COGNITIVE DYNAMIC NEURAL CONTROLLER DESIGN FOR MOBILE ROBOT BASED ON SELF-TUNING ON-LINE OPTIMIZATION ALGORITHM

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ABSTRACT :

This paper presents the design of a cognitive dynamic neural controller (CDNC) for the trajectory tracking of non-holonomic wheeled mobile robot based on the dynamic model with self-tuning on-line optimization algorithm. The aim of the proposed controller is to solve the trajectory tracking problem of the mobile robot by finding the optimal torque control action for the two wheels of mobile robot to follow a pre-defined continuous path precisely and quickly. Particle swarm optimization (PSO) used as a fast and stable self-tuning on-line algorithm to compute the optimal parameters for the proposed controller .The robustness and effectiveness of the proposed tuning algorithm are validated by Matlab simulation results in terms of the capability of overcoming the non-representative dynamic disturbances, minimizing tracking error and obtaining the smooth and optimal torque control signals with minimum number of fitness evaluation.

Keywords: Mobile Robot Dynamic Model; Cognitive Dynamic Neural Controller; Optimization Algorithm

تصميم مسيطر عصبي حركي مدرك لأنسان ألي مبني على اساس الخوارزمية الأمثلية ذات التنغيم الذاتي وبشكل حي متصل

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الخلاصة :

يقدم هذا البحث تصميم منظومة تحكم للسيطرة على مسارالحركة للربوتات ذات العجلتين مقيدة الاتجاه بأستخدام التحكم الديناميكي العصبي المدرك المبني على خوارزمية الامثل استنادا إلى النموذج الديناميكي والخوارزمية الأمثلية ذات التنغيم الذاتي وبشكل حي متصل . ان الهدف من وحدة التحكم المقترحة هو الحصول على منظومة سيطرة ذات ادراك للربوتات المتحركة ذات العجلتين في تتابع مسار محدد مسبقا بسرعة وبدقة. ويتم الحصول على القيم المثلى لعناصر وحدة التحكم على طول المسار باستخدام خوارزمية حشد الجسيمات الأمثلية. من خلال نتائج المحاكاة تم اثبات متانة وكفاءة خوارزمية تنغيم المسيطر المقترح و باستخدام لغة الماتلاب، حيث تم تتبع المسار المرغوب بأقل خطأ ممكن والتغلب على الاضطرابات الديناميكية غير الممثلة بالحصول على تحكم امثل لعزم عجلتي الروبوت اليمنى واليسرى مع استدعاء اقل لدالة التقيم .

1. INTRODUCTION

In the last few years, the rapid developments in the design of controllers for the mobile robots have exceeded the traditional control systems through modern controllers based on artificial intelligence systems. At this time the controller systems enable the mobile robot to behave as natural system interact with the environment and do their job autonomously. The controllers for complex behavior of mobile robots are still requiring the efforts of researchers worldwide. For real word application of non-holonomic wheeled mobile robots and to improve trajectory tracking of them, several approaches were suggested in this year and last few years. To stabilize wheeled mobile robot (WMR) according to the given reference trajectory, dynamic sliding mode controller (DSMC) which was based on dynamical model of WMR was developed as proposed in [Keighobadi et al, 2011]. For uncertain robot dynamics and unknown parameters adaptive back-stepping controllers was proposed where the controller gains are tuned on-line as presented in [Mohareri et al.,2012]. To increase the efficiency of trajectory tracking controllers, cascaded control methodology was proposed in which dynamic error was divided into first-order and second –order subsystems and the finite-time control technique with sliding mode control was combined as explained in [Zhang et al., 2014]. To deal with parametric and nonparametric uncertainties in mobile robot optimal Fuzzy PID controller based on dynamic model and PSO to optimize the PID coefficients was suggested for trajectory tracking of WMR as explained in [Abadi et al., 2015]. For unknown discrete-time adaptive dynamic programming (ADP) was used with neural networks to obtain the iterative performance index function and the tracking control policy as explained in [Huang et al., 2014]. To solve the difficulty of the models' building spiking neural networks (SNNs) was proposed as presented in [Wang et al., 2014]. To find the optimal velocity controller action, cognitive neural controller with PSO as tuning algorithm based on a kinematic model was proposed as explained in [Tawfik et al., 2014].

