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MOBILE ROBOT CONTROL BASED ON NEURAL NETWORK AND FEEDBACK ERROR LEARNING APPROACH

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Abstract- Neural network based controller is used for controlling a mobile robot system. Feedback error learning (FEL) can be regarded as a hybrid control to guarantee stability of control approach. This paper presents simulation of a mobile robot system controlled by a FEL neural network and PD controllers. This feedback error-learning controller benefits from both classic and adaptive controller properties. The simulation results demonstrate that this method is more feasible and effective for mobile robot system control.

Keywords: Feedback Error Learning, Mobile Robot, Neural Network, PD.

I. INTRODUCTION

In past decades, field of trajectory tracking control of mobile robot has been the focus of active research for both theoretic research and practical applications. During recent years, attention to mobile robots has grown considerably because of Mobile robots are dramatically used in industry, in service robotics, for domestic needs (vacuum cleaners, lawn mowers, pets), in difficult to access or dangerous areas (space, army, nuclear-waste cleaning, mining, forestry, agriculture) and also for entertainment (robotic wars, robot soccer), etc. [1]. Various approaches and strategies have been proposed for these challenges of mobile robots with non-holonomic constraints.

According to [2], if a system has constraint equations that involve velocities, accelerations, or derivatives of system coordinates, the constraint equations are said to be non-holonomic, or kinematic, and the mechanical system is said to be a non-holonomic system. An extensive review of non-holonomic control problems can be found in [3]. Two main approaches to controlling mobile robots are stabilization and trajectory tracking.

The aim of trajectory tracking is to controlling robots to follow a given time varying trajectory (reference trajectory). It is a fundamental motion control problem and has been intensively investigated in the robotic community. To solve these problems, many researchers investigate various tracking control designs [4-6].

The [7] used a Lyapunov function to design a local asymptotic tracking controller. Global tracking was explored by dynamic feedback linearization techniques in [8], back stepping techniques in [9, 10] and sliding mode techniques in [11], Furthermore, adaptive control [12], fuzzy control [13], and neural network control [14], etc. In this paper, we considered a mobile robot system and proposed a modified FEL-PD controller for mobile robot system. The proposed approach demonstrates the advantages of the adaptive, neural network and PD control strategies [15, 16].

The rest of the paper is organized as follows. Section II contains the mathematical model of the mobile robot system. Section III deals with FEL controller in detail, Sections IV discusses the PD controller. Sections V discuss the simulation results of the proposed control schemes. Finally, the conclusion is given in Section VI.

II. MATHEMATICAL MODEL OF THE SYSTEM

The kinematic model of the mobile robot is given in Equation (1) [17]:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \cos\theta & 0 \\ \sin\theta & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v \\ \omega \end{bmatrix} \tag{1}$$

where, v and ω are forward and the angular velocities that they are inputs. The non-holonomic constraint (no-slip condition, no lateral velocity) is given in Equation (2):

$$\dot{x}\sin\theta + \dot{y}\cos\theta = 0 \tag{2}$$

A desired reference $(x_r, y_r, \theta_r, v_r, \omega_r)^T$ is given and written as following equations:

$$\begin{bmatrix} \dot{x}_r \\ \dot{y}_r \\ \dot{\theta}_r \end{bmatrix} = \begin{bmatrix} \cos\theta_r & 0 \\ \sin\theta_r & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v_r \\ \omega_r \end{bmatrix} \tag{3}$$

where, v_r and ω_r are reference inputs and can be obtained:

$$v_r = \sqrt{\dot{x}_r^2 + \dot{y}_r^2} \quad , \quad \omega_r = \frac{\dot{x}_r\,\ddot{y}_r - \dot{y}_r\,\ddot{x}_r}{\dot{x}_r^2 + \dot{y}_r^2} \tag{4}$$

In Figure 1, the reference vehicle follows the reference path and the real vehicle has some error when following the reference path. The trajectory tracking error as shown in Figure 1 is given by [17]:

$$e=\begin{bmatrix}e_x\\e_y\\e_\theta\end{bmatrix}=\begin{bmatrix}\cos\theta & \sin\theta & 0\\-\sin\theta & \cos\theta & 0\\0 & 0 & 1\end{bmatrix}\begin{bmatrix}x_r-x\\y_r-y\\\theta_r-\theta\end{bmatrix} \tag{5}$$

