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An adaptive neural control methodology design for dynamics mobile robot

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ABSTRACT

The paper demonstrates an enhancement in the mobile robot's performance during trajectory tracking with static obstacles. An adaptive artificial neural network (ANN) control methodology with online tuning evolutionary slice genetic algorithm is used for the motion control of the nonlinear dynamics mobile robot system. This paper aims at locating the optimal path from the starting point to the target point and designing an ANN trajectory tracking control methodology. The algorithm is simulated with fixed-global environment obstacles to demonstate the effectiveness of the ANN controller and the evolutionary optimization algorithm in terms of the shortest path length generated and the minimum number of the evaluation cost function calculated. The simulation results illustrate that the ANN controller's parameters are obtained quickly, generating smooth wheels' torque actions for the mobile robot platform with a minimum cost function evolution that lead to minimize the tracking error to approximately zero with no oscillation in the responses.

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1. INTRODUCTION

In the last decade, many commercial robots have been utilized in real-world applications such as robotic vacuum cleaners, lawnmowers, weather detection, mining envioronment, educational applications, entertainment, and military equipment [1], [2] therefore, to improve the mobile robot path planning and to track various trajectories that have several challenges, some design stages should be addressed such as simultaneous localization and mapping [3], [4], path-tracking and mobile robot platform object detection [5]-[7], and the static mobile surveillance systems convergence are proposed in [8], [9]. In this context, this work focuses on mobile robot path planning and how to generate the shortest path of the mobile robot platform in the obstacles environment between (the starting position and the target position) in order to avoid the collision, so many researchers use various optimization path-planning algorithms that they are tried to solve path-planning problems. For instance, in [10] the authors proposed an ant colony optimization (ACO) algorithm in which the behavior of the ants' search is controlled by a pheromone to obtain the global optimal direction towards food. The higher the pheromone level, the higher the probability of choosing the optimal path. Firefly algorithm was utilized in [11] to realize detailed and effective solutions, dealing with three separate aims including detection of the mobile robot road map, calculation length of the road planning, and generation of the smoothness route, which lead to minimize consumption of the energy .

In addition, nature inspired algorithms such as ant colony and bees optimizations were exploited in [12] using local-search techniques for optimizing the path of the environment map discovered by using local procedures series to find a mobile robot platform route based on different types of optimization path-planning inspired algorithms by various limitations, and the cost function in the road-map mobile robot workspace. Moreover, particle swarm optimization (PSO) algorithm with radial foundation function was developed in [13] for obtanning high accurcy mapping for moving robot's trajectory by using the working area describing of the moving mobile robot platforms. In addition, many types of designed trajectory tracking control tuning-algorithms for platform of mobile robot that used to solve the kinematics and dynamics motion control in order to make the platform follow the reference path with minimum position and orientation tracking error. For example, a nonlinear behivour of proportional integral derivative (PID)-like artificial neural network controller with a cognitive path-planning trained by the PSO algorithm was proposed in [14] to get the best path for the mobile robot and then to follow it. In [15], [16] the researchers proposed evolution algortithm such as a genetic tuning control algorithm that find the solution of the complex motion preparation problems of mobile robot platform that has uncertain states dynamics limitations based on dynamics actions. An artificial network and learning method that used Q-learning were proposed in [17] to determine route path-planning problems in the generated best solution. Furthermore, a nonlinear kinematics with predictive neural network controllers were demonstrated in [18] to achieve mobile robot trajectory tracking based on a posture identifier model. Moreover, Asif *et al.* [19] proposed a feedback inverse kinematics controller with a neural based feedforward controller are used for tracking different types of trajectories for a wheeled mobile robot. In another study, a wavelet neural network (WNN) controller for the route planning and tracking of the platform of mobile robot that has an uncertain area was proposed in [20]. A back-stepping nonlinear kinematics controller with an online slice genetic algorithm was suggested in [21] to develop a path tracking algorithm for a mobile robot.

In this work, the problem statement can be divided into two parts; the first part is to generate the best optimal reference path by achieving two limitions; namely, the path-planning should be avoid collision with static obstacles, and the path-planning algorithm has to reduce the path length to a minimum value. The second part is to design a kinematics and dynamics trajectory tracking motion controller for the mobile robot platform because it has high nonlinear kinematics and dynamics with time-variant output states. In addition, this robot will be considered as an under-actuated system. Therefore, to accurately tracking the reference path of the mobile robot platform in terms of minimum position tracking errors and orientation tracking errors, as well as, for solving the oscillation state and overshoot behaviour in the pose of the mobile robot system, so the problem statement are needed to be solved.