Some researchers compared between the learning algorithms of the neural trajectory controller as explained in [Al-Araji, 2014], it was clarified that the PSO algorithm is more effective than genetic algorithm. Some controllers were depend on a localization system as explained in [Villa et al., 2012], in this research a combination of dynamic controller with robot attitude observer was produced a stable controller. Partially-observed feedback controller as proposed in [Miah and Gueaieb, 2014], where the robot received signal in form noisy received signal strength released from radio frequency identification so the accurate mapping is not needed. To slow down full convergence of the controller parameters, Ant Colony Optimization (ACO) was used as tuning algorithm in fuzzy controller as proposed in [Castillo et al., 2015]. Bacterial Foraging Optimization (BFO) was used to find the destination of path planning as explained in [Hossain, Ferdous , 2015]. The challenge of designing control systems for path tracking of the non-holonomic wheeled mobile robot to behave autonomously awaiting further development to get the best performance with less errors and overcome the non-represented dynamic disturbances.

The contribution of this paper is to design a cognitive dynamic neural controller (CDNC) depends on the dynamic mobile robot model and the high accuracy analytical derive of the self-tuning control algorithm in terms of minimizing the tracking error even with non-represented disturbances.

The remaining of the paper is arranged as follows: Section two presents the dynamic model of the non-holonomic wheeled mobile robot. Section three describes the cognitive dynamic neural controller derivation based on particle swarm optimization algorithm. Section four shows the simulation results by using the proposed controller with elected track and finally section five presents some conclusions.

2. Non-holonomic mobile robot model

The non-holonomic mobile robot with two independent driving wheels is shown in Fig.1. on the same axis and two caster wheels for more stability of the mobile robot structure. The motion and orientation are achieved by two independent DC motors as actuators in order to provide the necessary torque for the right and left wheels. The wheels have the same radius (r) and the distance between them is L. Point (c) is the center of mass of the mobile robot and located at the center of axis of the wheel.

The position and the orientation of the mobile robot in an inertial coordinate frame $\{O, X, Y\}$is specified by the vector $q = [x, y, \theta]^T$, where x,y are the coordinates of the center of mass of the robot, and θ is the orientation of the mobile platform $\{c, x, y\}$ measured from X axis.

The movement of the robot is specified by the linear (v) and the angular velocities (ω) of center of mass (c) relative to the global coordinate. There is only one axis of rotation for the two wheels. The pure rolling and non-slipping constraint of the non-holonomic mobile robot means that the robot can only move normal to the axis of the two wheels [Blazic, 2011], the axial velocities relationship as:

$$- \dot{x}(t) sin\theta(t) + \dot{y}(t) cos\theta(t) = 0 \qquad (1)$$

Where $\dot{x}$ and $\dot{y}$ are the velocity of the robot in the direction of X-axis and Y-axis, respectively. It is assumed that the two wheels are ideally installed without skidding. The kinematic model for the mobile robot under the non-holonomic constraint of pure rolling without slipping can be expressed as [Cosic et al., 2013]

$$\begin{bmatrix} \dot{x}(t) \\ \dot{y}(t) \\ \dot{\theta}(t) \end{bmatrix} = \frac{r}{2} \begin{bmatrix} cos\theta & cos\theta \\ sin\theta & sin\theta \\ \frac{2}{L} & \frac{-2}{L} \end{bmatrix} \begin{bmatrix} \omega r(t) \\ \omega l(t) \end{bmatrix} \qquad (2)$$

Where ωr and ωl are the angular velocity of the right and left wheel respectively and selected as a control inputs for the kinematic model.

For the dynamic model (kinetic) the torques provides by the actuators to the right and left wheel of the robot act as control input. The dynamic equation can be derived as following:

$$F(t) = (\tau_r(t) + \tau_l(t))/r \qquad (3)$$

$$\tau_T(t) = L(\tau_r(t) + \tau_l(t))/2r \qquad (4)$$

Where τ_r , τ_l are the torques of the right and lift wheel respectively, F, τ_T are the total axial forces and total moment generated by the two actuators of the mobile robot. The mobile robot can only move normal to the axis of the two wheels according to constraint of the non-hololomic mobile robot and by using Newton's second law:

$$\dot{v}(t) = F(t)/m \qquad (5)$$

$$\dot{\omega}(t) = \tau_T(t)/I \tag{6}$$

From 3 and 4

$$\begin{bmatrix} \dot{v}(t) \\ \dot{\omega}(t) \end{bmatrix} = \frac{1}{2r} \begin{bmatrix} 2/m & 2/m \\ L/I & -L/I \end{bmatrix} \begin{bmatrix} \tau_r(t) \\ \tau_l(t) \end{bmatrix} \tag{7}$$

Where $\dot{v}$, $\dot{\omega}$ are linear and angular acceleration while m ,I *are* the mass and the moment of inertia for the mobile robot respectively. Where Eq. (7) is the dynamic model (kinetic) for the mobile robot under the non-holonomic constraint of pure rolling without slipping.