According to kinematic model is given by Equation (1), and model of reference vehicle is given by Equation (3), the nonlinear error model of the system is obtained by derivation of Equation (5):

$$\begin{bmatrix}\dot{e}_x\\\dot{e}_y\\\dot{e}_\theta\end{bmatrix}=\begin{bmatrix}v_r\cos e_\theta\\v_r\sin e_\theta\\\omega_r\end{bmatrix}+\begin{bmatrix}-1 & e_y\\0 & -e_x\\0 & -1\end{bmatrix}\begin{bmatrix}v\\\omega\end{bmatrix} \tag{6}$$

where, the tracking control problem is to find appropriate control laws for v and ω such that the tracking error $(e_x, e_y, e_\theta)^T$ converges to zero.

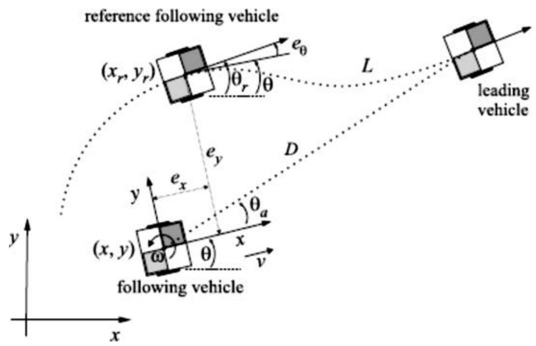


Figure 1. Illustration of the error transformation where the following vehicle follows the path [17]

III. FEEDBACK ERROR LEARNING ARCHITECTURE

The structure of FEL is shown in Figure 2, which is proposed by Kawato et al. [18]. In this structure, the neural network is used as a feed forward controller and trained using the output of a PD controller as error signal. The total control input U to the plant is equal to:

$$U(t)=U_C(t)+U_N(t) \tag{7}$$

where, $U_c(t)$ and $U_N(t)$ are outputs of PD and NN respectively. The feedback error-learning scheme has the following advantages:

a. The teaching signal is not required to train the neural network. Instead, error signal is used as the training signal,

b. The learning and control are performed simultaneously in sharp contrast to the conventional 'learn then control' approach,

c. Back-propagation of the error sign through the model of the controlled object or through the model of the controlled object is not necessary.

The feedback error learning is an algorithm [18], which gains the inverse model or systems. As shown in block diagram of the feedback error learning in Figure 2, the input value of the network is the desired output value of controlled object x_{1d}. The input value of the PD controller is the error between the desired output value and the output value of the controller x_{1d}-x_1 the command of the controlled object is the sum of the output values U_c and U_N of the PD controller and the neural network, respectively like Equation (7).

In order to train the neural network, the PD controller is used. The error back propagation algorithm in the feedback error learning process, so that the combinations of the input value and the desired output value of the neural network are needed as the training data, trains the neural network. The desired output of the neural network is the input values of the controlled object for obtaining the desired output of the controlled object x_{1d}, but the desired neural network output value cannot be obtain easily in the inverse modeling problem.

If the neural network obtains the desired output value, then the output value of the controlled object x_1 is equal to x_{1d} and the output value of the PD controller becomes zero. Therefore, our purpose is to decrease the output value of the PD controller. Hence, the output value U_c is used as an estimated error of the neural network. After the learning, the neural network functions effectively as the inverse model of the controlled object.

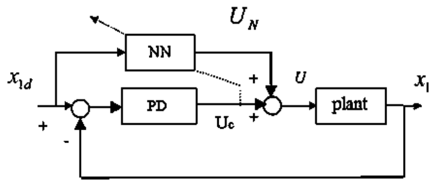


Figure 2. General structure of FEL

The PD controller guarantees the stability of the overall system and ensures adequate performance prior to convergence of the neural network weights, and reduces the steady-state output errors due to noise.

