Mobile robot heading adjustment using radial basis function neural networks controller and reinforcement learning

E. Ilhan Konukseven
Middle East Technical University

Mobile Robot Heading Adjustment Using Radial Basis Function Neural Networks Controller and Reinforcement Learning

GÖKHAN BAYAR[1], E. İLHAN KONUKSEVEN[1], A. BUĞRA KOKU[1]
[1]Mechanical Engineering Department
Middle East Technical University
Orta Doğu Teknik Üniversitesi, 06531, Balgat
Ankara / TURKEY

Abstract: - This paper proposes radial basis function neural networks approach to the solution of a mobile robot heading adjustment using reinforcement learning. In order to control the heading of the mobile robot, the neural networks control system have been constructed and implemented. Neural controller has been charged to enhance the control system by adding some degrees of strength. It has been achieved that neural networks system can learn the relationship between the desired directional heading and the error position of the mobile robot. The radial basis function neural networks have been trained via reinforcement learning function approach. The performance of the proposed controller and learning system has been investigated by using mobile robot that consists of a two driving wheels mounted on the same axis, and a front passive wheel for balance.

Key-Words: - Mobile robot, neural networks, radial basis function, reinforcement learning

1 Introduction

Desired heading adjustment and trajectory tracking problems for the mobile robots have been studied by the researchers over the last decade [1-3]. It is seen from the related researches that extensive works have not been given effort about the robustness of the control of the mobile robot heading adjustment [1-5]. Although most of the studies have been conducted on solving the problem of motion under nonholomonic constraints using the kinematic model, there is limited number of studies related to the problem of kinematic controller and the dynamics of the mobile robot [6, 7].

Another intensive area of research is neural networks advised for the applications consisting of intelligent and adaptive control [8, 9]. Lately, in order to control the nonlinear dynamics of the mobile robots, use of neural networks has been performed [10, 11]. These works have been achieved by leading of the most important capabilities of neural networks; ability to learn and good performance for the approximation of nonlinear functions [12, 13].

Traditionally the learning capability of a multilayer neural networks has been applied to the navigation problem in mobile robot applications [15, 16]. In these approaches the neural networks are trained in a preliminary off-line learning phase with navigation pattern behaviors [7].

Often, the control systems, which are used on the mobile robot applications, utilize multilayer neural networks. However, the system to be controlled cannot be introduced some degree of robustness by using the multilayer neural networks based controllers and the highly nonlinearity case occurring in the model parameters also cannot be avoided [14].

Ever so often, mobile robots are constructed with simple control schemes such as PID control. However, the capability for manual regulations of the parameters of the controller is to be deficient in order to compensate for disturbances acting upon the mobile robot such as deriving the mathematical model of the system with the ground interaction (i.e., including friction forces or observing differences of the inertial forces between one the modeled and the one obtained from the real case). After obtaining the proper system controller parameters manually, the controller adapted to the system is to be work well generally for small fluctuations. In the case of encountering with large fluctuations, however, the controller parameters have to be continuously adjusted according to the chancing of operating conditions. Since some parameters of the mobile robot's dynamics are going to show variety such as desired speed, terrain characteristics, motor voltage and current flow, tire inflation etc., the parameters of the controller should be regulated continuously. Using fixed or manually changed controller parameters is going to bring a load to the control system. Also these parameters may be inadequate. Consequently the undesired regulation may cause some unexpected cases on the system. So as to avoid these undesirable occasions, the control system should modify its parameters automatically under varying conditions.

In this paper, radial basis function neural networks approach has been chosen since multilayer neural networks can show highly nonlinear situation in the parameters. Using radial basis function neural networks, it will have a chance for avoiding from this situation of multilayer neural networks. In order to achieve the tracking of the desired heading of mobile robot, a reinforcement learning strategy has been developed. Radial basis function neural networks and the proposed learning strategy have been tuned. By the way the control system is to be introduced some degree of robustness.

