Application of Intelligent PID Control for Robot

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***Abstract*—On the basis of analysing the error of robot that results from walking in plane, a new PID controller with BP neural networks is proposed in the paper. The BP Neural Network algorithm is used in PID control because it could adjust parameters itself in real time. By using the BP Neural Network PID controller, the robot can go straight accurately. Simulation results demonstrate that the new PID controller with BP Neural Networks can not only overcome uncertainties and external disturbances, but also get rather good requirement of tracking precision, thus possess better robustness and control performance.**

***Keywords*—PID (Proportional Integral Derivative); BP Neural Networks; real time control**

I. Introduction

Robot is characterized by high nonlinear, closely coupled and time-varying dynamic system, so that its exact dynamic model is difficultly established. In order to satisfy the requirement of high-precision motion control for robot, some improvements have been made in traditional control methods on the premise of ignoring the uncertainties. However, because of these inherent unmodelled dynamics, the traditional control methods are not appropriate for robot control. On the other hand, robot not only possesses high nonlinear properties but also operates in an environment with external uncertainties in most cases. Therefore, it is more significant to investigate the robust learning control strategy for robot in the presence of uncertain disturbances, as in [1]

Artificial Neural Network (ANN) is a nonlinear model which simulates man nerve system and has the functions of self-organizing, self-study and associated memory. It is characterized with non-linearity, parallelism, high robustness, learning and generalization capability, as in [2]. As opposed to the traditional methods, ANN is data-driven self-adaptive methods. They learn from examples and capture subtle functional relationships among the data even if the underlying relationships are unknown or hard to describe as in [3]. The neural network based control strategy can overcome uncertainties and external disturbances, thus possess better robustness and control performance.

II. Conventional PID control for robot motion

In the experiment, we do not require robot response speed under control, but need to control the fluctuation and deviation of the robot, and make them approach to the setting value. Because the characteristics of the two motors are different, we can control them respectively.

The conventional PID control algorithm that adjust the three parameters according to deviation is the most mature and the most popular control strategy in continuous system. As its structure is simple, parameters are adjusted easily, so there is no need to know accurate mathematic model of controlled system, as in [4].Therefore, we adopt this adjustment method in the robot experiment first.

The structure of a conventional PID controller can be shown in Fig.1.

Where r(t) is input, y(t) is actual output, define error as $e(t)=r(t)-y(t)$, e(t) is used as the input of PID controller, u(t) is the output, so the PID control rule can be written as

$$u(t)=K_p\left[e(t)+\frac{1}{T_i}\int_0^t e(t)dt+T_d\frac{de(t)}{dt}\right]$$

Where K_p is proportion coefficient, T_i is integral coefficient, T_d is differential coefficient.

Introducing programming methods to realize the PID control, that is called digital PID algorithm, there are two types.

Position type

$$u(t)=K_pe(k)+K_i\sum_{j=0}^{k}e(j)+K_d[e(k)-e(k-1)]$$

Incremental type

$$\Delta u(t)=K_p[e(k)-e(k-1)]+K_ie(k)+K_d[e(k)-2e(k-1)+e(k-2)]$$

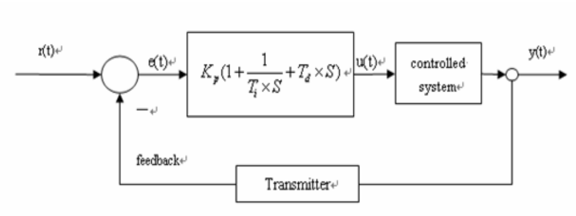

Figure 1 Structure of a conventional PID controller

Where, K_p is proportion coefficient , T_i is integral coefficient, T_d is differential coefficient; $u(t)$ is output in the kth trial; $e(k)$ is the deviation value in the kth trial, as in [2]. The paper introduced the incremental type.