The main contributions of this work are to try to solve the problem statement by:

- Generating the best optimal shortest path with no collisions using the evolutionary slice genetic algorithm
- Generating the smoothest torque control actions for the two wheels based on the proposed artificial neural network tuning-control algorithm by using numerical simulation

Therefore, the simulation results of the proposed neural network tuning-control strategy has effectiveness and leads to stabilize the platform of mobile robot and track the reference (locations and orientations) with minimum tracking errors by controlling the mobile robot's posture. The organization of this paper is as follows: section 2 explains the mobile robot kinematics and dynamics mathematical models. Section 3 illustrates the proposed controller design. Section 4 presents the simulation results of the proposed control structure effectiveness. The conclusions for this work are shown in section 5.

2. MOBILE ROBOT DYNAMICS MODEL

In general, Figure 1 shows the mobile robot cart which contains of two individual direct current (DC) motors used as actuators for the right and left wheels for motion and orientation, and one castor wheel to stabilize the mobile robot platform [22], [23]. Hence, the kinematics model of the mobile robot platform at the global coordinate frame $[O \quad X_{axis} \quad Y_{axis}]$ depend on the same radius of the two wheels which can be denoted as r. Moreover, the distance between these actuators' wheels is represented as L. c represents the center of gravity for the mobile robot. The pose vector (the position coordinates (x, y) and the orientation angle θ) at point c in the surface of the mobile robot cart can be written as in (1):

$$q = [x \quad y \quad \theta]^T \tag{1}$$

Therefore, the kinematics wheeled mobile robot equations in the global frame *w.r.t.* the right and left angular velocities can be defined as follows [24]:

$$\dot{x}(t) = \frac{r(w_r(t)+w_l(t))}{2}\cos(\theta(t)) \tag{2}$$

$$\dot{y}(t) = \frac{r(w_r(t)+w_l(t))}{2}\sin(\theta(t)) \tag{3}$$

$$\dot{\theta}(t) = \frac{r(w_r(t) - w_l(t))}{L}, \tag{4}$$

Where $w_r(t) and\ w_l(t)$ are the right wheel angular velocity and left wheel angular velocity respectively.

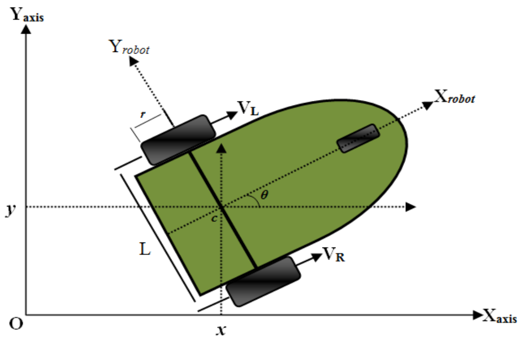

Figure 1. The mobile robot platform

The state of pure-rolling of non-holonomic conditions must be achieved as well as the non-slipping state as in (5) [25].

$$-\dot{x}(t)\sin(\theta(t)) + \dot{y}(t)\cos(\theta(t)) = 0 \tag{5}$$

Euler Lagrange formulation is used to demonstrate the dynamics model of the mobile robot platform as in (6) [24], [25].

$$\begin{bmatrix} M & 0 & 0 \\ 0 & M & 0 \\ 0 & 0 & I \end{bmatrix} \begin{bmatrix} \ddot{x} \\ \ddot{y} \\ \ddot{\theta} \end{bmatrix} = \frac{1}{r} \begin{bmatrix} \cos(\theta) & \cos(\theta) \\ \sin(\theta) & \sin(\theta) \\ 0.5L & -0.5L \end{bmatrix} \begin{bmatrix} \tau_L \\ \tau_R \end{bmatrix} + \begin{bmatrix} -\sin(\theta) \\ \cos(\theta) \\ 0 \end{bmatrix} \lambda, \tag{6}$$

Where τ_L denotes the left wheel's torque, τ_R denotes the right wheel's torque, M denotes the mass of the platform, I denotes the inertia of the platform structure and λ denotes the dynamics constraint forces.

3. STRUCTURE OF THE CONTROL METHODOLOGY DESIGN

In general, the proposed structure of the intelligent neural controller is very important because of its necessity to keep the steady-state position and orientation-tracking error to zero; therefore, the strutcture of the controller consists of three parts as shown in Figure 2:
- The evolutionary slice genetic algorithm part
- The intelligent desired path equation part
- The adaptive neural network trajectory tracking controller part

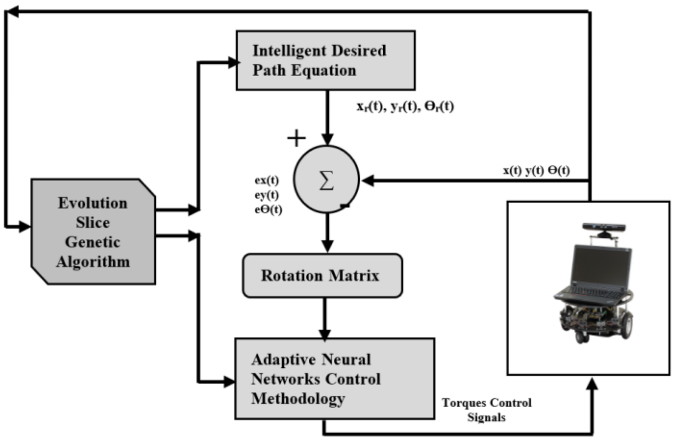

Figure 2. An intelligent neural controller structure

3.1. Evolutionary slice genetic algorithm

This part explains the use of the evolutionary slice genetic algorithm for planning and finding the reference path equation of the mobile robot cart [26]. In addition, it uses to train and tune the parameters of the neural network gains of the proposed controller to provide an improved solution of the control performance and to obtain fast and optimal torques control actions in the real-time mobile robot application. In this work, the dimensions of each evolutionary slice is proposed as in (7).

