⊙ 研究論文

선박용 디젤엔진을 위한 지능적인 속도제어시스템의 설계

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Design of an Intelligent Speed Control System for Marine Diesel Engines

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Key words : Speed control system(속도제어시스템), Marine diesel engine(선박용 디젤엔진), Neural networks(신경회로망), Inverse dynamics model(역동적 모델)

Abstract

An intelligent speed control system for marine diesel engines is presented. The approach adopted is to use a conventional PID controller for normal operation and a feedforward controller for adaptive control. The feedforward controller is a neural network. The neural network is the inverse dynamics model of the plant, which is being trained on line. The parametric model of the diesel engine is represented in a linear second-order system, with a first-order combustion part and a revolution part each at a normal operating point. The time delay in the control of the combustion part is approximated to the first-order system. The tuned PID parameters are set based on the model for normal operating point. To obtain the inverse dynamics of the diesel engine system, two neural networks are used, one for inverse, the other for forward dynamics. The former is positioned across the plant to learn its inverse dynamics during operation, and the latter is placed in series with the controlled plant. Simulation results are presented to illustrate the applicability of the proposed scheme to intelligent adaptive control of diesel engines.

INTRODUCTION

In conventional theory, PID control schemes are widely used for controlling diesel engines in ships and industrial fields. The tuned PID parameters are set based on the parametric model of the plant [1-2]. However, the plant parameters heavily depend on the engine speed due to load and set point changes. Thus, the fixed PID gains are not generally enough to obtain good control performance, namely, the PID parameters must be retuned according to

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the operating speed.

The conventional adaptive control approaches are generally based on the assumption that the plant is linear time invariant and that the plant model has a known form, but unknown parameters. The computational complexity in conventional adaptive control grows with the number of unknown parameters. These problems cause difficulties to achieve high performance in the control of varying dynamic systems, such as diesel engines, operating in varying environment.

Recently, there has been much interest in applying neural networks to identification and adaptive control since the model of a plant (both the forward dynamics and inverse dynamics parts) can be learnt automatically by a neural network and immediately utilised for control.

An adaptive controller for time-varying systems can be realised by neural networks without a priori knowledge, thus only a suitable network topology and an appropriate adaptation mechanism need to be chosen. A variety of approaches have been proposed, such as the supervised control approach, model reference control [3], and self-tuning adaptive control [4]. In learning the inverse dynamics of the plant as a controller, there are two main approaches to the neural-network-based identification, i.e. direct and indirect inverse learnings.

This paper presents an intelligent adaptive speed control scheme for marine diesel engines by using neural networks. The scheme is based on a feedforward inverse controller trained according to the direct inverse learning approach [5], and based on a feedback PID controller [6] for controlling diesel engines operating at various speed. The diesel engine system and control scheme are described in Section II, and simulation results are given in Section III.

II. CONTROL SYSTEM

In this section, a diesel engine system and an adaptive intelligent PID-neural control scheme are described. The diesel engine system is represented by a second-order linear parametric model. The adaptive control scheme is described, that employs a conventional PID controller as a feedback error controller, and an adaptive neural controller as a feedforward controller in parallel. The PID controller parameters are set for the plant which works at a normal operating point. The adaptive neural controller is a neural network which is trained on-line for the inverse dynamics of the plant. The neural controller employs the direct inverse learning scheme for adaptive control of the plant with unknown-structures[5].

The control network, a direct copy of the inverse learning network, is placed in series with the controlled plant. The initial weights of the networks are assumed to be obtained from off-line training [5]. The control input is generated by the feedforward controller by taking as inputs the desired output (reference) and the feedback error and by the PID controller.

A. Diesel Engine System

The diesel engine system is composed of a combustion mechanism and a revolution mechanism. The linear parametric model of a diesel engine can be represented as [6-7] :

$$G(s)=\frac{K_c}{1+T_f s}\cdot\frac{K_r}{1+T_r s} \tag{1}$$

where G(s) is the plant transfer function, Kc, Kr represent gains of the combustion mechanism and revolution mechanism, and T_f, T_r are time constants of the combustion mechanism and revolution mechanism respectively. In the above equation, the first term represents the combustion mechanism, and the second, the revolution mechanism. T_f is to be given to minimize the integral of the squared error between the indicial responses of the first-order time delayed combustion system and that of first-order without time delay [6].

