International Conference on Green Energy & Environmental Engineering (GEEE-2018)
Proceedings of Engineering and Technology – PET
Vol.37 pp.45-49

Tracking Control of Wheeled Mobile Robot through Neural Networks

Zidani ghania[#1], Djalal Djarah[*2], Abdeslam Benmakhlouf[*3]

[#]*Department of Pharmacy, University of Batna 2*
Route de Tazoult, 05000 Batna, Algeria
[1]gh.zidani@gmail.com, g.zidani@univ-batna2.dz

[*]*LAGE, Research Laboratory, Kasdi Merbah University of Ouargla*
Route de Ghardaia, BP.511, 30000 Ouargla, Algeria
[2]d.djarah@gmail.com
[3]ab.benmakhlouf@gmail.com

***Abstract*— The problem addressed in this article, constituted the intersection of the domains of the mobile robotics and the artificial neural networks (ANNs). The navigation of a mobile robot is one of the key problems in the robotics community. A control architecture based on ANN is developed in the context of the control of a mobile robot (car type). In this work, we are interested in two approaches to ensure a tracking reference trajectory, issued by a planner. The first is an inverse model approach, concerning the second approach is a neural PD controller with adaptive coefficients, learning is done online. Numerical simulation show that the proposed controllers ensure good path tracking.**

***Keywords*— Kinematic artificial neural network, tracking trajectory, neural PD controller, adaptive coefficients, wheeled mobile robot**

I. Introduction

The techniques based on the use of artificial neural networks arouse today is growing interest in the areas of control and robotics. Processing speed, learning and adaptive capacities, but also the robustness of these approaches largely motivate many studies in the area command mobile robots [1], [2], [3]. The networks of artificial neurons are mainly procedures allowing to approach any linear function or not [4], [5]. It is this property which motivates their use for the realization of nonlinear systems of command by learning. The conception of the organ of command is preceded by a phase of modeling of the process [1], [6], [7]. The central problem in this paper is control of nonholonomic wheeled mobile robot. In this context may be mentioned the works of Barraquand and Latombe, Divelbiss and Wen, Li and Gurvits, Jacob and al., Laumond, Laumond and al. Mirtich and Canny and Sahai. In (Tanner and Kyriakopoulos, 2003) a combined kinematic/torque controller law is developed using backstepping algorithm. (Tanner and Kyriakopoulos, 2003) solve the problem of mobile robot stability using nonlinear backstepping algorithm, (Oriollo and al., 2002) with the known functions and (Fierro and Lewis, 1997) with constant parameters [8], [9].

This paper is organized as follows: Section 2 provides the kinematic model of the mobile robot of unicycle-type. The first approach, inverse model, is investigated in Section 3. In Section 4, the neural PD controller with adaptive coefficients is presented. Finally, Section 5 concludes the paper.

II. Robot Model

We restrict ourselves with the unicycle type wheeled mobile robot. We appoint by the latter, a robot actuated by two motorized independent wheels, its structure is illustrated in Fig. 1. [9], [10], [11]. Immediate Center of Rotation (ICR): wheels having the same axis of rotation, the ICR is a point on this axis, as showing in Fig. 2. Where v is the velocity of the center of surface of robot, v_l and v_r are the velocities of the left and right wheels respectively, r is the radius of each wheel, L is the distance between both wheels, x and y are the position of the mobile robot and θ is its orientation [12].

The kinematic model is given by [6].

$$\begin{aligned} \dot{x} &= v\cos\theta \\ \dot{y} &= v\sin\theta \\ \dot{\theta} &= w \end{aligned} \tag{1}$$

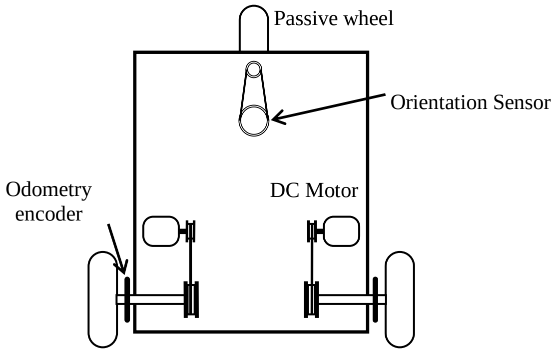

Fig. 1 Mobile robot structure

Technical tracking: The path to follow is stored in the memory as a vector of three elements (x_d , y_d , θ_d). The Fig. 2 illustrates the principle of displacement of the robot from the current point to the target point.