$$\left[no.of\ parameters \quad \frac{population\ size}{no.of\ swarm\ slices}\right] \tag{7}$$

The steps of the online evolutionary slice genetic algorithm for obtaining and tuning the parameters are given below:

- Step 1: initialize 8 slices randomly with a dimension based on (7)
- Step 2: calculate the individual cost function in each slice
- Step 3: find the global minimum cost function in each slice vertically
- Step 4: find the horizontal optimal solution for all slices, in this step the optimal individual for the first slices' will be obtained
- Step 5: duplicate the individuals who have minimum a horizontal cost function value
- Step 6: make a selection by using the roulette or tournament method
- Step 7: apply arithmetic crossover with 0.85 probabilities to produce individuals
- Step 8: apply the mutation with 0.01 probability
- Step 9: determine the cost function vertically then find the global minimum cost function
- Step 10: find the horizontal optimal solution for all slices
- Step 11: compare step 11 to step 4 for finding the optimal global solution
- Step 12: create new population by picking out the best individuals and this will be done by comparing the individual's cost function in the current generation with the previous one
- Step 13: steps 6 to 13 are repeated until the number of iterations is satisfied

3.2. Intelligent desired path equation part

Based on the map of the mobile robot cart, an intelligent desired path equation is used to plan and find the best road from the starting pose to the goal pose with global environment static obstacles based on the evolutionary slice genetic algorithm. The first challenge in this section is how to generate the optimal path based on the minimum smooth distance with obstacle avoidance. The generated desired path equation can be described in the following steps:

- Step 1: proposing seven points from the starting point to the target point that represent the desired path. Based on the evolutionary slice genetic algorithm described in (7), the number of parameters is equal to fourteen [x_1, y_1 to x_7, y_7] and the population size is equal to 32 and this will represent the minimum number of the random solutions to determine and fine-tune the best path parameters of the desired path. These solutions are divided into eight slices to increase the selection pressure towards the optimal solution for the used desired path in this paper as shown in Figure 3.
- Step 2: the path must avoid collision with obstacles, and the length of the road of the mobile robot must be minimized to minimum values as follows: every seven points must lie outside the obstacle region as well as the segment line between (x_i, y_i) and (x_{i+1}, y_{i+1}) must not pass through the obstacle region. Then, to find the minimum distance of the desired path, (8) in [27] is used as the fitness function for the shortest distance condition:

$$Cost_{Fun} = \sum_{i=1}^{6} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \tag{8}$$

- Step 3: the proposed fourth-degree polynomial equation to represent the optimal path equation based on the evolutionary slice genetic algorithm for finding the best values of the coefficients of the desired path equation is presented in (9):

$$y(x) = b_4x^4 + b_3x^3 + b_2x^2 + b_1x^1 + b_0, \tag{9}$$

Where $b_{4,3,2,1,0}$ are the coefficients' values.

The number of parameters is equal to five [$b_{4,3,2,1,0}$] and the population size is equal to 32 and this will represent the minimum number of the random solutions to find and tune the coefficients of the desired path equation with eight slices to increase the selection pressure towards the best solution for the used desired path equation as shown in Figure 4.

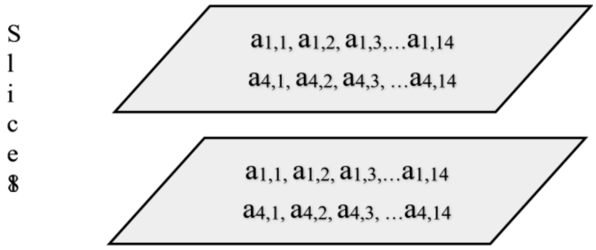

Figure 3. The evolutionary slice genetic population structure for determining seven points

Figure 4. The evolutionary slice genetic population structure for the proposed path equation

Then a cost function equation is proposed to estimate the desired path based on the seven points obtained from step 2, and this equation is given in (10).

$$CostEqu_{Fun} = \sum_{i=1}^{7} \sqrt{\left(x_{ref(i)} - x_{(i)}\right)^2 + \left(y_{ref(i)} - y_{(i)}\right)^2} \tag{10}$$

