Adaptive Inverse Control of an Omni-Directional Mobile Robot

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Abstract. The omni-directional mobile robot developed by Shanghai Jiaotong University was introduced. The inverse kinematics and dynamics of the robot were modeled for decoupled control simulation. An adaptive inverse control (AIC) scheme incorporating Dynamic neural network (DNN) controller and conventional feedback controller was presented. Finally, linear and circular trajectories following simulation results demonstrate that the AIC can decouple the dynamic control of the robot motion in the plane to direct rotational speed control of independent wheels, and precise trajectory following is achieved.

1 Introduction

Omni-directional mobile robots have good maneuverability that make them widely studied in the dynamic environmental applications, such as the RobCup competition. The Omni-directional mobile robot named JiaoLong developed by Shanghai Jiaotong University is a cross-disciplinary research platform for the full integration of AI and robotics research. It has three Swedish wheels [1], which are arranged 120^{o} apart and locate at the vertices of the frame that has the form of an equilateral triangle. A DC motor installed with shaft optical encoder and a gear train drives each wheel. A DSP (digital signal processor) is used for the motion control.

From the robot testing and competition at the past games, it is realized that a precise trajectory control for the robot is one of the key areas to improve the robot's performance. It appears that most research on the control of omni-directional mobile robot is based on dynamic model and feedback method, such as PID control, self-tuning PID control, fuzzy control, and trajectory linearization control [2-4]. The robot dynamic models are generally assumed that the robot motors' dynamics is identical, and the motors are controlled by ideal servos, and the motor output can perfectly follow the command [2-5]. In fact, the motors and servos' dynamics could hardly be identical, and their constraints can greatly affect the behavior of the robot. Since the omni-directional robot is a complex coupled nonlinear dynamic plant, it is difficult to precisely modeling the plant dynamics in an analytic way.

In this paper, an adaptive inverse control scheme incorporating dynamic neural network and conventional feedback control was developed for the omni-directional mobile robot. When it is difficult to model the robot dynamics precisely in an analytic

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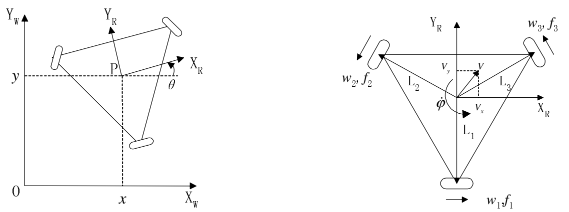
way, the neural network adaptive inverse controller can adapt its weights to achieve optimal dynamic performance by learning the output of the conventional feedback controller [6-7].

2 Kinematics Modeling

We assume that the robot under study is moving on a horizontal plane. The posture is defined in Fig. 1(a), where X_WOY_W is the world coordinate system, point O is the reference point; X_RPY_R is the robot coordinate system, point P is the center of the robot chassis. We define the 3-vector describing the robot posture:



(a) Posture definition (b) Kinematic diagram

Fig. 1. Kinematic parameters definition of the omni-directional robot

$$\xi = (x \quad y \quad \theta)^T \, . \tag{1}$$

where x, y are the coordinates related to the reference point P in the world frame, θ is the orientation of the robot frame with respect to the world frame. In our design, the inverse kinematic equations are given by

$$\begin{pmatrix} w_1 & w_2 & w_3 \end{pmatrix}^T = \tfrac{1}{r} A R(\theta) \begin{pmatrix} \dot{x} & \dot{y} & \dot{\theta} \end{pmatrix}^T \cdot \tag{2}$$

where w_i, i=1,2,3, is the rotational speed of each wheel of the robot, r is the wheel radius, $A = \begin{bmatrix} 1 & 0 & L_1 \\ -\frac{1}{2} & -\frac{\sqrt{3}}{2} & L_2 \\ -\frac{1}{2} & \frac{\sqrt{3}}{2} & L_3 \end{bmatrix}$, $R(\theta) = \begin{bmatrix} \cos\theta & \sin\theta & 0 \\ -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$, L_i is the distance from the center of the robot chassis to the contact point to the ground of each wheel along a radial path (see Fig. 1(b)). Using equation (2), we can calculate the rotational speed command given to each wheel of the robot from trajectory planner that specifies the vector ξ.