2 Model of Mobile Robot

The mobile robot considered here is shown in Figure 1. It has two driving wheels mounted on the same axis, and a front passive wheel for balance. The two driving wheels are controlled independently by DC motors. The dynamic property of the mobile robot and the kinematic relationships are given by the following equations [17, 18].

$$I\ddot{\phi} = f_r 2b - f_l 2b \tag{1}$$

$$m\dot{v} = f_r + f_l \tag{2}$$

$$I_t\ddot{\theta}_i + c\dot{\theta}_i = pu_i - rf_i \quad (i = r, l) \tag{3}$$

$$r\dot{\theta}_r = v + 2b\dot{\phi} \tag{4}$$

$$r\dot{\theta}_l = v - 2b\dot{\phi} \tag{5}$$

where m is the mass of the mobile robot. f_l and f_r are the driving forces for the left and right wheels. $2b$ is the distance between left and right wheels. ϕ is the orientation of robot according to the absolute coordinate system OXY. I and I_t are the moment of inertia of the mobile robot and wheel, respectively. r is radius of the wheel. u is the driving input. θ is the rotational angle of the wheel. v is the velocity of the mobile robot.

Using the equation sets given above, one can define the state variables for the mobile robot as;

$$x = \left[v \ \phi \ \dot{\phi}\right]^T \tag{6}$$

The manipulated input and output variables are constructed as;

$$u = \left[u_r \ u_l\right]^T, \ y = \left[v \ \phi\right]^T \tag{7}$$

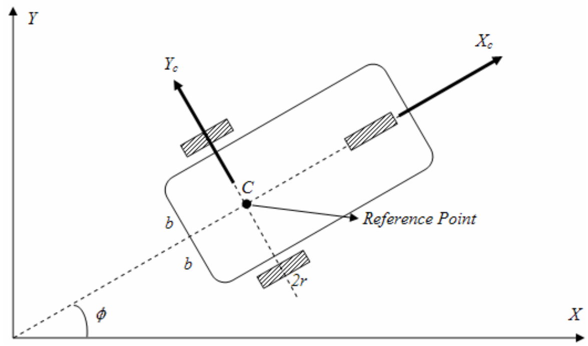

Fig.1. Model of the mobile robot.

State space representation of the system is given as;

$$\begin{pmatrix} \dot{v} \\ \dot{\phi} \\ \ddot{\phi} \end{pmatrix} = \begin{pmatrix} a_1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & a_2 \end{pmatrix} \begin{pmatrix} v \\ \phi \\ \dot{\phi} \end{pmatrix} + \begin{pmatrix} b_1 & b_1 \\ 0 & 0 \\ b & -b_2 \end{pmatrix} \begin{pmatrix} u_r \\ u_l \end{pmatrix} \tag{8}$$

where

$$a_1 = -\frac{2c}{mr^2 + 2I_t}, \quad a_2 = -\frac{4cb^2}{Ir^2 + 2I_t(2b)^2}$$

$$b_1 = \frac{pr}{mr^2 + 2I_t}, \quad b_2 = -\frac{2prb}{Ir^2 + 4I_t b^2}$$

Equation (8) can be represented as ;

$$\begin{aligned} \dot{x} &= Ax + Bu \\ Y &= Cx \end{aligned} \tag{9}$$

The governing equation for the mobile robot's motion can be given as;

$$\dot{v} = a_1 v + b_1\left(u_r + u_l\right) \tag{10}$$

$$\ddot{\phi} = a_2\dot{\phi} + b_2\left(u_r - u_l\right) \tag{11}$$

$$\ddot{v} = a_1\dot{v} + b_1\left(\dot{u}_r + \dot{u}_l\right) \Rightarrow \dot{u}_r = \frac{\ddot{v} - a_1\dot{v}}{b_1} - \dot{u}_l \tag{12}$$

3 Control System of Mobile Robot

The proposed radial basis function neural networks control system is given in Figure 2.

The control system consists of the model, radial basis function neural networks controller, reference desired orientation generator, learning mechanism structure, controller parameters regulator and a reference model for generating the reinforcement learning signal.

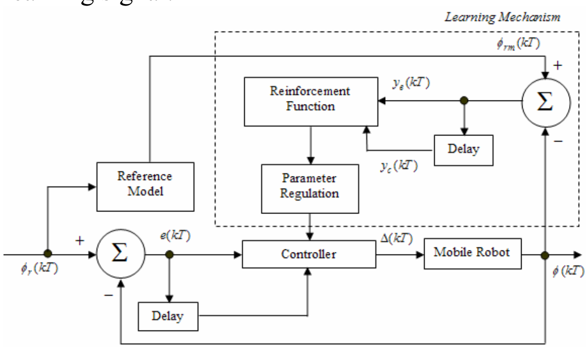

Fig. 2. Mobile robot motion control system [19].