3.3. Adaptive neural network control methodology part

The adaptive neural network trajectory tracking control methodology consists of a feedforward neural network structure and it uses an evolutionary slice genetic algorithm for training the proposed neural network controller. Figure 5 illustrates the structure of the nonlinear controller, which represents a multi-input multi-output controller based on the mobile robot model which has two inputs states that descripted (left and right torques control actions) and three outputs states (*x*-position, *y*-position, and the orientation). Thus, the adaptive neural network trajectory tracking controller is necessary to follow the mobile robot platform on the proposed desired road equation and stabilize the tracking error during executing the desired path equation with free navigation in the environment. The polywog wavelet nonlinear function [28], which is shown in Figure 6, is used in the hidden nodes of the network, as given in (11).

$$O_\gamma = \left(3\left(net_\gamma\right)^2 - \left(net_\gamma\right)^4\right) e^{-0.5\left(net_\gamma\right)^2}, \tag{11}$$

Where γ denotes 1, 2, 3, 4, 5, and 6.

Therefore, the proposed structure aims to find and tune the weights of the neural network controller to attain certain abilities including a fast adaptability behaviour, a strong robustness performance, and a high dynamic performance. On the other hand, a linear function is used in the output layer of the neural network. Therefore, the signals of the x-position error and the signals of the orientation error are used to generate the neural control law of the right wheel torque for the mobile robot cart as presented in (12).

$$\tau_r(t) = O_1V_{19} + O_2V_{20} + O_3V_{21} + O_4V_{22}, \tag{12}$$

And the proposed left-wheel-torque control law for the mobile robot card uses the y-position error signals and the signal of the orientation error as expressed in (13).

$$\tau_l(t) = O_3V_{21} + O_4V_{22} + O_5V_{23} + O_6V_{24}, \tag{13}$$

Where the neural network outputs based on the polywog nonlinear function are represented by $O_1, O_2, O_3, O_4, O_5, and\ O_6$ that are given below:
The feedforward net of each node is expressed as follows:

$$net_1(kt) = V_1ex(kt) + V_2ex(kt-1) + V_3ex(kt-2) \tag{14}$$

$$net_2(kt) = V_4ex(kt) + V_5ex(kt-1) + V_6ex(kt-2) \tag{15}$$

$$net_3(kt) = V_7e\theta(kt) + V_8e\theta(kt-1) + V_9e\theta(kt-2) \tag{16}$$

$$net_4(kt) = V_{10}e\theta(kt) + V_{11}e\theta(kt-1) + V_{12}e\theta(kt-2) \tag{17}$$

$$net_5(kt) = V_{13}ey(kt) + V_{14}ey(kt-1) + V_{15}ey(kt-2) \tag{18}$$

$$net_6(kt) = V_{16}ey(kt) + V_{17}ey(kt-1) + V_{18}ey(kt-2) \tag{19}$$

Where the error input signals to the neural network are represented as $x(kt), ey(kt), and\ \theta(kt)$.