This paper made the rotate speed of the two wheels approach to the same set value, using conventional PID control algorithm to execute closed loop control. Theoretically, the digital PID algorithm integrates the advantages of proportion, integral and differential controllers, so that the control effect would be the best. But in practice, taking the PID controller can not get the regulation done once and for ever. In the condition that the mathematical model of the controlled system is known, we can gain the three parameters of the PID controlled by using transfer function. But it is very difficult to establish accurate mathematic model for some system. In this condition, experimental measurement is the only way to gain the three parameters. There are two general methods :transient process characteristic curve method and critical stable state measurement. In fact, the three parameters need to be adjusted in real time according to the change of the controlled system, or else, the predicted control effect can not be obtained perfectly.

Robot is characterized by high nonlinear, closely coupled and time-varying dynamic system, so that its exact dynamic model is difficultly established. So experimental measurement is the only way to gain the three parameters if we adopt the conventional PID controller.

III. THE BP-ANN BASED PID CONTROL ALGORITHM

BP——Back Propagation is the most widely used learning process in neural networks today. The presentation of Back Propagation by Rumelhart et al.in 1986 is probably responsible for the popularization of the algorithm in the areas of science and engineering. The BP algorithm considers supervised learning in a feedforward multilayer network. The standard feedforward multilayer network is composed of a number of interconnected simple processing elements called neurons or nodes. There are input layer, output layer and hidden layer. In general, there can be any number of hidden layers in the architecture; however, from a practical perspective, only one or two hidden layers are typically used. The connection weights can be adjusted according to a defined learning rule. The transfer function can be a linear or nonlinear function. There are many different types of transfer functions. Selection of one type over another depends on the particular problem that the neural network is to solve. The back-propagation (BP) neural network is adopted in this study, as in [5].

When the operating state of controlled system changed, it is difficult to adjust the three parameters in real time in practice. Thanks to ANN for its functions of self-organizing, self-study and associated memory, we take the BP algorithm to train and study the controlled system in real time in order to adjust the control parameters.

Adding a BP-ANN based PID controller into the controlled system in order to attain the closed loop control effects, the three parameters in PID controller Kp、 Ki、 Kd are all adjusted in real time. According to the operating state of controlled system, the outputs of ANN will correspond to the three parameters in PID controller under a certain optimal control rule, as in [6].

The BP neural network adjust the parameters of PID controller according to the operating state of controlled system, and the outputs of the output layer are corresponding with the three parameters of PID controller, Kp、 Ki、 Kd respectively. The BP-ANN based PID control algorithm as follows

The BP-ANN takes 4-5-3 architecture, the inputs of the input layer can be written as

$$O_j^{(1)} = x(j) \qquad (j = 1,2,3,4)$$

Where, x(1) is Rin, x(2) is Yout, x(3) is error, x(4) is 1 as network modified value, these have been shown in Fig.2.

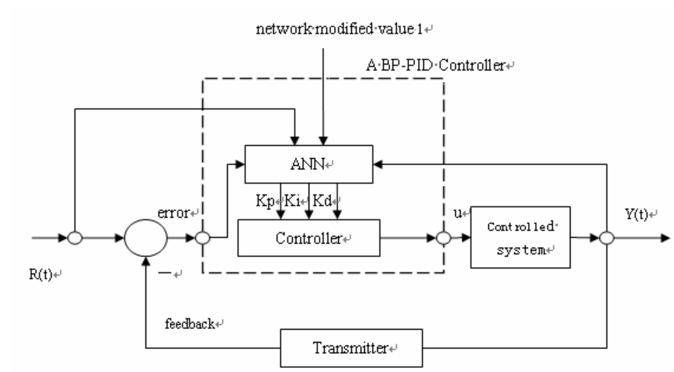

Figure 2 Structure of the BP- PID controller

the inputs and outputs of the hidden layer can be written as

$$O_i^{(2)}(k) = f(net_i^{(2)}(k)) = f(\sum_{j=0}^{4} w_{ij}^{(2)} O_j^{(1)}(k)) \quad (i = 1,2,3,4,5)$$