4 Construction of Radial Basis Function Neural Networks

A radial basis function neural networks is shown in Figure 3. x_i is the inputs ($i=1,2,\ldots,n$) and $y=F(x)$ is the output. Here whole radial basis function neural networks in process are denoted by $F(x)$.

$$y = F(x,\theta) = \sum_{i=1}^{n_R} \zeta_i \Gamma_i(x) \qquad (13)$$

The input to the receptive field unit is x and its output is shown by $\Gamma_i(x)$. The receptive field unit has a strength, ξ_i.

Let the receptive field unit be

$$\Gamma_i(x) = e^{\left(-\frac{\left|x-c^i\right|^2}{\left(\sigma^i\right)^2}\right)} \qquad (14)$$

where σ^i is Gauss spread function.

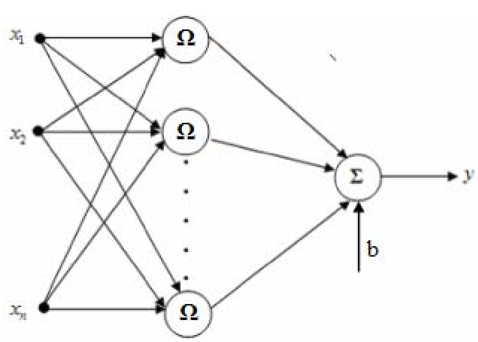

Fig. 3. Radial basis function neural networks model.

The parameters of the neural networks should be regulated. These regulations are performed in order to obtain better responses. The regulation conducted on the structure of the neural networks is to be related with the continuously modifying of the strengths of the receptive field units. It is assumed that the strengths of the receptive field units have been regulated by the approach;

$$\xi_i(kT+1) = \xi_i(kT) + \lambda(kT+1)\Gamma_i(kT) \qquad (15)$$

where $\Gamma_i(kT)$ is the output of the i^{th} receptive field unit, $\lambda(kT)$ is the reinforcement signal.

5 Design of Reinforcement Function for Employing the Learning Mechanism

In order to obtain good response from the system that is controlled, reinforcement learning strategy is one of the preferred adaptive control approaches. In this study, a proper reinforcement learning procedure for the radial basis function neural networks has been developed. For this procedure, the basis of the mechanism regulates the neural networks by reinforcement signal generated via reinforcement function, λ. The procedure guarantees that the controller tries to learn with evaluating the generated plant inputs and the measured plant output (plant denotes the mathematical model of the mobile robot). The reinforcement learning structure checks whether the action fails or not.

After the action is performed, the response is evaluated by the target. In case of approaching the target, the strengths of the learning mechanism is given weight. If result is the direct contrary, the strength of the signal is to be weakened. While the controller evaluates the relationships between the generated plant inputs and the measured plant outputs, it efforts to learn how the system behaves, how the system is detained into the range of desired field and how the action reaches the target.

The reinforcement function, which generates the reinforcement signal, fulfills its mission using the data collected from the system. In order to create a reinforcement function generally a reference model is used [19,20,21]. The reference model is constructed for organizing the performance of the system. The model tries to generate signal which corresponds the output of the plant. Reference model can be selected by the designer as a first, second or higher order transfer function. In this work, reference model has been selected as a first order transfer function for obtaining a smooth response for changes in the desired mobile robot motion (Equation 16);

$$G(s) = \frac{b}{s+a} \tag{16}$$

Reference model can be given in discrete form as;

$$y_{rm}(kT) = \frac{1}{aT+2}\begin{pmatrix}(2-aT)y_{rm}(kT-T)+...\\ \xi T\left(R(kT)+R(kT-T)\right)\end{pmatrix} \tag{17}$$

y_{rm} and R denote input and output of the reference model in discrete form, respectively. After giving reference input, the difference between the response of the system and the response of the reference model produces the error. The error form is given as;

$$y_{error}(kT) = y_{rm}(kT) - y(kT) \tag{18}$$

In order to characterize the performance of the system, the first derivative has been used for obtaining the error between the reference model output and plant output.