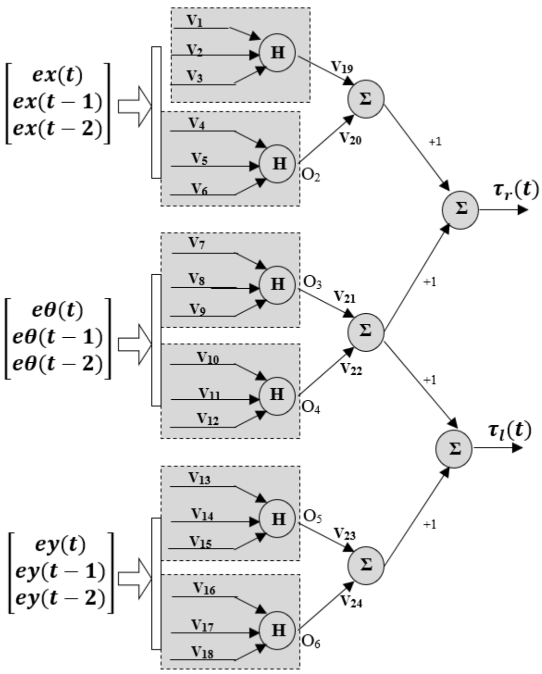

Figure 5. The proposed neural network controller structure

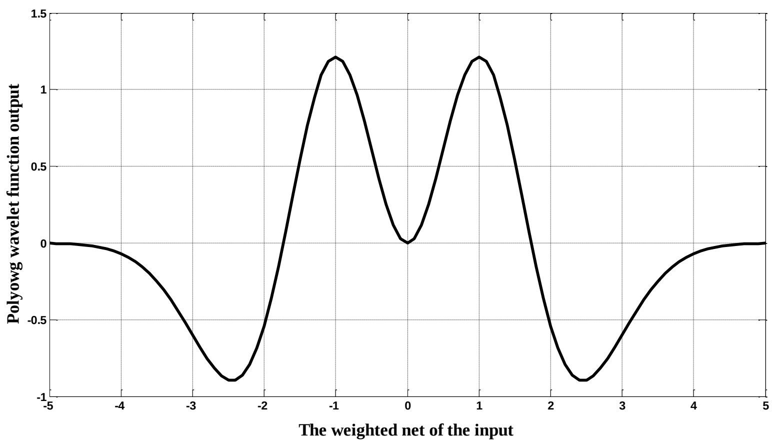

Figure 6. The polywog wavelet function

In this work, we needed 24 weight parameters and we used the evolutionary slice genetic algorithm to tune these control parameters. The number of parameters is equal to 24 [V_1 to V_{24}] and the population size of the evolutionary slice is equal to 64 representing the minimum number of the random solutions to find and tune the optimal parameters of the proposed control laws. These solutions are divided into eight slices as shown in Figure 7 to increase the selection pressure towards the optimal solution for the two neural control laws used in this paper.

We used the cost function as mean square error function as in (20) [29] to check the behaviour of the tuned neural network controller based on the evolutionary slice genetic algorithm.

$$MSE = \frac{1}{Nit}\sum_{i=1}^{Nit}[(x_{ref} - x)^2 + (y_{ref} - y)^2 + (\theta_{ref} - \theta)^2, \quad (20)$$

Where t : is denote the number of iterations.

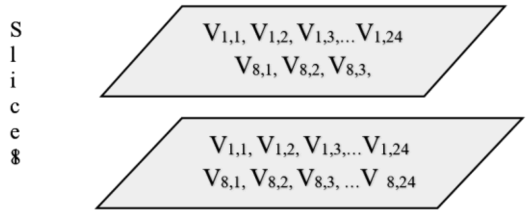

Figure 7. The evolutionary slice genetic population structure for the neural network controller

4. SIMULATION RESULTS

A mobile robot model is taken as an Eddie platform with the following specifications (platform mass is 12 kg; the inertia of the platform structure is 1.536 kg m^2; the radius of the wheel is 0.075 m and the distance between two actuators wheels is 0.39 m and these values were taken from [30]. The numerical simulation was performed using an m-file of the Matlab package for the intelligent control approach with the online evolutionary slice genetic algorithm to follow the proposed desired path equation with free navigation using a sampling time of 0.25 sec. The evolutionary slice genetic algorithm is used to generate the perfect points of the desired road then to find the intelligent desired path equation as well as to find and tune the parameters of the nonlinear neural network gains controller, which can produce the best right and left torque control actions and by reducing the tracking pose error to approximately zero. In this paper, the evolutionary slice genetic algorithm is used three times in order to confirm the proposed structure and the parameters arelisted in Table 1. After carrying out the structure of the adaptive neural network control methodology for the map as shown in Figure 8, the intelligent reference path equation is used to generate four paths using the extended stochastic gradient (ESG) algorithm to avoid the static obstacles. Path number 2 was the optimal path from these paths based on the shortest distance from the starting point to the target point, where the distance of each path is given in Table 2.

Table 1. The parameters of the ESG algorithm

Parameters of ESG	Path planning	Desired path equation	Neural network controller
Number of populations	32	32	64
Number of slices	8	8	8
Number of weights	14	5	24
Crossover probability	0.88	0.88	0.88
Mutation probability	0.01	0.01	0.01
Number of iterations	20	20	20

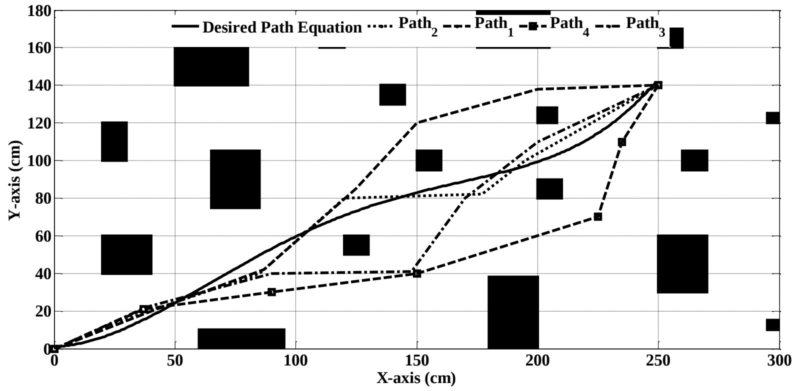

Figure 8. An optimal path that using the ESG algorithm

Table 2. The distance of each generated path

Number of path	Distance
Path_1	303.12 cm
Path_2	296.77 cm
Path_3	313.65 cm
Path_4	302.97 cm

Then we will find the desired path equation based on the 4-degrees polynomial ESG algorithm as in (9) for Path number 2 only, which will start from point (0, 0) and stop at the target point (250, 140).

$$y(x) = 1.88 \times 10^{-7}x^4 - 9.32 \times 10^{-5}x^3 + 0.013x^2 + 0.032x + 1.03 \quad (21)$$