Where, $w_{ij}^{(2)}$ is the connection weights of the hidden layer; the superscripts (1) (2) (3) denote the input layer、 the hidden layer and the output layer respectively. The transfer function of the hidden layer neurons is a sigmoid function that can be written as

$$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

the inputs and outputs of the output layer can be written as

$$O_l^{(3)}(k) = g(net_l^{(3)}(k)) = g(\sum_{i=0}^{3} w_{li}^{(3)} O_i^{(2)}(k)) \qquad (l = 1,2,3)$$

$$O_1^{(3)}(k) = K_p$$

$$O_2^{(3)}(k) = K_i$$

$$O_3^{(3)}(k) = K_d$$

The three outputs of the output layer are corresponding to the three parameters Kp、 Ki、 Kd, since the parameters can not be minus, so the transfer function of the output layer neurons is a sigmoid function that can be written as $g(x)=\frac{1}{2}(1+\tanh(x))=\frac{e^x}{e^x+e^{-x}}$

The sum-of-square error cost function is defined as $E(k)=\frac{1}{2}(rin(k)-yout(k))^2$

To obtain the optimal values of the connection weights when E（k） is a minimum, we can search the error surface using a gradient descent method and find the minimum value. To guarantee network convergence, and avoid the oscillations during the training, a backpropagation with momentum updating is introduced. Namely, the weights are updated according to

$$\Delta w_{li}^{(3)}(k) = -\eta \frac{\partial E(k)}{\partial w_{li}^{(3)}} + \alpha \Delta w_{li}^{(3)}(k-1)$$

Where, η is commonly referred to as the learning rate parameter. It specifies the magnitude of the update step for the weights in the negative gradient direction. If the value is chosen to be too small, the learning algorithm will modify the weights sluggishly and relatively large number of iterations will be required before the bottom of the error surface is reached. On the other hand, if the value of the learning parameter is set too large, the learning rule can become numerically unstable. α is commonly referred to as forgetting factor and is typically chosen in interval (0,1), as in [5]:

IV. Simulation Results and Discussion

The experimental robot discussed in this paper adopt four-wheel organization, the two driven wheels mounted in the front and back are universal wheel. Springs fixed in the axles keep robot dynamic balance and realizing certain abilities of evading obstacle. The two action wheels are controlled respectively by two direct current motors in order to accomplish the differential motion. By controlling action wheel rotation rate and torque respectively, we can make the experimental robot move straight, turn backward , turn left , turn right , circumvolve according to the direction and speed those are demanded. Besides, this organization can enhanced the flexibility of robot when taking the Curvilinear motion.

The BP-ANN takes 4-5-3 architecture, the learning rate parameter $\eta = 0.28$, the forgetting factor $\alpha = 0.04$, The connection weights are randomly initialized in interval [-0.5,0.5]. Input signal is step signal with 0.02 seconds delay. Compared to conventional PID controller, taking transient process characteristic curve and critical stable state measurement to adjust the three parameters, finally, Kp=0.2, Ki=0.05, Kd=0.002.