3. Cognitive Dynamic Neural Controller Design:

Cognitive control methodology is the source of inspiration and guidance to overcome the controller design limitations in the complex and adaptive systems this, due to its embedded aggregation knowledge and the autonomous structuring for this knowledge. The structure of the proposed (CDNC) compounds from two units: the first unit is the cognitive dynamic neural network. The second unit is optimization algorithm, which is used as a powerful self-tuning on-line algorithm to find the optimal stable parameters of the controller based on particle swarm optimization. Fig.2. shows the structure in block diagram form for the proposed controller for mobile robot system.

3.1. Cognitive Dynamic Neural Network:

The cognitive dynamic neural network structure is shown in Fig.3 which it consists of three layers with eight input signals, the position and orientation errors between the desired and the actual trajectory of the robot with respect to the local coordinates of mobile robot and the torques of the two wheels, and two output signals which they are the torque of each actuator for the right and left wheels.

The configuration errors for position and orientation can be presented in discrete time as follows:

$$e_x(k) = \left(x_d(k) - x(k)\right)cos\theta(k) + \left(y_d(k) - y(k)\right)sin\theta(k) \tag{8}$$

$$e_y(k) = \left(y_d(k) - y(k)\right)cos\theta(k) - \left(x_d(k) - x(k)\right)sin\theta(k) \tag{9}$$

$$e_\theta(k) = \left(\theta_d(k) - \theta(k)\right) \tag{10}$$

Where : e_{x}, e_{y}, e_θ are the errors of the Robot location according to the local coordinates.

The torques τ_r , τ_l of the right and left wheels , respectively, as a control action can be obtained from the following equations:

$$neto_x = e_x(k)v_{11} + (e_x(k) + e_x(k-1))v_{12} + (e_x(k) - e_x(k-1))v_{13} \tag{11}$$

$$neto_y = e_y(k)v_{24} + (e_y(k) + e_y(k-1))v_{25} + (e_y(k) - e_y(k-1))v_{26} \tag{12}$$

$$neto_\theta = e_\theta(k)v_{37} + \left(e_\theta(k) + e_\theta(k-1)\right)v_{38} + \left(e_\theta(k) - e_\theta(k-1)\right)v_{39} \tag{13}$$

$$o_x = \frac{2}{1+e^{-neto_x}} - 1 \quad (14)$$

$$o_y = \frac{2}{1+e^{-neto_y}} - 1 \quad (15)$$

$$o_\theta = \frac{2}{1+e^{-neto_\theta}} - 1 \quad (16)$$

$$net_1 = o_x w_{11} + o_y w_{12} + o_\theta w_{13} \quad (17)$$

$$net_2 = o_x w_{21} + o_y w_{22} + o_\theta w_{23} \quad (18)$$

$$\tau_r(k) = net_1 + M_1 \tau_r(k-1) \quad (19)$$

$$\tau_l(k) = net_2 + M_2 \tau_l(k-1) \quad (20)$$

The function for equations (14, 15, 16) is sigmoid activation function.

3.2. Optimization Algorithm:

The particle swarm optimization algorithm (PSO), as evolutionary technique, is used to compute the optimized values of the cognitive controller parameters. In PSO algorithm each member of the population is called a particle and the population is called a swarm. Starting with a randomly initialized population and moving in randomly chosen directions, each particle goes through the searching space and remembers the best previous positions of it (best value of each particle) and other particles (best value of particle in the entire swarm). Particles of a swarm dynamically adjust their own position and velocity derived from the best position of all particles. The next step all particles gradually fly into best positions in the searching space and ubdating itself with the best solution until they move close to an optimum value. The global best PSO is used in this paper, where the position of each particle is influenced by the best-fit particle in the entire swarm. The particles are twenty sets of the seventeen parameters of the cognitive neural controller. The objective function is the mean square error of the robot location according to (e_x, e_y, e_θ) and angular velocities of the two wheels to track the trajectory.

The steps for tuning the seventeen parameters (weights) of the proposed controller by the PSO algorithm are as follows:

1. The weights (particles) and all parameters for the algorithm are initialized randomly within sensing range.
2. The best value of each particle be specified by computing the error value, according to a proposed error function, for each and compared with old one, if it is better than the current value of the particle is the best (pbest). Then if the best value of the (pbest) for all particles is better than old global best (gbest), this value be the new (gbest).