$$y_p(kT) = \frac{y_{error}(kT) - y_{error}(kT-T)}{T} \tag{19}$$

Let choose the reinforcement function as [19,20,21];

$$\lambda\left(y_{error}, y_p\right) = \hbar\left(-\hbar_{error} y_{error} - \hbar_p y_c\right) \tag{20}$$

where $\hbar$, $\hbar_{error}$, $\hbar_p$ are the design parameters;

6 Simulation Results

In order to check the reliability of the radial basis function neural networks controller and learning mechanism developed for the mobile robot heading adjustment control, a set of demonstrations has been constructed. Desired orientation for the mobile robot has been tried to track by using the developed controller. The overall system has been designed and implemented using Matlab environment.

The physical parameters of the mobile robot are $I=10kg.m^2$, $M=200kg$, $b=0.15m$, $I_t=0.005kg.m^2$, $c=0.05kg/s$, $p=g$, $r=0.1m$. Moreover, the reference heading velocity, v, is $1m/s$ [17, 18].

The results of position, orientation, linear and angular velocities have been simulated. Desired and the actual orientation obtained using the neural networks controller with the parameters of the reference function (*a= b=0.02*) is given in Figure 4. In Figure 5, the parameters are changed to *a=b=0.0667*. Using two different set of parameters, the model has been exposed to the desired orientation profile. As seen from Figure 5, with the second parameter set, control system, which is continuously modified by neural network, tries to track the desired profile.

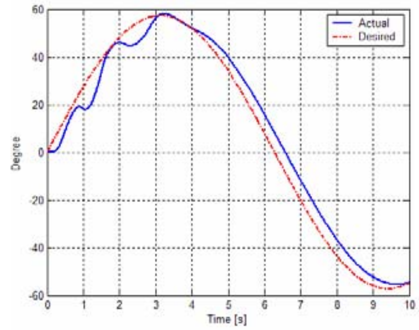

Fig. 4. Orientation of the mobile robot with the parameters of the reference function *a=b=0.02.*

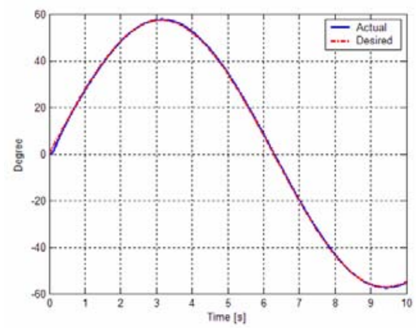

Fig. 5. Orientation of the mobile robot with the parameters of the reference function *a=b=0.0667.*

In Figure 6, output of the proposed radial basis function neural networks controller is given. Neural controller tries to keep the system at the desired orientation; meanwhile, the learning mechanism endeavors to adapt the controller to the coming portion of the desired trajectory.

As seen from Figure 7, orientation error carried out from the actual and desired headings has been given. Control system enhances itself via improved signal generated by learning system. The improvement in the control system can be recognized.

A basis controller to be adjusted has been constructed for employing the reinforcement learning mechanism. When reinforcement signal is very small, it is made to zero. Hence, reinforcement signal can not make a response to small fluctuations during regulating the neural controller. By this way the learning mechanism is only charged when the regulation is required.

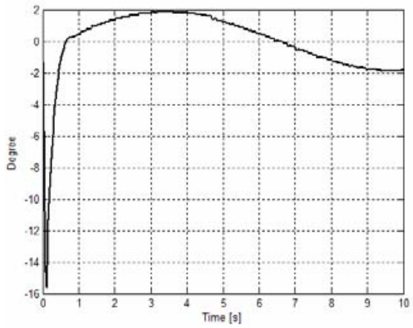

Fig. 6. Radial basis function neural networks controller output.

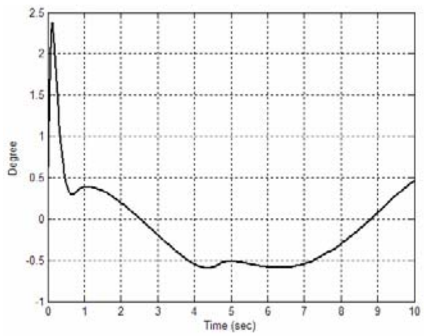

Fig. 7. Orientation error between actual and desired one.