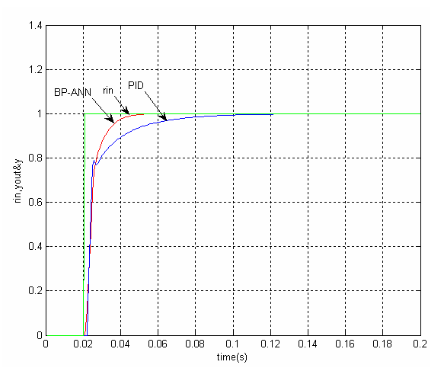

Figure 3 Responses of the BP- PID controller & PID controller

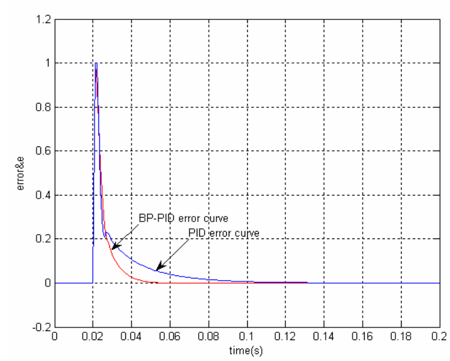

Figure 4 The tracking error curves of BP-ANN controller & PID controller input

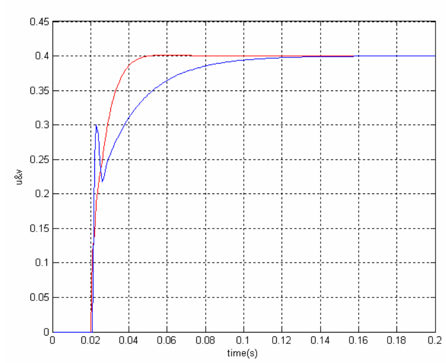

Figure 5 The outputs of BP-ANN controller & PID controller

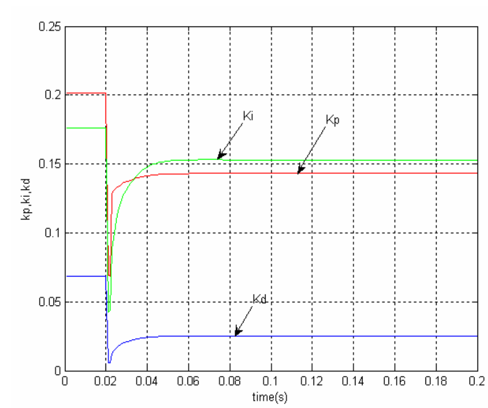

Figure 6 The adjusting curves of the BP-PID parameters for step input

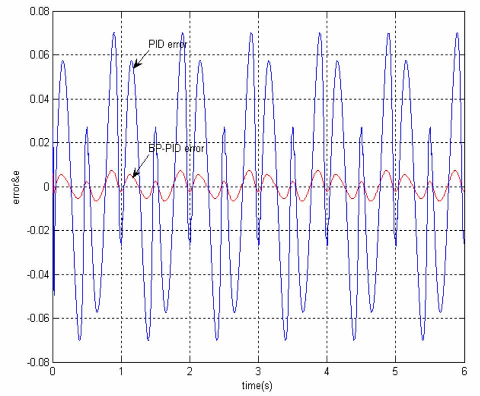

Figure 7 The tracking error curves of BP-ANN controller & PID controller to Sine input

Fig. 3 illustrates that the BP-ANN based PID controller has faster convergence rate compared to PID controller. Fig.4 and Fig.5 illustrate that the BP-ANN based PID controller has high-precision tracking coming with fast convergence rate. Fig. 6 illustrates that the BP-ANN based PID controller can adjust the PID parameters in real time self-adaptively. And the Kp and Kd parameters altered obviously in the process. Figure 6 illustrates that the BP-ANN makes the PID controller can eliminate the influences of uncertainties and external disturbances of the dynamical model.

Fig.7 and Fig.4 both show the tracking error curves of BP-ANN controller & conventional PID controller. Fig.7 shows the tracking error curves to Sine input. Fig.7 illustrates the error value changes with the sine signal, and the BP-ANN based PID controller has more high tracking precision. the ability of self-learning obviously. The results approve the ability of self-learning and self-adaptive of BP- neural network.

V. Conclusion

The simulation result shows that the conventional PID control algorithm can complete moving straight motion task for robot, but there still exist some problems. First, it is the most difficult to adjust the parameters in real time. The transient response is slow, and the oscillations are large. What is the most important, the PID parameters are different for different experimental robot.

The BP-ANN makes the PID controller have the ability of self-learning and eliminate the influences of uncertainties and external disturbances of the dynamical model. The three parameters in PID controller Kp、 Ki、 Kd can all be adjusted in real time according to the operating state of controlled system. This kind of controller is characterized with high convergence rate and high-precision tracking and high robustness. Introducing this algorithm to the experimental robot, the robot can move straight accurately. Nevertheless, further work will be done to improve the performance of the architecture, considering that neural network architecture has highly fitting precision for the controlled system.

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