The initial position of the mobile robot is $q(0) = [0, 10]$ and to execute the desired path equation, the proposed an adaptive neural network controller is used based on the ESG algorithm. From the simulation results, the excellent the free-navigation for the mobile robot and high tracking performance are depicted in Figure 9. Table 3 demonstrates the performance of the proposed controller compared with those of other nonlinear controllers utilized in [25], [29], [30] in terms of the minimum value of the performance index, X-axis and Y-axis maximum error values as well as the number of iterations. Figure 10 shows the online cost index mean square error (MSE) response which shows the performance improvement of the proposed neural network controller in terms of minimizing the mobile robot's position error after 50 samples. To investigate the robustness of the neural network controller, bounded-dynamics disturbances were added to the left wheel actuated and right wheel actuated of the mobile robot as in (22), which is taken from [29]. Figure 11 shows the minimum position error for the mobile robot obtained during 50 samples.

$$\tau_d(t) = 0.01\sin(2t) \quad (22)$$

Figure 12 shows the neural network controller performance in terms of generating suitable torque actions to follow the desired path equation without oscillation. The best values and the smooth responses for the wheeled mobile left and right angular velocities are shown in Figure 13.

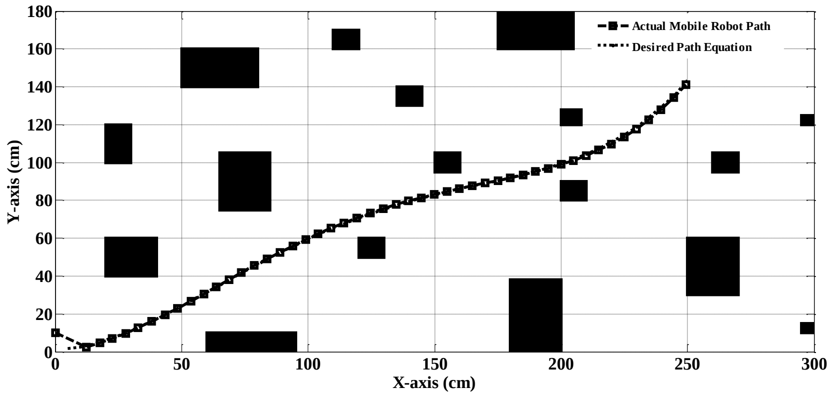

Figure 9. The mobile robot platform's actual path tracking

Table 3. Comparison results of the proposed controller and other controller types

Controllers types	Minimum value of performance index	X-axis maximum error	Y-axis maximum error	No. of iterations
[25] Nonlinear PID controller like neural networks	On-line algorithm MSE = 0.009	6 cm	2.5 cm	20
[29] Predictive neural network Controller	Off-line algorithm MSE = 0.035	5 cm	4 cm	3000 epoch
[30] Slice genetic PID controller	On-line algorithm MSE = 0.07	5.3 cm	3.3 cm	25
The proposed controller	On-line algorithm MSE = 0.0036	3.11 cm	2.82 cm	20

Another case was taken as shown in Figure 14. The mobile robot has initial position as in $q(0) = [0, 150]$ and the intelligent structure generated three suitable paths of 339.67, 307.87, and 337.53 cm, respectively so as to avoid the static obstacles. Therefore, Path 2 is the best and optimal path because it has the shortest distance. Then we calculate the 4-degrees polynomial given in (9) based on the ESG algorithm to obtain the desired path in (23):

$$y(x) = 1.8 \times 10^{-8}x^4 - 1.25 \times 10^{-5}x^3 + 0.0016x^2 - 0.61x + 158 \quad (23)$$

