BASE FOR $e_2, \dot{e}_2$ AND u_2

$\dot{e}_2$	***PL***	NVL	NL	Z	PL	PVL
	PS	NVL	NL	Z	PL	PVL
	Z	NVL	NL	Z	PS	PVL
	NS	NVL	NS	Z	PL	PVL
	NL	NVL	NL	Z	PL	PVL
		NL	***NS***	***Z***	***PS***	***PL***
				e_2		

TABLE VII
RULE BASE FOR $e_3, \dot{e}_3$ AND u_3

$\dot{e}_3$	***PL***	NVL	NL	Z	PL	PVL
	PS	NVL	NL	Z	PL	PVL
	Z	NVL	NL	Z	PS	PVL
	NS	NVL	NS	Z	PL	PVL
	NL	NVL	NL	Z	PL	PVL
		NL	***NS***	***Z***	***PS***	***PL***
				e_3		

A flowchart of the control algorithm for this system is shown in Fig. 4. The inputs are obtained from sensors. The inputs enter into the neural network unit which cooperates with the genetic algorithm in order to provide a data base and minimizes the performance index. According to the appropriate values of the input, error, changes of error and consequently the control action (which is the exerted torque) the rule bases are defined and generated for the ANFIS controller in the next step. Finally, these values will be sent to the actuators as electrical or voltage signals.

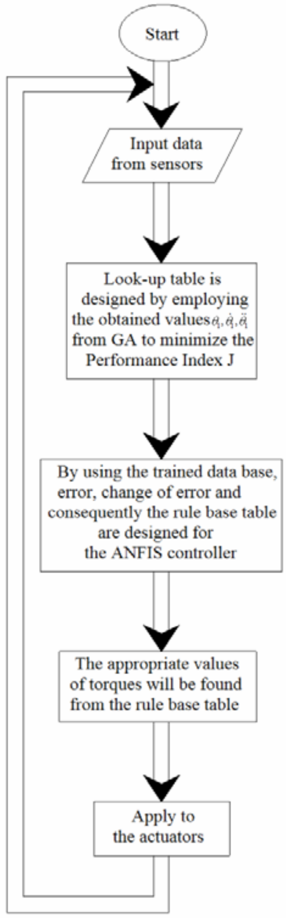

Fig. 4 Flowchart of soft computing algorithm applied for a mobile manipulator

VI. SIMULATION RESULTS

The range of [-5, 5] is assumed for the error and change of error to cover a wide space of inputs. The 3-dimensional surfaces of $e_i, \dot{e}_i$ and $u_i, (i = 1, 2, 3)$ before training are shown in Fig. 5.

This figure depicts that the outputs (T_1, T_2, T_3) are more sensitive to the error than to the change of error. The coefficients of the fuzzy reasoning, c_{ij}, in Eq. (11), are trained and are then used in the ANFIS structure. In addition, the 3-dimensional surfaces are obtained after training in right column of Fig. 5.

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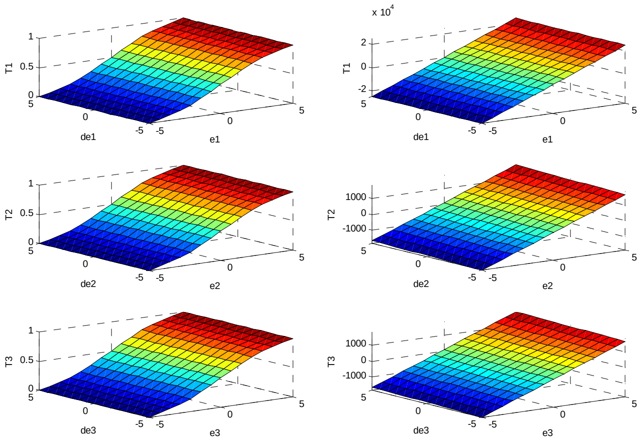

Fig. 5 3-dimensional surfaces of e_i , $\dot{e}_i$, and u_i, $i = 1,2,3$ before training (left column) and after training (right column)

A linear relation is governing between inputs and output. For checking the validity of the designed ANFIS controller, the closed-loop response of the system is shown in Figs. 6 and 7. Actuators apply the suitable torques achieved from the controller to their related joints and each joint is led to the appropriate value which is given by the look-up table. In this case an appropriate configuration for the manipulator is created that enhances the tipover stability of the system. The ANFIS toolbox of MATLAB is used for designing the controller of this system. The program is run for 30 epochs until the training error leads to a very small value ($\approx 2\times10^{-4}$). Fig. 6 indicates that for x=1 meter, each joint is reached to its optimal configuration after about 0.15 second. Fig. 7 shows the same results for x=2.4 (m).