The proposed error function:

$$MSE = \frac{1}{N}\sum_1^N e_x^2 + e_y^2 + e_\theta^2 + (w_{rr} - w_r)^2 + (w_{rl} - w_l)^2 \quad (21)$$

Where:

N are the numbers of particles.

3. The particles value are updated by using the dynamically adjustment relationship :

$$V = w * V + c1 * r1(Xp_{best} - Y) + c2 * r2(G_{best} - Y) \quad (22)$$
$$Y = Y + V \quad (23)$$

Where:

$c1$ and $c2$ are the acceleration constant with positive values
$r1$ and $r2$ are a random numbers between 0 and 1
w is the inertia weight factor
V is the velocity vector of weight
Y the weight sets
Xp_{best} is the best value of the set
G_{best} is the best set

4. The steps 2 , 3 are repeated until the iteration number is reached.

4. Simulation Results:

In order to analyze the effect of the proposed controller, simulation using MATLAB was run through which the PSO as an on-line self-tuning algorithm to compute the best values of the controller's parameters. The proposed controller in this section is verified with computer by using Mobile robot type (Eddie Robotic), where the parameters of the robot, as present in [Ortigoza et al., 2013], were taken as: r=0.075 m, L=0.39 m, maximum linear velocity of the robot (v) $1m/s^2$, maximum angular velocity of each wheel (w_r, w_l) 13.33 $rad/s$and a sampling time 0.4 sec. The proposed cognitive methodology with optimization algorithm is set to the following parameters:

The population size is equal to 20. The number of weights in each particle is equal to 17 because there are seventeen parameters for cognitive neural trajectory tracking controller. The number of iteration is equal to 25. The desired motion trajectory can be described as follows:

$$x_r(t) = 1.5 \times \cos(\pi t/60) - \cos(5\pi t/60) \quad (24)$$
$$y_r(t) = 1.5 \times \sin(\pi t/60) - \sin(4\pi t/60) \quad (25)$$
$$\theta_r(t) = 2\tan^{-1} \Delta y_r(t)/\Delta x_r(t) \quad (26)$$

The initial posture of the reference trajectory is $q_r = [0.5 \ \ 0 \ \ 0]^T$ and the actual initial posture is $q_{ac} = [0.2 \ \ 0 \ \ 0]^T$ and the unmodeled kinematic disturbances are $= [0.01\sin(2t) \quad 0.01\sin(2t) \ \ ]^T$ in order to prove the robustness ability of the proposed tuning cognitive control algorithm. Figure (4) shows the Matlab simulation results for the proposed controller of the Eddie mobile robot trajectory-tracking. The auto-tuning control parameters and robustness of cognitive neural controller based on cognitive methodology with (PSO) algorithm; show excellent position and orientation tracking performance, as well as very small effect of the disturbances because the cognitive neural methodology has the capability to obtain smooth values of the controller's parameters .

Fig.5. demonstrates the effectiveness of the proposed tuning cognitive neural control algorithm by showing its ability to generate small and smooth values of the control input (the right and left wheel torque); therefore, smaller power is required to drive the DC motors of the Eddie mobile robot model. A high torque was needed for the left wheel at start to let the robot rotates clockwise to track the desired orientation.

The maximum linear velocity of the wheels is about 0.35 m/s as shown in Fig.6. and maximum angular velocity for the robot is about ± 1 rad/sec. It is clear that the robot start with rectilinear velocity to reach the desired point and then rotate clockwise then counterclockwise to track the desired trajectory.

Fig.7. shows the angular velocities of the right and left wheels to get the desired trajectory. It is very clear that the robot was started with high left wheel angular velocity than the right one because of the shifted location at the starting for the desired one according to the desired trajectory.

The performance index MSE for pose path and orientation errors for the mobile robot model motion for 25iterations are shown in Fig.8. As clear from the figure a high performance index was computed in the starting period because the robot rectified its starting position, and a six periods in the sampling time described the position of the sharp spikes in the direction of the desired trajectory.

CONCLUSIONS :

A cognitive auto-tuning on-line dynamic neural trajectory tracking controller for differential wheeled mobile robot model has been presented in this paper. The proposed controller consists of a dynamic neural networks and on-line PSO technique to find and tune the optimal parameters of the controller that has been designed and tested using Matlab package.