ISSN 2356-5608

International Conference on Green Energy & Environmental Engineering (GEEE-2018)
Proceedings of Engineering and Technology – PET
Vol.37 pp.45-49

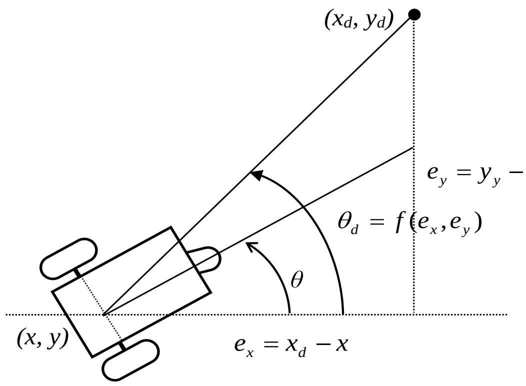

Fig. 2 Approach movement between elementary

III. Approach Model Inverse

We use this approach as first technique in our work, it requires two separate phases, one for the learning then the other one for the use of the network. During the phase of learning the network and the process are placed in parallel, a command u ($u = \Delta v$: velocity variation) is supplied in the process, so the output θ of the process will be considered as input by the network which is driven so as to find the output commands u. The network so learns an inverse model of the process, that is a function giving the applied command $u(t)$ from the current output $\theta(t)$ and possibly of its past output $\theta(t-1)$ [1], [4], [6].

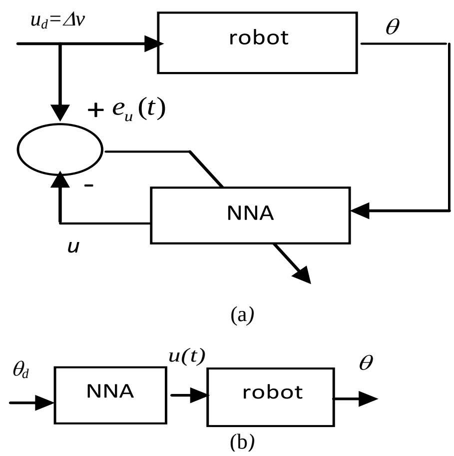

Fig. 3 (a) Learning phase (b) Use phase

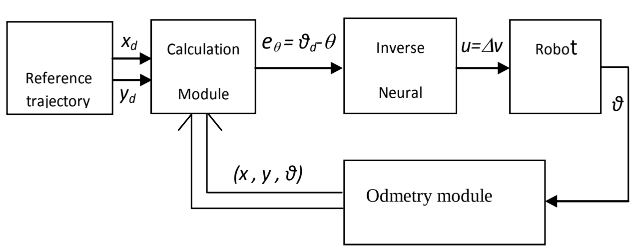

Fig. 4 Structure of neural controller

After the training phase, the system is theoretically capable of providing the control of supplying the command $u(t)$ necessary to obtain an output $\theta_d(t)$ supplied as input. The neural controller is thus placed directly in series with the commanded system, as shown in Fig. 3. During the learning phase, it is necessary to go through the process all of its possible states, or at least all the states that will be used during the control phase [1], [4], [6].

The general structure is illustrated in the previous figure.

A. Network selection

The multilayer network has a single input, two hidden layers of neurons with sigmoid activation functions and one output with linear activation function. Its learning is carried out using the algorithm of backpropagation of the gradient based on the error e=desired output-real output, the results are:

- Quadratic Average Learning Error, $\mathrm{QALE} = 9.9550\mathrm{e}{-}004$.
- Quadratic Average Learning Error Test, $\mathrm{QALT} = 9.2389\mathrm{e}{-}004$.

