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Learning from adaptive neural network output feedback control of a unicycle-type mobile robot

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ABSTRACT

This paper studies learning from adaptive neural network (NN) output feedback control of nonholonomic unicycle-type mobile robots. The major difficulties are caused by the unknown robot system dynamics and the unmeasurable states. To overcome these difficulties, a new adaptive control scheme is proposed including designing a new adaptive NN output feedback controller and two high-gain observers. It is shown that the stability of the closed-loop robot system and the convergence of tracking errors are guaranteed. The unknown robot system dynamics can be approximated by radial basis function NNs. When repeating same or similar control tasks, the learned knowledge can be recalled and reused to achieve guaranteed stability and better control performance, thereby avoiding the tremendous repeated training process of NNs.

1. Introduction

A unicycle-type mobile robot is one of the most well-known benchmark nonholonomic systems. In recent decades, considerable efforts have been devoted to the tracking control and stabilization of this kind of nonholonomic systems, for example see [1–10] and the references therein. Difficulties in the trajectory tracking issue for such systems are the uncontrollability of their linear approximation and dissatisfaction of the well-known Brockett's theorem [11]. To overcome those difficulties, various methods have been investigated: linear feedback control [12,13], time-varying feedback control [14], discontinuous hybrid feedback control [15,16], sliding mode control [17–19], fuzzy logic control [20,21], neural network (NN) control [22–25] and so on.

Despite much of the progress, all schemes based on the full-state-feedback control require additional sensors to obtain the velocity information which is necessary for the implementation of controllers. However, in practice such devices may not be used either because they are contaminated by noise or they are expensive and increase the cost, volume and weight of the system. In case complete state measurements (especially for velocities of the mobile robots) are not available, adaptive output feedback controllers using observers have been studied [26,27]. The main difficulty in designing an observer-based output feedback controller for Lagrange systems is because of the nonholonomic constraints and the Coriolis matrix which result in quadratic cross terms of unmeasured velocities. For example, many solutions proposed for robot manipulator control ([1,28] and references therein) cannot directly be applied. To our knowledge, adaptive output feedback control for nonholonomic mobile robots still remains an open research problem. Do et al. [2] proposed a method to design a time-varying global output-feedback controller (i.e., the controller uses only position and orientation measurements) for both stabilization and tracking of unicycle-type mobile robots at the torque level. Guechi et al. [29] proposed an output feedback approach based on a nonlinear predictor to estimate the state variables using the delayed measurements. Do [30] proposed cooperative formation tracking controllers for a group of *N* unicycle-type mobile robots with limited sensing ranges and without velocity measurement.

Another difficulty in controlling nonholonomic mobile robots is that in the real world there exist uncertainties in their modeling. The precise knowledge of system dynamics may not be available which makes many of the aforementioned schemes hardly be directly applied to the mobile robots. Shojaei and Shahri [31] proposed an adaptive robust output feedback controller to solve the trajectory tracking problem of nonholonomic wheeled mobile robots including actuator dynamics in the presence of parametric and non-parametric uncertainties. Li et al. [32] proposed adaptive motion/force control using dynamic coupling and output feedback in the presence of unmodeled dynamics, or parametric/functional uncertainties. Huang et al. [33] proposed a high-gain observer

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based scheme to address the output feedback tracking control of mobile robots in the presence of parametric uncertainties. Park et al. [34] developed an adaptive observer to estimate the unmeasured velocities of electrically driven nonholonomic mobile robots. The dynamic surface technique was applied to design the controller with robot system uncertainties. Based on the self-learning characteristics and good approximation capabilities of the neural networks (NNs), methods using adaptive control techniques based on NNs are also useful to deal with the unknown/uncertain dynamics problem of the mobile robot system [25,35,36]. Xu et al. [24] proposed a robust NN based sliding mode controller, which has used the NN to identify the unstructured system dynamics directly. Al-Araji et al. [37] proposed a trajectory tracking controller for a nonholonomic mobile robot using an optimization algorithm based predictive feedback control and a modified Elman neural network while following a continuous and a non-continuous paths.

Though much progress has been achieved, the learning capability of NNs in adaptive NN control, including for adaptive NN output feedback control with observers, is actually very limited. The employed NNs need to recalculate (or readapt) the parameters (neural weights) even for repeating exactly the same or similar control tasks. Recently, a deterministic learning (DL) theory [38,39] was proposed for NN approximation of nonlinear dynamical systems with periodic or recurrent trajectories. It is shown that, by using localized radial basis function (RBF) NNs, almost any periodic or recurrent trajectory can lead to the satisfaction of a partial persistency of excitation (PE) condition. This partial PE condition leads to exponential stability of a class of linear time-varying adaptive systems, and accurate NN approximation of the system dynamics is achieved in a local region along the periodic or recurrent trajectory. The learned knowledge can be used for same or similar control tasks without recalculating the NN parameters.

In this paper, based on DL theory, we propose a high-gain observer based scheme to address the adaptive NN output feedback control of nonholonomic unicycle-type mobile robots in the presence of unknown robot system dynamics. To accomplish this and achieve the purpose of learning, we propose a new adaptive control scheme including designing a new adaptive NN output feedback controller and two high-gain observers to estimate the unknown linear and angular velocities, respectively. It is shown that the stability of the closed-loop robot system and the convergence of tracking errors are guaranteed. The unknown robot system dynamics can be approximated by RBF networks in a local region along the estimated state trajectory and the learned knowledge is stored in constant RBF networks. When repeating same or similar control tasks, the learned knowledge can be recalled and reused to achieve guaranteed stability and better control performance, thereby avoiding the tremendous repeated training process of NNs.