Simulation results show evidently that the proposed dynamic neural controller model has demonstrated the capability of tracking a complex continuous gradients reference trajectory and effectively minimization the tracking position and orientation mean square errors of the differential wheeled mobile robot type Eddie robotic; and has the capability of generating smooth and optimum suitable torque control actions without sharp spikes.

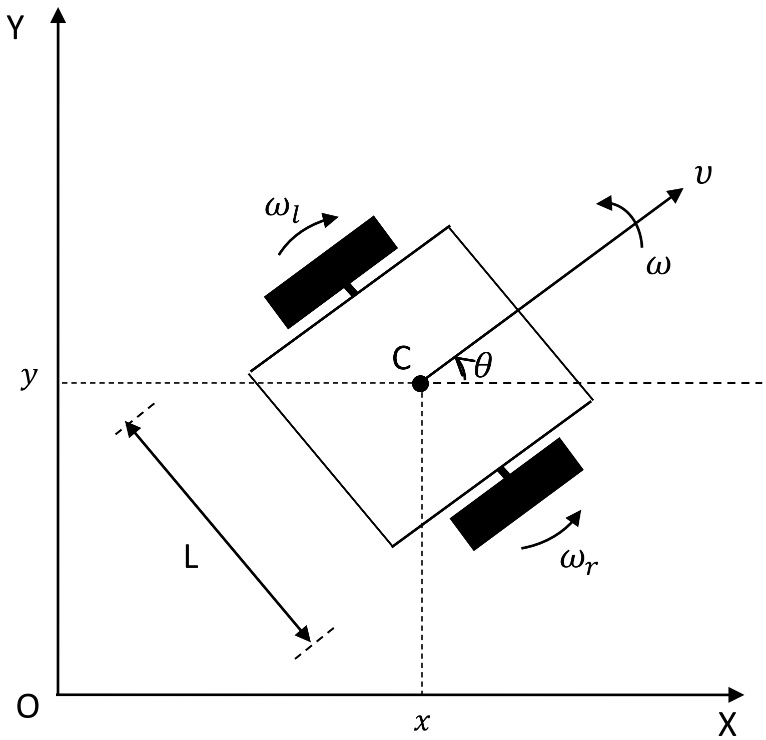


Fig.1. Mobile robot configuration and it's motion coordination.