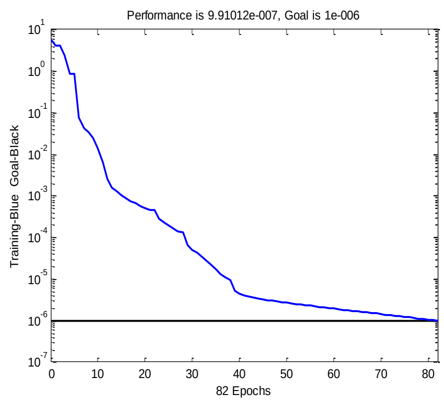

Fig. 5 Sequence learning

B. Simulation results

To show the effectiveness of the proposed controller, simulations were performed in Matlab Simulink. The examples are for the tracking of an echelon path, a square path and sinusoidal path, the results are illustrated in Figs. 6–9.

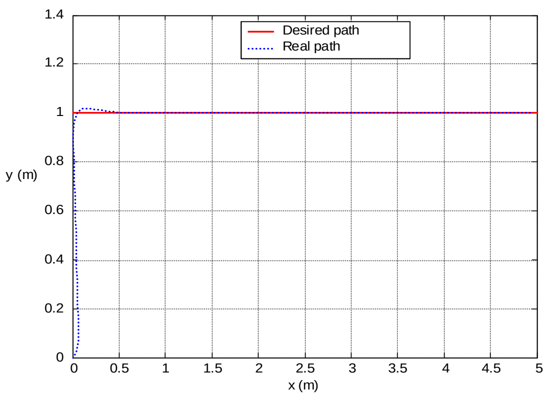

Fig.6 Echelon trajectory

ISSN 2356-5608

International Conference on Green Energy & Environmental Engineering (GEEE-2018)
Proceedings of Engineering and Technology – PET
Vol.37 pp.45-49

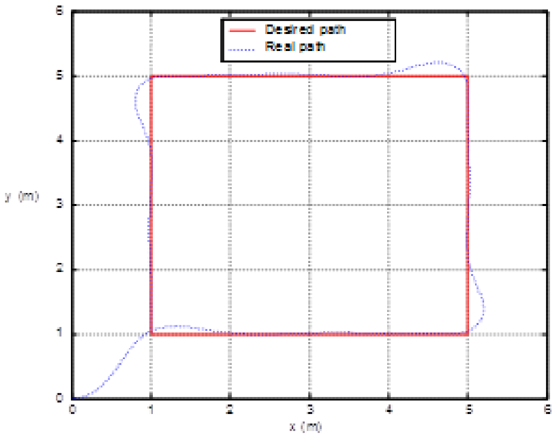

Fig. 7 Square trajectory

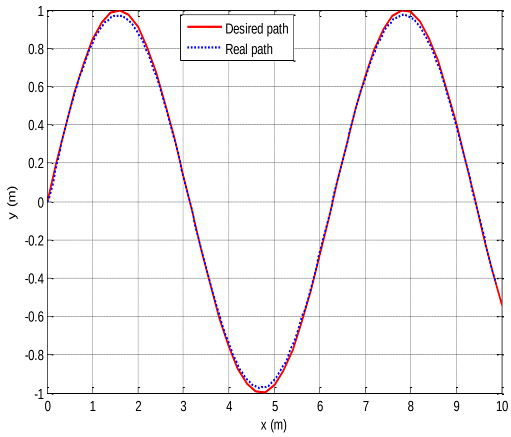

Fig. 8 Sinusoidal trajectory

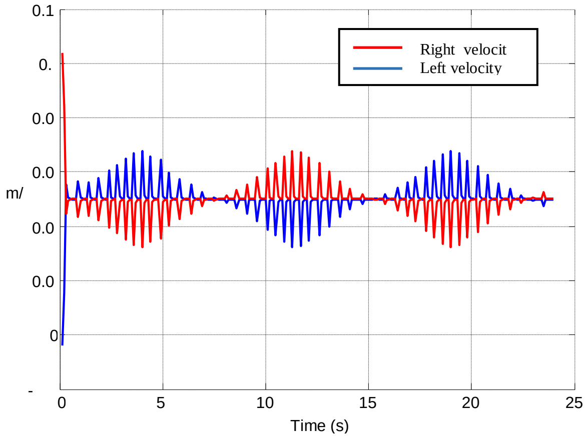

Fig. 9 Velocities of right and left motors

The first approach, inverse model, gave good performances. It is noted that it ensures the flexibility of movements, with the observation of a small tracking error value.