IV. PD CONTROLLER

Considering the following PD control for the Figure 2 block diagram for eliminate error between x_{1d} and x_1:

$$U_c(t)=k_p e(t)+k_d\frac{d}{dt}e(t) \tag{8}$$

where, $e(t)=x_{1d}-x_1$.

V. SIMULATION RESULTS

In this section, simulation results are presented. For PD controller k_p and k_d for first control input (v) are set as 20 and 26, and for second control input (ω) are set as 100, 1. Desired reference is considered circle (x=cos(t), y=sin(t)).

The simulation results are shown in the following figures. Figure 3 shows the PD controller of plant and Figure 4 shows the FEL controller of plant. In Figure 5, we compare FEL controller result with PD controller. The MSE (Mean Square Error) of tacking for different controller shows in Table 1. MSE is calculated by Equation (9):

$$MSE=\frac{1}{n}\left[\sum_{i=1}^{n}(e_{1i}^2+e_{2i}^2+e_{3i}^2)\right] \tag{9}$$

where, n is number of data and $e_1=x_d-x$, $e_2=y_d-x$, $e_3=\theta_d-\theta$.

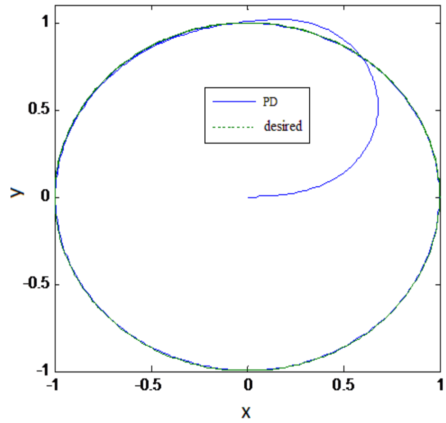
Table 1 shows that although there is not a great deal of difference between the MSE of PD and FEL, the MSE of FEL with Noise is significantly lower than MSE of PD with Noise.

Table 1. MSE for controller

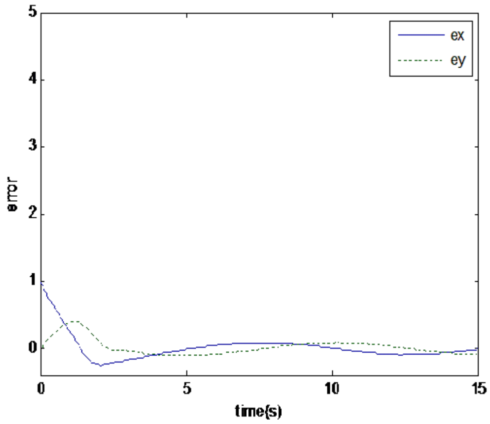
controller	MSE
PD	0.0649
FEL	0.0572
PD with noise	2.96
FEL with noise	0.0639

Although in Figures 3 and 4(b), error signals were shown that are very small signal around zero and converge to it, the MSE measurement is a best way for showing difference of FEL and PD. Comparison of PD and FEL controllers was shown in Figure 5 that FEL is more near than PD to desired signal. However, they do not have a very difference without Noise. With adding Noise to system with both PD and FEL controller, idealistic performance of FEL controller shows itself, while system with PD controller cannot track the desired path and it have an irreparable error, as shown in Figure 7.

For showing the application of classic and intelligent controller, noise is used as shown in Figure 6. Mobile robot trajectory tracking in the presence of noise is studied. The white noise is combined with first state (x) and results of PD and FEL in the presence of noise show in Figure 7.

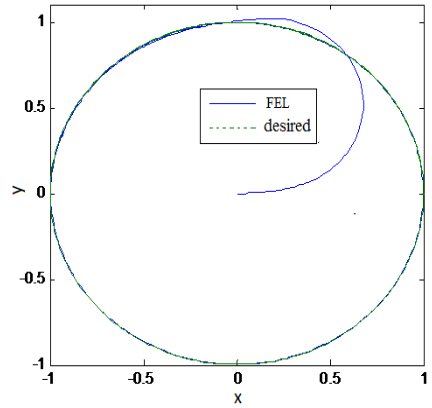


(a)