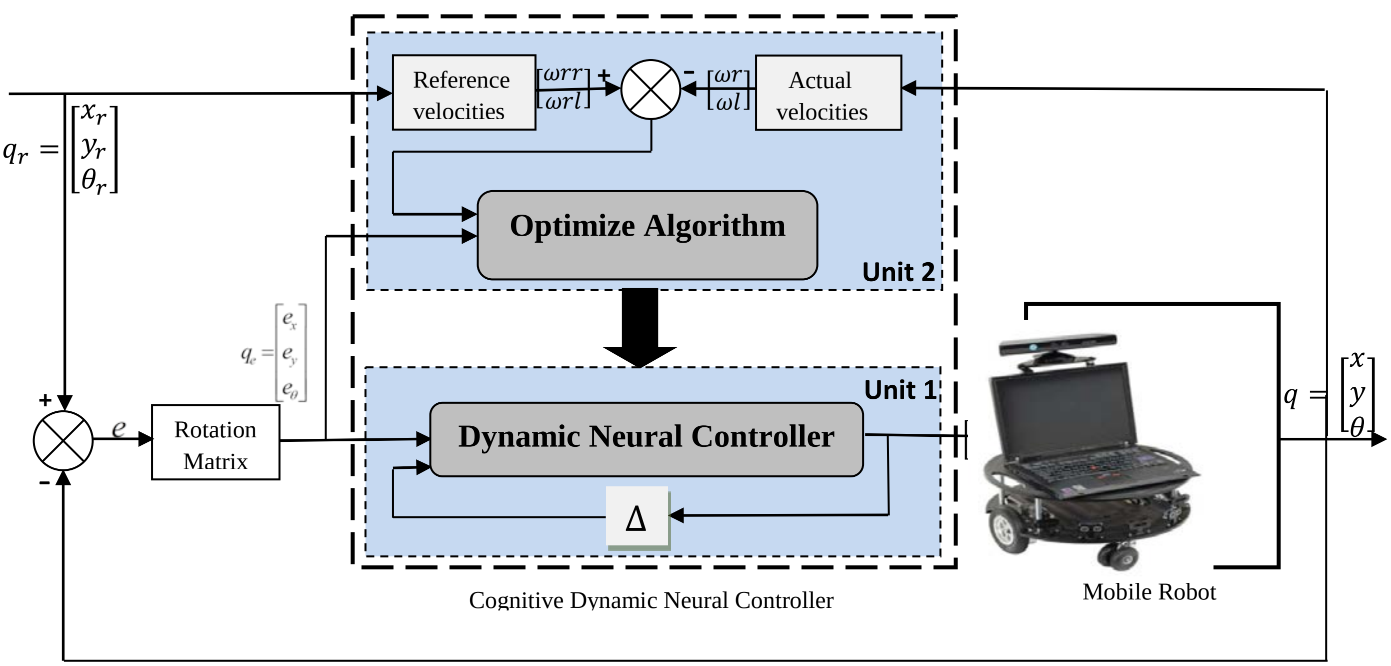


Fig.2. The proposed cognitive dynamic neural controller structure for mobile robot.

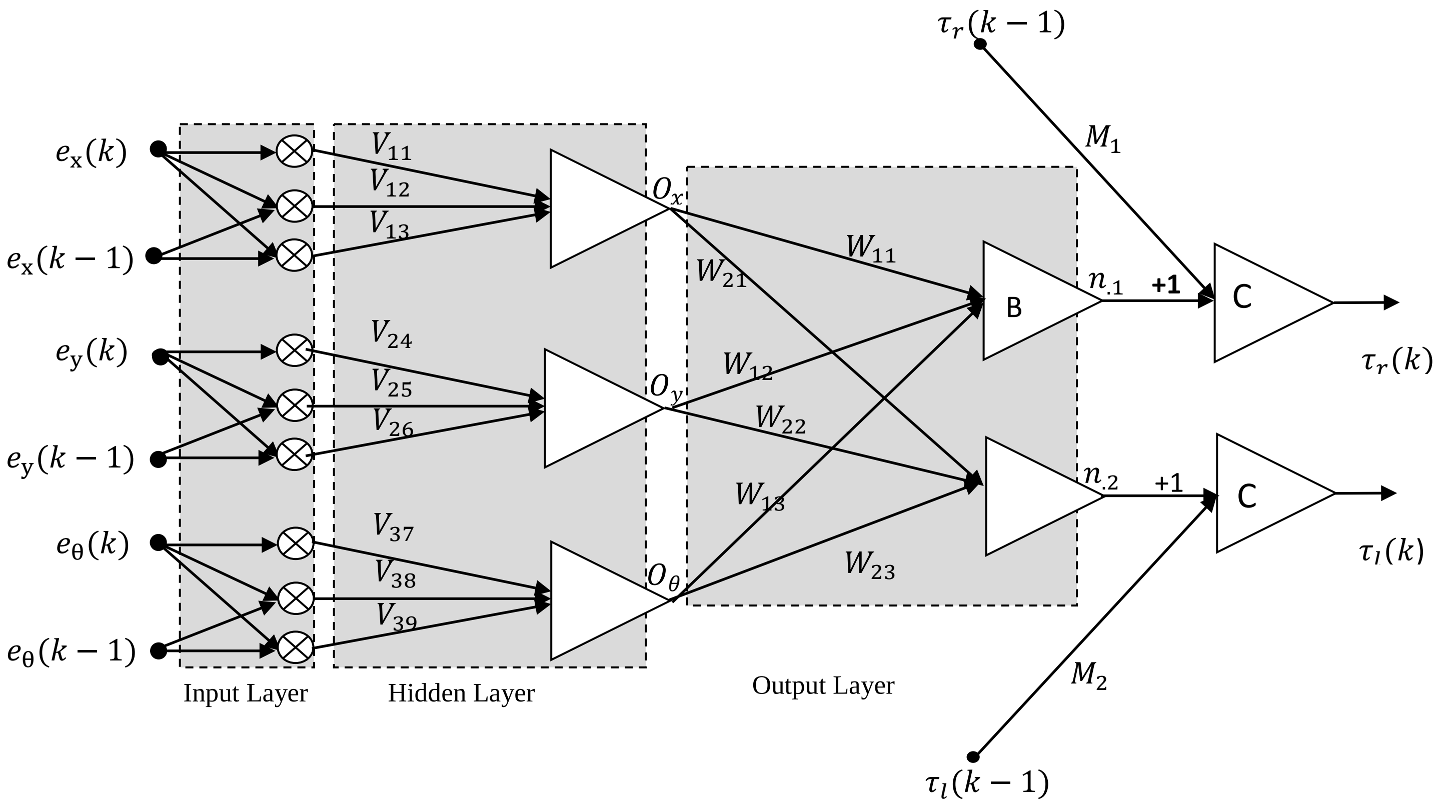
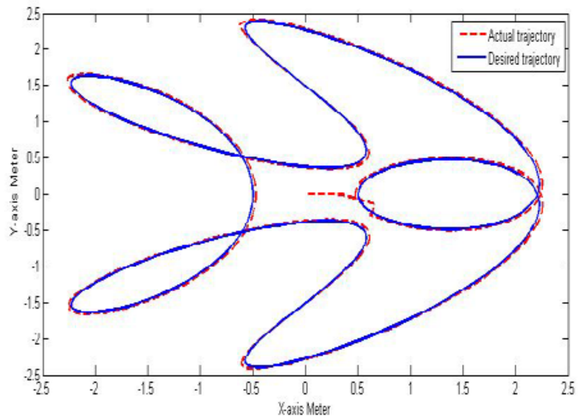