3 Robot Dynamics Modeling for Decoupled Control Simulation

By Newton's Law we have $\begin{pmatrix} m\ddot{x} & m\ddot{y} & J_R\ddot{\theta} \end{pmatrix}^T = A^T (f_1 \quad f_2 \quad f_3)^T$, so there is

$$(f_1 \quad f_2 \quad f_3)^T = (A^-)^T \begin{pmatrix} m\ddot{x} & m\ddot{y} & J_R\ddot{\theta} \end{pmatrix}^T \cdot \tag{3}$$

Where m is the robot mass, J_R is the robot moment inertia, f_i is the traction force of each wheel. Assuming the robot can follow the command fast, f_i will be very closely approximate the real traction force given by each motor driving unit.

The dynamics of each wheel driven by a DC motor can be described as

$$J_m \dot{w}_m = -(\frac{C_m C_e}{R_a} + b_m) w_m - \frac{r}{n} f + \frac{C_m}{R_a} u \cdot \tag{4}$$

Where J_m is the combined moment of inertia of the motor, gear train and wheel referred to the motor shaft, w_m is the rotational speed of the motor shaft, R_a is the armature resistance C_e is the electromotive force (EMF) constant, C_m is the motor torque constant, b_m is the vicious friction efficient of the combination of the motor and gear train, n is the gear ratio, f is one of f_i, u is the applied armature voltage. Similarly, we can copy equation (4) for the other two wheel dynamic models. Using Equation (3) and (4), we can construct the simulation model for the following adaptive inverse control scheme.

4 Adaptive Inverse Control of Nonlinear Plant

The overall adaptive inverse control scheme based on neural network is depicted in Fig. 2, where z^{-1} is unit delay of the discretized time. The neurocontroller is a dynamic neural network with tapped-delay-line (TDL). The input of the plant is the output sum of the neurocontroller and the PID controller: $u=u_N+u_F$. The main idea is to adapt the neurocontroller via learning the output of the PID controller u_F, which is called feedback error method. When the neurocontroller is converged, there will be $u_F \rightarrow 0$, $u_N \rightarrow u$, $y \rightarrow r$, $e \rightarrow 0$, and the PID controller will not act, then the neurocontroller approaches the inverse model of the plant.

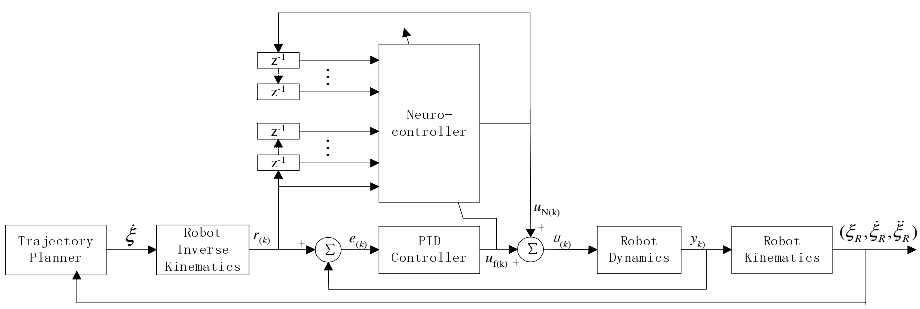


Fig. 2. Adaptive inverse control scheme

5 Simulation

We designed two trajectories in the simulation to follow by the robot: a linear trajectory and a circular trajectory. For linear trajectory, the command is to accelerate the robot from the original position to the desired speed $\dot{x} = 1\text{m/s}$, $\dot{y} = 1\text{m/s}$, $\dot{\theta} = 0.15\text{rad/s}$

with fixed acceleration $\ddot{x} = 1\text{m/s}^2$, $\ddot{y} = 1\text{m/s}^2$, $\ddot{\theta} = 0.1\text{rad/s}^2$. The linear speed error is 1.2mm/s and the rotational speed error is 0.0013 rad/s. For circular trajectory, the robot is commanded to accelerate from initial state to circle around the center of the trajectory with the desired angular rate 0.754 rad/s. The center of the circular trajectory is at [0 0.5], the radius of the circular trajectory is 0.5m. The position error is 0.8mm and the orientation error is 0.0011rad.

6 Conclusion

In this paper, the inverse kinematics and dynamics of an omni-directional mobile robot was analyzed. The adaptive inverse controller was designed for dynamic decoupled control. So unlike those model-based control methods, it is not sensitive to the parameters of the robot dynamic model. The simulation results demonstrate that the adaptive inverse control can decouple the control of the robot motion in the plane to direct rotational speed control of the independent wheels, and the robot can be controlled to follow different trajectory precisely. The next step is to implement and test the control scheme on the real robot that is controlled by a DSP system.

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