IV. NEURAL PD WITH ADAPTIVE COEFFICIENTS

The PD controller Proportional Diverter is the combination of two modules, the proportional P module that provides the function of basic setting and module diverter D which improves stability and accelerates the setting. This regulator supplies a control signal proportional to the deviation and its derivative [1], [4], [7].

By exploiting the learning ability of neural networks, we develop a system to estimate these two parameters.

A. *Auto adjusting the parameters of a PD*

In this approach, the neural network will be used to adjust k_p and k_d, parameters of the conventional controller in PD the same way as when they are adjusted by a human operator [1], [4], [7].

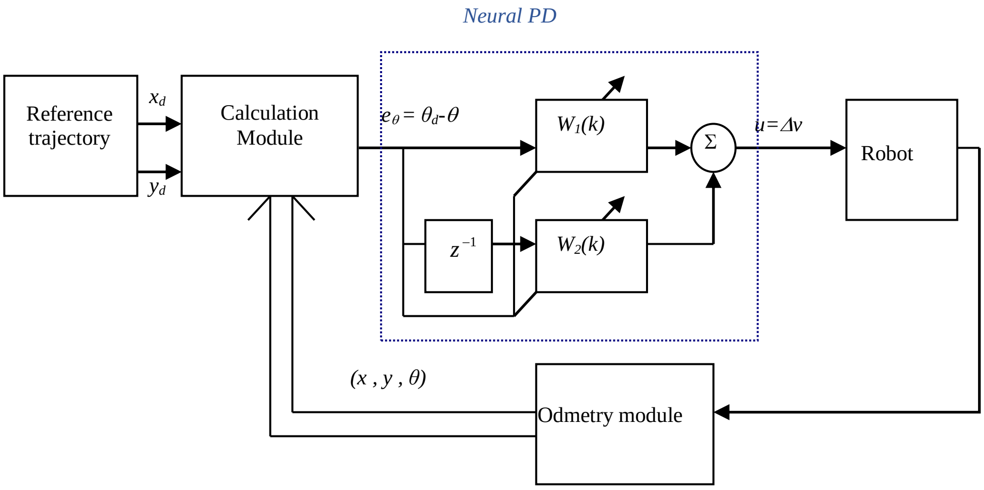

Fig. 10 Structure of neural PD control

ISSN 2356-5608

The basic structure for estimating these parameters is detailed in the followings figure.

Gains k_p and k_d, proportional and derivative gains are determined in real time by the neural network. The network input vector has two components. The error and its derivative. Weights, $w_1(t)$ and $w_2(t)$ weighted the error input and the input of the error derivative are associated to the factors P and D, respectively.

The error of learning is $e = \theta_d - \theta$ and the algorithm of update of the weights is that of modified Widrow-Hoff. A learning is stopped when the system arrives to follow the trajectory planned and the according to the criteria originally set. The network behaves as an adaptive PD. If significant changes occur in the system to control, learning can take back.

B. Simulation results

To test this controller on the tracking performance, we applied this approach to different trajectories and for different values of l_r and m, learning coefficient and coefficient of term time, respectively, representing parameters in the neural network.