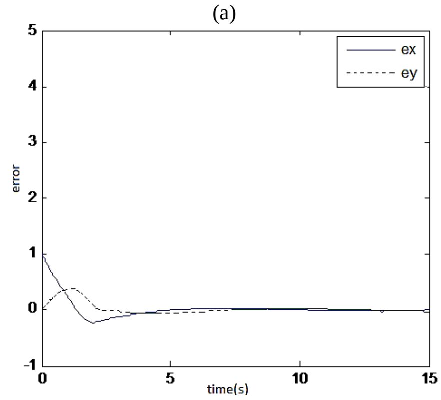


(b)

Figure 3. PD controller (a) path tracking (b) error signals



(a)



(b)

Figure 4. FEL controller (a) path tracking (b) error signals

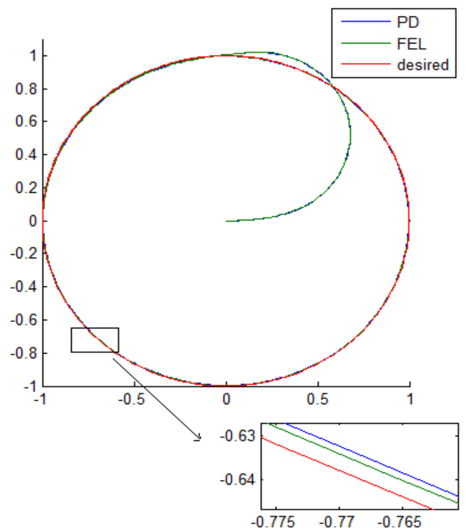


Figure 5. Comparison of PD and FEL controllers

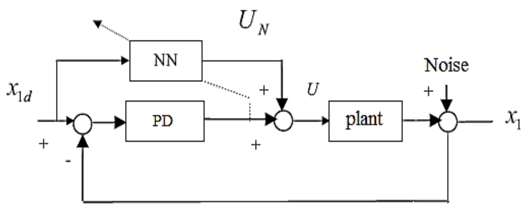
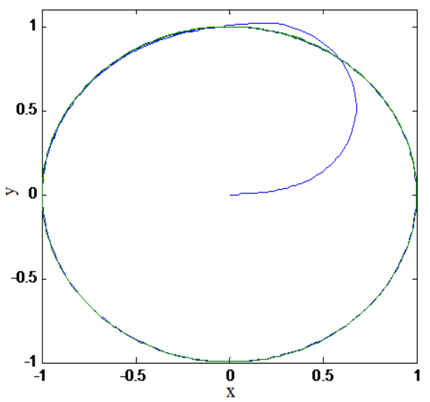
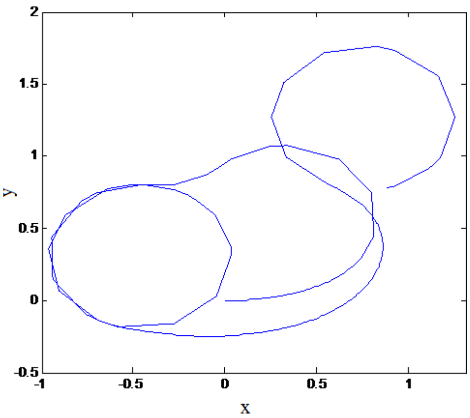


Figure 6. Block diagram of FEL control system in the presence of noise



(a)



(b)

Figure 7. Path tracking for controlling with noise (a) FEL controller (b) PD controller

VI. CONCLUSIONS

The problem of the mobile robot tracking control is difficult, due to variety and diversity of Mobile Trajectory in real environments. In this paper, two type of path tracking controllers has been introduced and discussed by intelligent approaches. In this paper, a FEL base control method and PD controller for mobile robot is proposed, which combines the adaptive neural network and PD control. The designed FEL controller has more abilities and better performance in tacking paths with noise in compares with the PD one.

This paper investigates and compares the designed controller basted on FEL and PD and of course that is required to explain, however the performance of PD based controller was acceptable, the usage of learning ability of neural networks in FEL algorithm can improve efficiency and performance of tracking the difficult trajectories. In conclude, Simulation and MSE results show that designed FEL base control system has great precision and tracking ability. In addition to online network, it has noticeable resistance to noise because of its intelligent algorithm.

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