The position of the mobile robot in the global frame *{XOY}* can be defined by the position of the mass center of the mobile robot system, denoted by *C*, which is the center of mobile robot, and the angle between robot local frame *{XcCYc}* and global frame.

Kinematic equations of the mobile robot are;

	$$\begin{pmatrix} \dot{x} \\ \dot{y} \\ \dot{\phi} \end{pmatrix} = \begin{pmatrix} \cos\phi & 0 \\ \sin\phi & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} v \\ \omega \end{pmatrix}$$	(21)
	$$\begin{pmatrix} v \\ \omega \end{pmatrix} = \begin{pmatrix} r & 0 \\ \frac{r}{2b} & -\frac{r}{2b} \end{pmatrix} \begin{pmatrix} v_r \\ v_l \end{pmatrix}$$	(22)

where x and y are coordinates of the center of the mobile robot, v and w are linear and angular velocities of the robot, v_r and v_l are velocities of right and left wheels.

Position of the mobile robot in the global frame is given in Figure 8. Desired response obtained by the reference orientation trajectory, and the actual response obtained by the system controlled, have been get in quick succession. Time histories of X and Y coordinates are exhibited in Figure 9 and 10.

In Figure 11, time histories of X and Y coordinate errors are given.

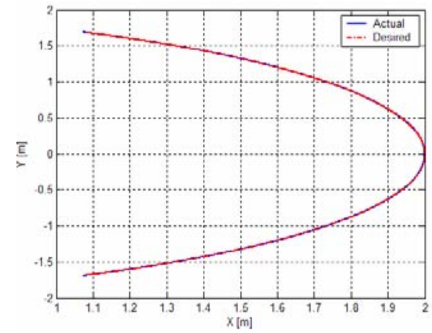

Fig. 8. Position of the mobile robot in the global frame.

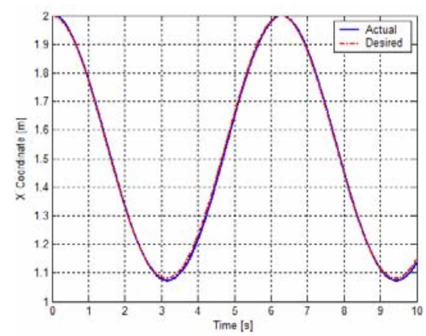

Fig. 9. Time history of X-Coordinate.

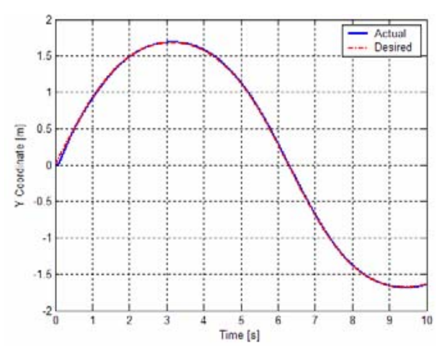

Fig. 10. Time history of *Y* Coordinate.

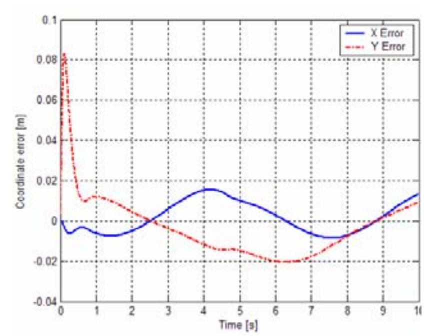

Fig. 11. *X* and *Y* coordinate errors.

7 Conclusion

In this paper, design of radial basis function neural networks controller and proper reinforcement learning mechanism for tracking of desired heading profile of the mobile robot have been presented. For the modeling and simulation sections, both dynamic and kinematic models of the mobile robot have been utilized. The system has been exposed to a desired orientation trajectory. The proposed neural controller has enhanced itself with the cooperation of learning mechanism to track this trajectory. Simulation results demonstrate the effectiveness of the proposed neural control system and the learning mechanism.

References:

[1] M. L. Corradini, G. Ippoliti, S. Longhi and S. Michelini, Neural Networks Inverse Model Approach for the Tracking Problem of Mobile Robot, *Proc. of RAAD 2000, Maribor, Slovenia*, 2000, pp. 17-22.