For $l_r = 00001$ and $m = 0.8$

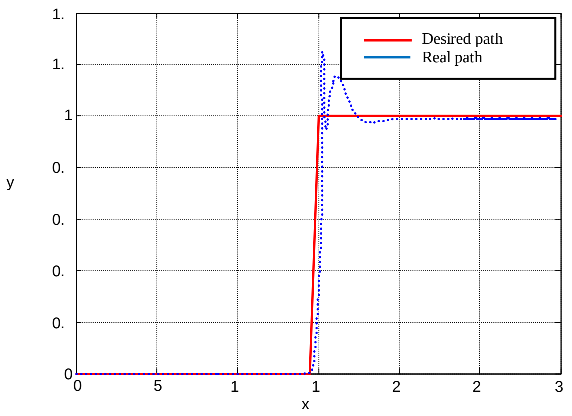

Fig. 11 Echelon trajectory

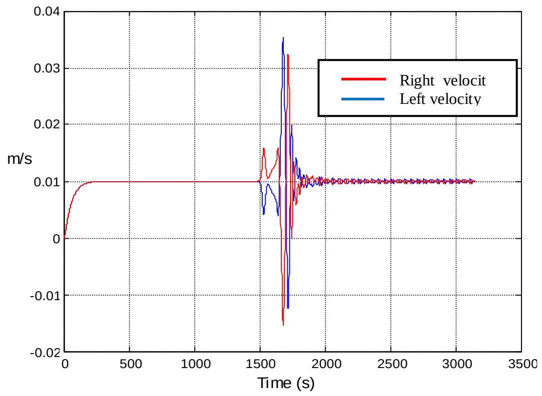

Fig. 12 Velocities of right and left motors

For $l_r = 0.000009$ and $m = 0.9$

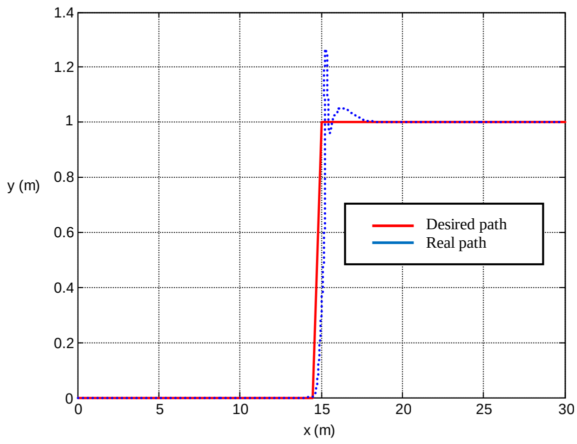

Fig. 13 Echelon trajectory

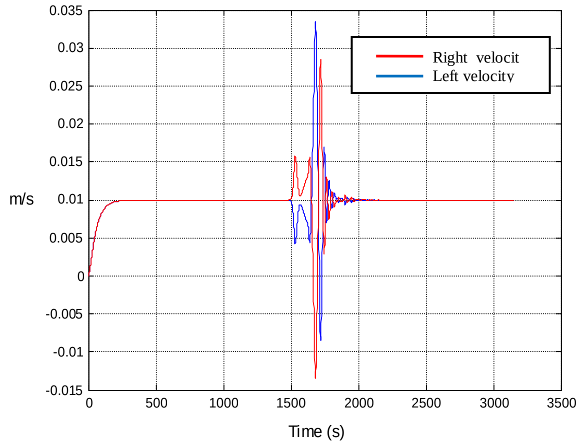

Fig. 14 Velocities of right and left motors

For $l_r = 0.00002$ and $m = 0.9$

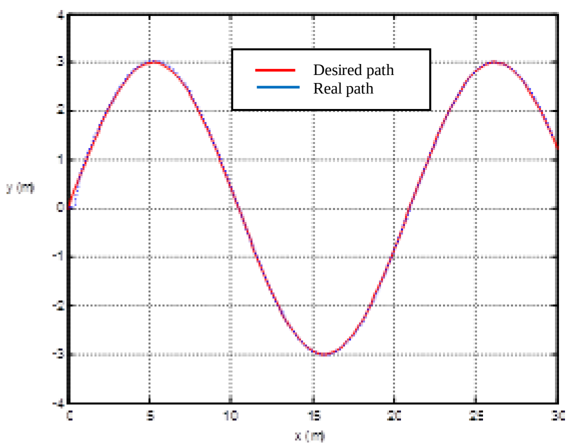

Fig. 15 Sinusoidal trajectory

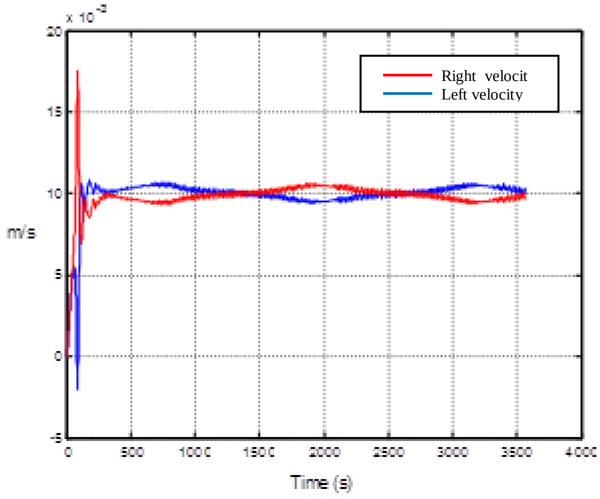

Fig.16 Velocities of right and left motors

We Note that with this neural controller "PD to adaptive learning coefficient is done online, we first applied for a echelon, sudden change of trajectory to determine the stability and accuracy then for tracking of a sinusoidal trajectory, we observe that the change l_r and m, learning coefficient and coefficient of the term time respectively, has a large influence on the results. It is noted that the use of the latter approach gives satisfactory results.