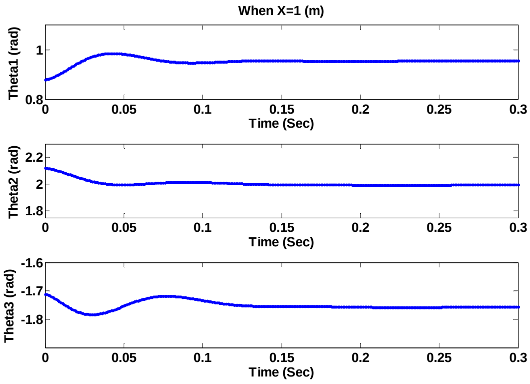

Fig. 6 Performance of the designed ANFIS controller in taking the appropriate configuration of the manipulator (for enhancing the tipover stability of the mobile manipulator when x=1(m))

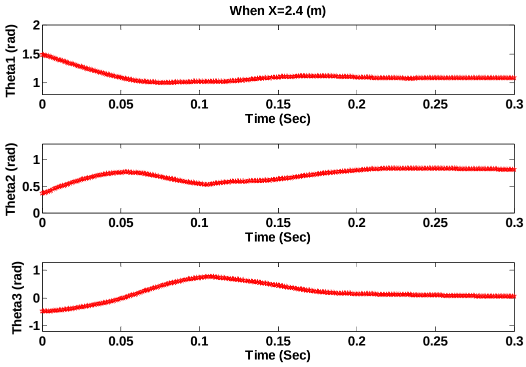

Fig. 7 Performance of the designed ANFIS controller in taking the appropriate configuration of the manipulator (for enhancing the tipover stability of the mobile manipulator when x=2.4(m))

Upward forces of tires 1 and 2 (i.e. $F_{y1} = F_1, F_{y2} = F_2$) are presented in Fig. 8. The differences between the values of these forces are very small such that the maximum difference is about 2 N.

These forces directly affect the performance index J. As illustrated in Fig. 9, the value of performance index is always less than 1 (N-m). It is obviously realized from this system that if the dynamic interaction between the vehicle and the manipulator would not exist, the tires upward forces could be exactly equal to each other. In the case of existence of this interaction, it can be inferred that the system has a safe moving without overturning.

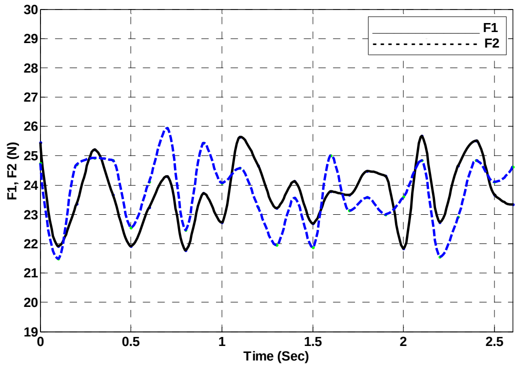

Fig. 8 Upward forces of tires number 1, 2

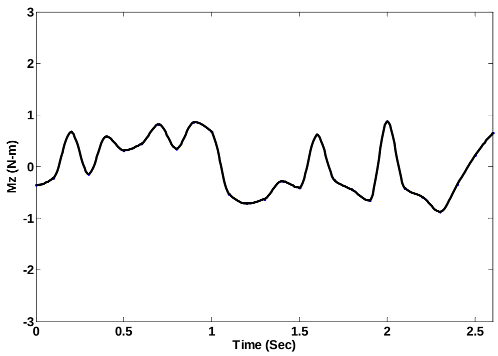

Fig. 9 The minimized performance index

To examine the proposed algorithm, the tracked trajectory by the end-effector is compared with the desired trajectory that is expected to be tracked by the end-effector as shown in Fig. 10. This figure demonstrates that the end-effector is able to track the predefined path significantly while the tipover stability of the mobile manipulator is simultaneously guaranteed in an optimal way for this case. A comparison between this work and some previous works reveals that the combination of the proposed algorithm for the optimal stability and implemented adaptive neuro-fuzzy controller in this paper are more simple and fast enough for the stability enhancement of mobile manipulators while robust against disturbances exerting on the system.

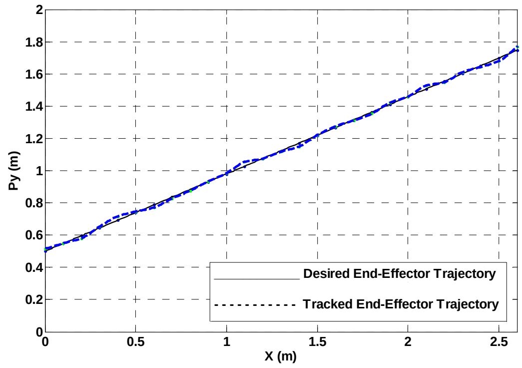

Fig. 10 Comparison between the desired and tracked trajectory by the end-effector

VII. Conclusion

When the paths of the end-effector and the vehicle of a mobile manipulator are predefined, an extra degree-of-freedom is proposed.

In this paper, an algorithm for designing an ANFIS controller-based for enhancing the tipover stability of mobile manipulators is presented. For real-time control, a neural network is applied such that its data base is generated by using the genetic algorithm approach to minimize the performance index. With regards to this trained neural network, the rule bases for the ANFIS controller are also designed and exerted on the corresponding actuators such that by dynamic compensation of manipulator motions, a situation for the system is created that increases the tipover stability of the mobile manipulator. The validity of the proposed controller is considered by a numerical example and the results give evidence that the controller is able to compensate the manipulator in a significant manner for the desired purpose. The results of the robust stability are revealed by considering the values of the performance index such that the end-effector is able to follow the desired trajectory significantly.

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