The rest of the paper is organized as follows. Section 2 briefly describes the robot model, problem formulation and preliminaries. Learning from NN output feedback control of unicycle-type mobile robots is presented in Section 3. The neural learning control scheme to guarantee the output tracking performance in same or similar control tasks is presented in Section 4. Simulation results are included in Section 5. Section 6 contains concluding remarks.

2. Preliminaries and problem formulation

2.1. Robot model

Consider a unicycle-type (two-wheel driven) mobile robot in Fig. 1, which has two actuators and a passive wheel. In this figure, r is the wheel radius and R is the half-width of the robot. To simplify, it is supposed that the mass center is coincident with the

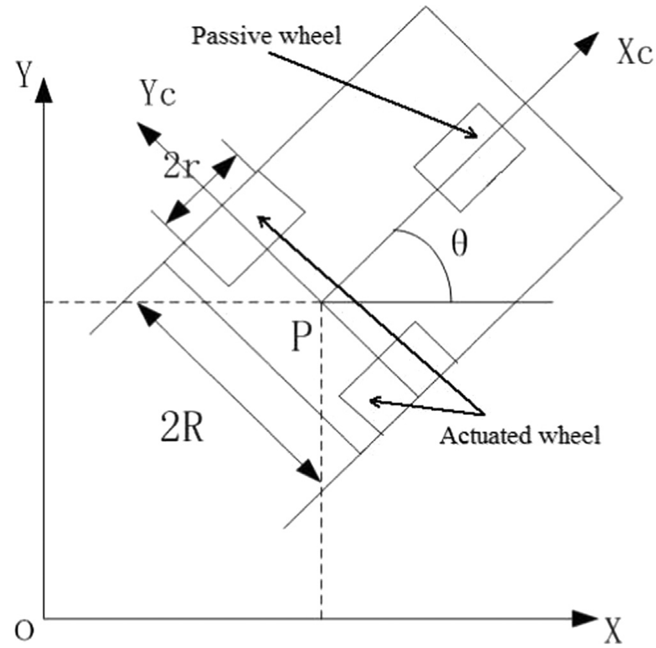

Fig. 1. A unicycle-type mobile robot.

robot's centroid, in other words, the mass center $P(x,y)$ is located on the axis center between the two wheels in the OXY world coordinate system. The local coordinate system X_c–Y_c is fixed to the robot with P as the origin. Then the postures of the mobile robot could be described by three state variables: the two coordinates of the gravity center x and y and the orientation angle θ of the mobile robot. Therefore the equation of dynamic motion of the mobile robot is governed by:

$$M(q)\ddot{q}+C(q,\dot{q})\dot{q}+F(\dot{q})+G(q)+\tau_d=B(q)\tau-A^T(q)\lambda \tag{1}$$

where $q=[x\ y\ \theta]^T\in R^3$ is a vector of the position and orientation of the mobile robot, $M(q)\in R^{3\times3}$ is a symmetric positive-definite inertia matrix, $C(q,\dot{q})\in R^{3\times3}$ is the centripetal and Coriolis matrix. Note that $C(q,\dot{q})=0$ when the mass center is coincident with the centroid. $F(\dot{q})\in R^3$ is the friction vector, $G(q)\in R^3$ is the gravitational loading vector, $\tau_d\in R^3$ is the vector representing external disturbance, $B(q)\in R^{3\times2}$ is the input transformation matrix, $\tau\in R^2$ is the torque vector applied to the left and right driving wheels, $A(q)\in R^{1\times3}$ is a full-rank matrix, and $\lambda\in R^1$ is a vector of Lagrange multipliers, which denotes constraint forces. The nonholonomic constraint can be written as $A(q)\dot{q}=0$. Using Lagrange's equation to determine the elements of the matrices in Eq. (1), the system matrix can be given by

$$M(q)=\begin{bmatrix} m & 0 & 0\\ 0 & m & 0\\ 0 & 0 & I\end{bmatrix},\quad C(q,\dot{q})=\begin{bmatrix} 0&0&0\\0&0&0\\0&0&0\end{bmatrix},\quad B(q)=\frac{1}{r}\begin{bmatrix}\cos(\theta) & \cos(\theta)\\ \sin(\theta) & \sin(\theta)\\ R & R\end{bmatrix},$$

$$A^T(q)=\begin{bmatrix}-\sin(\theta)\\ \cos(\theta)\\ 0\end{bmatrix},\quad \lambda=-m(\dot{x}\ \cos(\theta)+\dot{y}\ \sin(\theta))\dot{\theta},$$

where m is the mass of the mobile robot, I is the moment of inertia to the midpoint of the axis of two wheels. More details could be explored in [1].

The nonholonomic constraint of pure rolling and nonslipping, introduced on a kinematic level is given by

$$\begin{bmatrix}\dot{x}\\ \dot{y}\\ \dot{\theta}\end{bmatrix}=\begin{bmatrix}\cos(\theta) & 0\\ \sin(\theta) & 0\\ 0 & 1\end{bmatrix}\begin{bmatrix}\nu(t)\\ \omega(t)\end{bmatrix}=H(q)V(t) \tag{2}$$