[2] P. Jiang and H. Nijmeijer, Tracking Control of Mobile Robots: A Case Study in Backstepping, *Automatica*, Vol.33, 1997, pp. 1393-1399.

[3] C. Canudas de Wit, H. Khennouf, C. Samson and 0. J. Sordalen, Nonlinear Control Design for Mobile Robots, *Recent Trends in Mobile Robots*, World Scientific, Vol.11, pp. 121-156.

[4] J. M. Yang and J.H. Kim, Sliding Mode Motion Control of Nonholonomic Mobile Robots, *IEEE Control Systems*, Vol.19(2), 1999, pp. 15-23.

[5] R. Fierro and F. L. Lewis, Robust Practical Point Stabilization of a Nonholonomic Robot Using Neural Networks, *Journal of Intelligent and Robotic Systems*, Vol.20, 1997, pp. 295-317.

[6] C. Samson, Velocity and Torque Feedback Control of a Nonholonomic Cart, *Lecture Notes in Control and Information Science*, C. Canudas de Wit, Ed. Berlin, Germany: Springer-Verlag, 1991, pp. 125–151.

[7] R. Fierro, F. L. Lewis, Control of a Nonholomonic Mobile Robot Using Neural Networks, *IEEE Transactions on Neural Network*, Vol.9, No.4, 1998, pp. 589-600.

[8] A. G. Barto, Neuronlike Adaptive Elements that can Solve Difficult Learning Control Problems, *IEEE Transactions on Systems, Man and Cybernetics*, Vol.13, 1983, pp. 834-846.

[9] Z. Hendzel, Adaptive Critic Neural Networks for Motion Control of Wheeled Mobile Robot, *Nonlinear Dynamics*, Vol.50, No.4, 2007, pp. 849-855.

[10] K. S. Narenda, K. Pathasarathy, Identification and Control of Dynamic Systems Using Neural Network, *IEEE Transactions on Neural Networks*, Vol.1, No.1, 1990, pp. 4-27.

[11] D. Nguyen, B. Widrow, Neural Networks for Self-Learning Control Systems, *IEEE Control Systems Magazine*, Vol.10, No.1, 1990, pp. 18-23.

[12] K. Hornik, M. Stinchombe, H. White, Universal Approximation of an Unknown Mapping and Its Derivatives Using Multilayer Feedforward Networks, *Neural Networks*, Vol.3, 1990.

[13] J. Velagic, N. Osmic, B. Lacevic, Neural Network Controller for Mobile Robot Motion Control, *Proceedings of World Academy of Science*, Eng. And Tech. Vol.30, 2008, pp. 810-815.

[14] A. D'Amico, G. Ippoliti, S. Longhi, A Radial Basis Function Networks Approach for the Tracking Problem of Mobile Robots, *IEEE/ASME Int. Conference on Advanced Intelligent Mechatronics Proceedings*, 2001, pp. 498-503.

[15] K. Berns, R. Dillman, and R. Hofstetter, An application of a backpropagation network for the control of a tracking behavior, *in Proc. IEEE Int. Conf. Robot. Automat.*, Vol.3, Sacramento, CA, 1991, pp. 2426–2431.

[16] S. Nagata, M. Sekiguchi, and K. Asakawa, Mobile robot control by a structured hierarchical neural network, *IEEE Contr. Syst.*, 1990, pp. 69-76.

[17] K. Watanabe, J. Tang, M. Nakamura, S. Koga and T. Fukuda, Mobile Robot Control Using Fuzzy-Gaussian Neural Networks, *Proc. of IEEE/RSJ International Conf. on Robots and System*, 1993, pp. 919-925.

[18] J. Peng, Y. Wang, W. Sun, Trajectory Tracking Control for Mobile Robot Using Recurrent Fuzzy Cerebellar Model Articulation Controller, *Neural Information Processing*, Vol.11, No.1, 2007, pp. 15-23.

[19] K. M. Passino, Biomimicry for Optimization, Control and Automation, *Springer-Verlag* London, 2005.

[20] D. M. Skapura, Building Neural Networks, *ACM Press*, New York, USA, 1996.

[21] M. H. Hassoun, Fundamentals of Artificial Neural Networks, *MIT Press*, Londan, England, 1995.