Fig.3. Neural network controller.

A.



B.

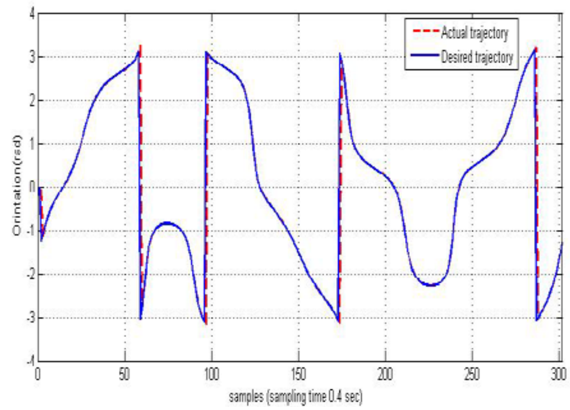


Fig. 4. Simulation results, A. actual and desired trajectory B. actual and desire orientation

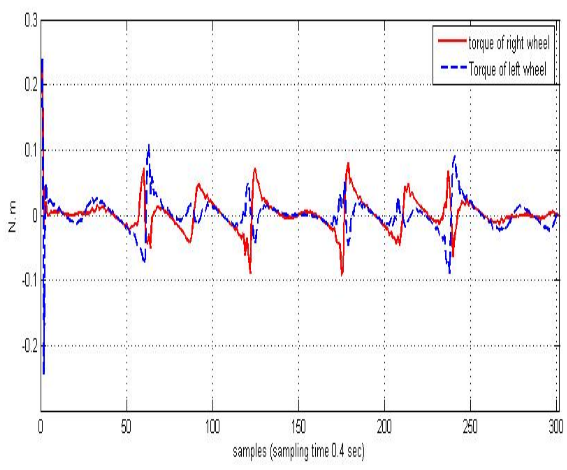
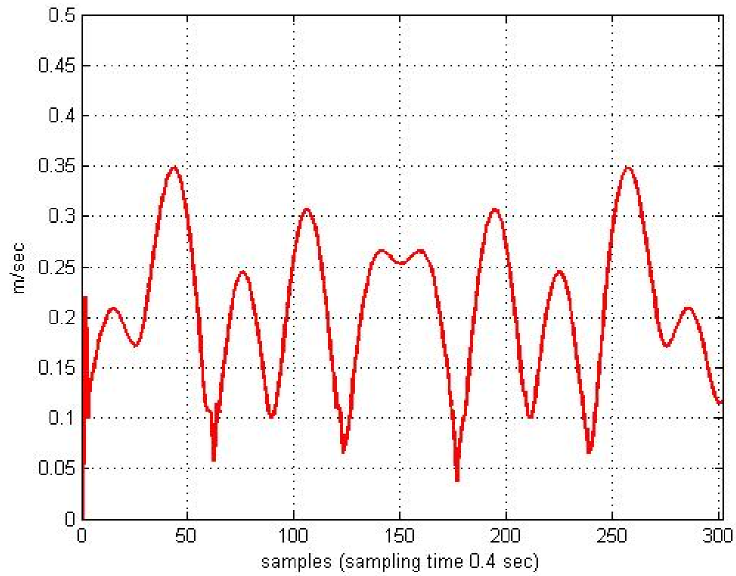


Fig.5.The torque of right and left wheels.

A.



B.