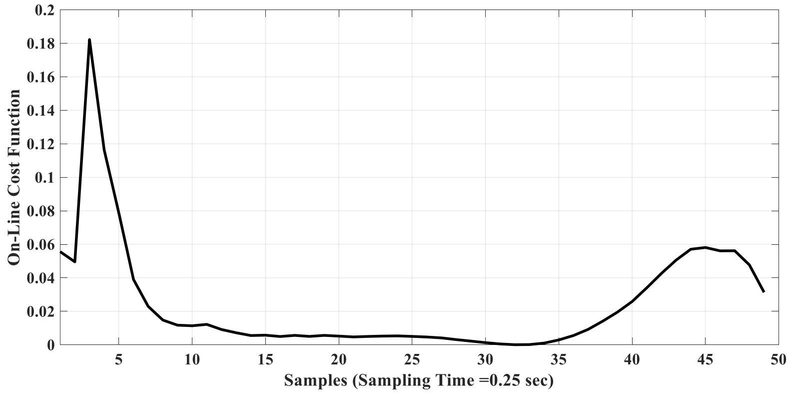

Figure 10. On-line cost function response

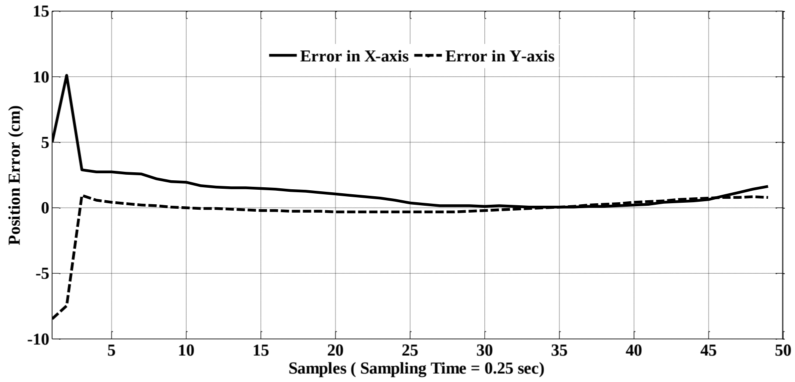

Figure 11. Position error of the mobile robot

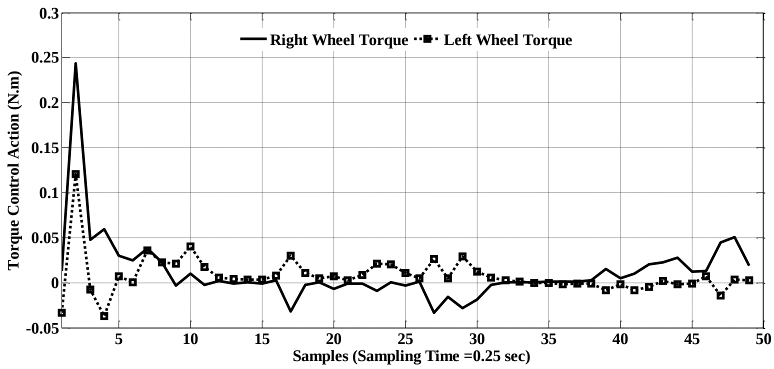

Figure 12. Torque control action responses

Figure 15 demonsates the mobile robot platform that followed the desired path equation with free navigation from the starting point (0, 160) to the goal point (250, 0) with excellent tracking performance. The cost function mean-square-error equation, which is given in (20), is used to show the performance of the proposed controller by reducing the position error for the mobile robot during 50 samples, as shown in Figure 16. Then, Figure 17 demonstrates the minimum position error for the mobile robot obtained during 50 samples. Figure 18 illustrates the suitable torque control actions responses generated from the proposed neural network controller to follow the desired path equation without oscillation. The best values and the smooth responses of the left angular velocity and right angular velocity for the wheeled mobile robot are shown in Figure 19.