The purpose of this approach is to design an adaptive PI controller and exploit the simplicity of setting Adaline networks.

V. Conclusions

In this paper a control approach using multilayer artificial neural networks is realized. A second approach uses the principle of a PD controller and use a network to adapt the proportional and derivator parameters, Learning is done online. Several tests validations of these approaches are tested, the results are acceptable in particular the response of the system following the application of a echelon.

Neural networks are a credible means for the control of mobile robots and determination of PD parameters.

References

[1] I. Rivals, Modélisation et commande de processus par réseaux de neurones : application au pilotage d'un véhicule autonome, Paris VI, Doctorart thesis, University of Pierre and Marie Curie, 1995,.

[2] E. Beaudry, Planification en intelligence artificielle pour la robotique mobile, Doctorart thesis, University of Sherbrooke, Québec,, 2006.

[3] O. Mohareri, R. Dhaouadi and A. B. Rad, Indirect adaptive tracking control of a nonholonomic mobile robot via neural networks. Neurocomputing, pp 54-66. ISSN 0925-2312. DOI: 10.1016/j.neucom.2011.06.035, 2012, vol. 88.

[4] L. Personnaz,. I. Rivals, Réseaux de neurones formels pour la modélisation, la commande et la classification, Ed. CNRS, Paris, 2003.

[5] H. Zeng-Guang, A. M. ZOU, L. Cheng, and M. Tan, Adaptive control of an electrically driven nonholonomic mobile robot via bbackstepping and fuzzy approach, IEEE Transactions on Control Systems Technology, pp. 803-815. ISSN 1063-6536. DOI: 10.1109/TCST.2009.2012516, 2009, vol. 17.

[6] Z. Ryad, Contribution à la surveillance des systèmes de production à l'aide des réseaux de neurones dynamiques: Application à la e-maintenance, Doctorat thesis, L'UFR des Sciences et Techniques de l'Université de Franche-Comté, France, 2003.

[7] M. Zerikat, M. Bendjebbar and N. Benouzza, Dynamic Fuzzy-Neural Network Controller for Induction Motor Drive, Proceedings of world academy of science, engineering and technology, pp. 1577–1582. ISSN 1307-6884. DOI: 10.15598/aeee.v12i6.1255, 2005, vol 10.

[8] F. Giamarchi, Petits robots mobiles, ISBN 978-2-10-049514-6, France: Ed. Dunod, 2006.

[9] V. Jasmin, B. Lacevic and N. Osmic, Nonlinear motion control of mobile robot dynamic model, University of Sarajevo Bosnia and Herzegovina, pp 529-550, Croatia

[10] B. Bayle, Robotique mobile. National School of Physics of Strasbourg, 2004–2005.

[11] A. El Hajjaji, S. Bentalba. Fuzzy path tracking control for automatic steering of vehicles, Robotics and Autonomous Systems 43, pp. 203-213. DOI:10.1016/S0921-8890(03)00003-4, 2003,.

[12] G. Zidani,, S. Drid, L. Chrifi-Allaoui and D. Arar. Nonlinear Tracking of a Wheeled mobile robot. The 15th international conference on sciences and techniques of automatic control & computer engineering.. ISBN: 978-1-4799-5907-5. DOI 10.1109/STA.2014.7086727, Tunisia, 2014.

Acknowledgment

The motor and robot parameters are as follows

Resistance	$R = 1\Omega$
Inductance	$L = 1.5H$
friction	$f = 0.1$
Inertia	$J = 0.01Kgm^2$
Counter electromotive force constant	$K = 0.01$
torque constant	$K = 0.01$
Radius of wheel	$r = 0.1m$
Width of the robot	$L = 1m$

ISSN 2356-5608