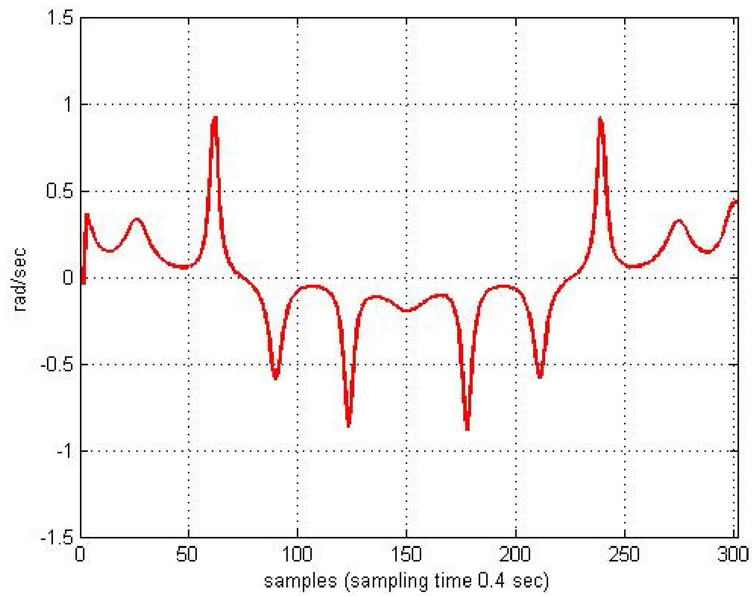


Fig.6. The velocities of mobile robot, A.the linear velocity,

B. the angular velocity.

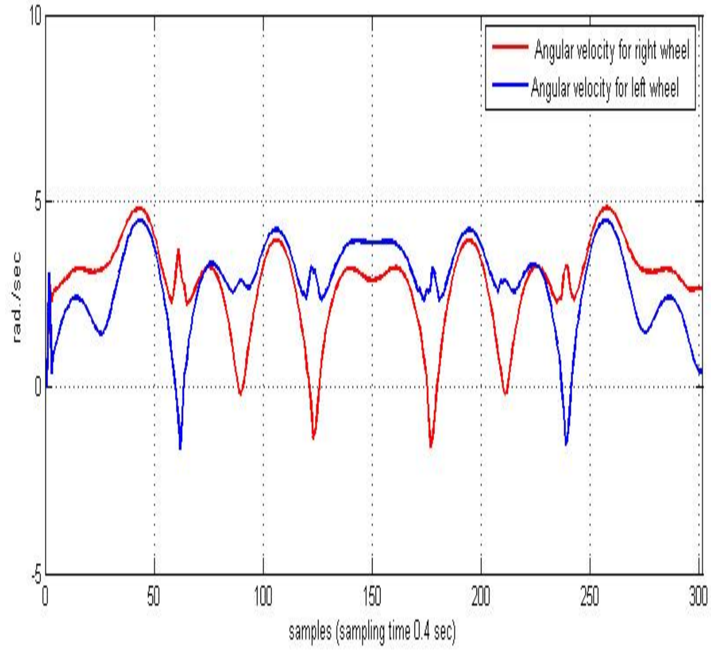


Fig. 7. The actual angular velocities of the right and left wheels

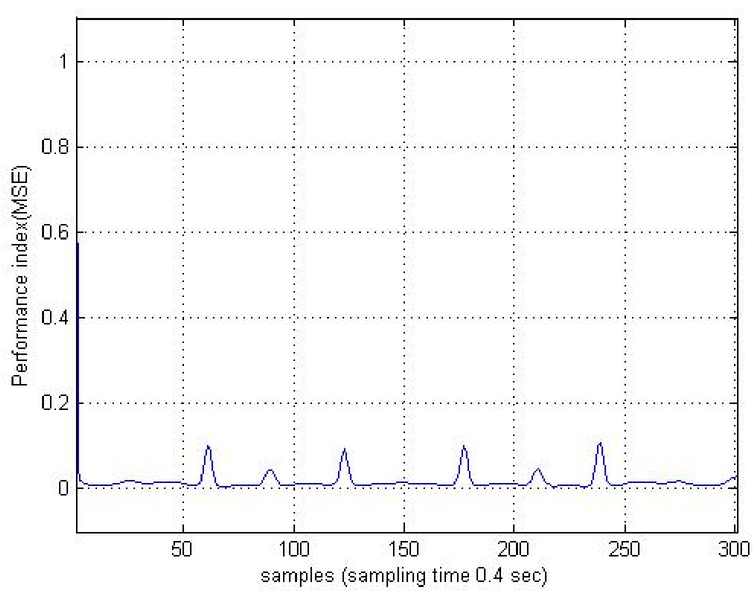


Fig.8. The performance index MSE

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