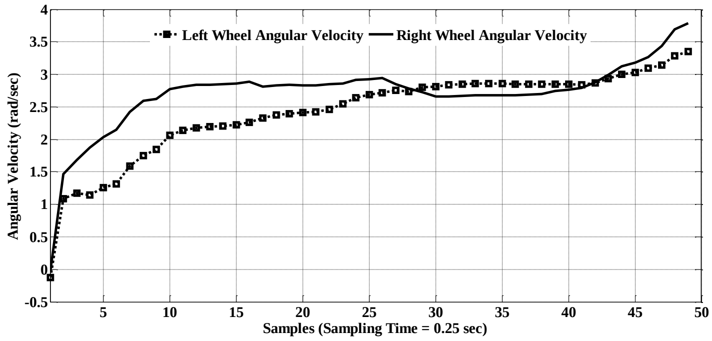

Figure 13. Angular velocities responses of the mobile robot

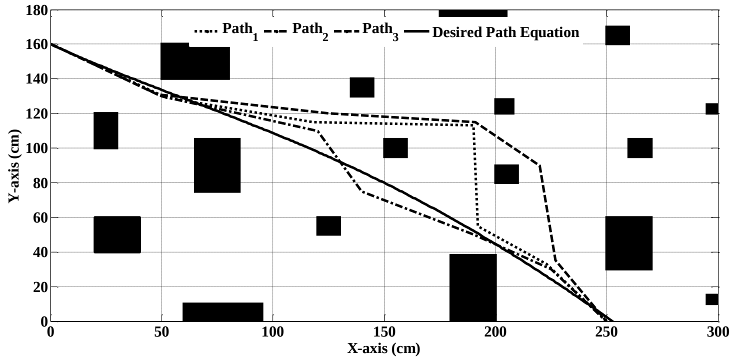

Figure 14. An optimal path that using the ESG algorithm

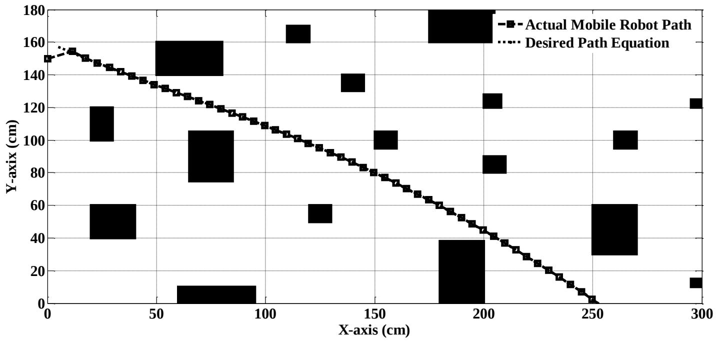

Figure 15. The mobile robot platform actual path tracking

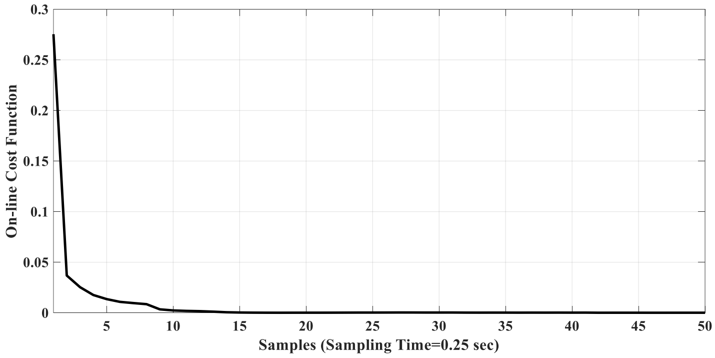

Figure 16. The online cost function response

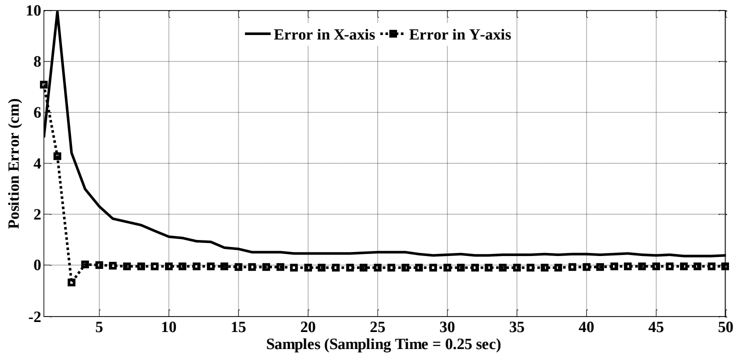

Figure 17. Position error of the mobile robot

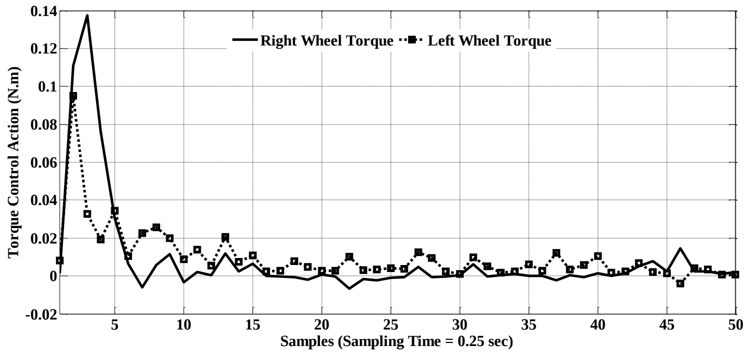

Figure 18. Torque control action response

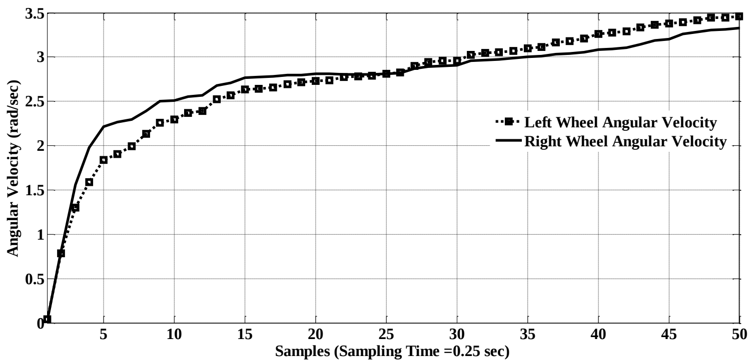

Figure 19. Angular velocities responses of the mobile robot

5. CONCLUSION

In this paper, the design and simulation of an online-tuned neural network controller for the nonlinear dynamics mobile robot model have been proposed using the Matlab package to track the desired path equation which was generated from the evolutionary slice genetic optimization algorithm. The proposed structure of the neural-network path-tracking control-tuning algorithm that combined with the optimized path-planning algorithm show that the high ability for the problem path-trajectory tracking statement for the mobile robot platform as follows: generating the best smooth reference path based on the evolutionary slice genetic algorithm; reducing the number of iterations, and the number of function evaluations during the generation of the desired path; obtaining the best value of torques actions without spikes and saturation states of the under-actuated system and the nonlinear dynamics and kinematics mobile robot platform model behaviour. The global environment of the mobile robot platform successfully tracked the path-planning, and thus, it reached the target position precisely and no oscillation behaviour happened.

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