The diesel engine system can be represented in the discrete input-output format with a zero-order holder and sampling time T as follows :

$$y(k+1)=a_1y(k)+a_2y(k-1)+b_1u(k)+b_2u(k-1) \quad (2)$$

where k is time instant, y and u represent the output and input of the plant, a_1, a_2,, b_1, b_2 are respectively,

$$a_1=(e^{-T/T_f}+e^{-T/T_r})$$
$$a_2=-e^{-T(1/T_f+1/T_r)}$$
$$b_1=-K_c K_r\left(e^{-T/T_f}+e^{-T/T_r}+\frac{T_r e^{-T/T_r}-T_f e^{-T/T_f}}{T_f-T_r}-1\right)$$
$$b_2=K_c K_r\left(e^{-T(\frac{1}{T_f}+\frac{1}{T_r})}+\frac{T_r e^{-T/T_f}-T_f e^{-T/T_r}}{T_f-T_r}\right)$$

B. Control Architecture

The intelligent adaptive control scheme for the marine diesel engine adopted in this work comprises two control mechanism in parallel. First, a conventional PID controller is used as a feedback error controller. The tuned PID parameters are fixed for the diesel engine plant operating under normal working condition. The PID gains are obtained based on the plant model of equation (1) [6]. The transfer function of the PID controller adopted in this paper is

$$G_p(s)=K_p(1+\frac{1}{T_i s}+T_d s) \quad (3)$$

where K_p, T_i and T_d represent the proportional gain, integral time and derivative time, respectively.

The adaptive neural controller is used as a feedforward controller. The neural controller is a neural network whose dynamics is the inverse dynamics of the plant to be controlled. The neural network is trained based on the direct inverse learning scheme on-line for adaptive control with unknown-structures [5].

For the neural controller, consider a dynamic plant of equation (2) as follows (because of assumption of the unknown structures) :

$$y(k+1)=h\{y(k), \ldots, y(k-n_a+1), u(k), u(k-1), \ldots, u(k-n_b+1)\} \quad (4)$$

where h is a function mapping the present and past inputs to the plant and the present and past outputs from the plant to the next output of the plant, n_a and n_b represent the maximum dynamic lags in the plant output and input, respectively.

By assuming that there exists a function g() such that equation (4) is invertible, the inverse description for the plant can be given as follows :

$$u(k)=g\{y(k+1), y(k), \ldots, y(k-n_a+1), u(k-1), \ldots, u(k-n_b+1)\} \quad (5)$$

Equation (5) can be implemented by a controller, $\Phi(\cdot)$, with input vector x(k), where

$$\mathbf{x}(k)\equiv[y_d(k+1)\ \mathbf{y}\ \mathbf{u}]^T \quad (6)$$

In equation (6), $\mathbf{y}=[y(k)\ \ldots\ y(k-n_a+1)]^T$ is the vector of present and past outputs (output dynamic memory), $\mathbf{u}=[u(k-1)\ \ldots\ u(k-n_b+1)]^T$ is the vector of past inputs (input dynamic memory), and $y_d(k+1)$ is the next desired output.

The controller output u(k) and the plant output y(k+1) are, respectively,

$$\begin{aligned} u(k)&=\Phi\{x(k)\} \\ &=u_d'(k) \end{aligned} \quad (7)$$

$$\begin{aligned} y(k+1)&=h\{\mathbf{y}, \mathbf{u}, \Phi\{\mathbf{x}(k)\}\} \\ &=y_d(k+1) \end{aligned} \quad (8)$$

In equation (7), the ideal control input $u_d'(k)$ represents the controller output needed to produce the output of the plant $y(k+1)$. Thus, if the output of $\Phi(\cdot)$ approximates sufficiently accurately that of $g(\cdot)$ for a corresponding input, the plant output $y(k+1)$ will be equal to the desired output, $y_d(k+1)$.

According to equations (6)-(8), the actual plant output y can be arbitrarily controlled to any desired output y_d if a complete inverse mapping is available. However, in practice, when one considers Φ to be the inverse model of the plant, the identity of equation (8) is generally very difficult to realise due to noise, modelling uncertainty, and changes in the environment.

To control the plant with a practical inverse controller, the feedforward neural controller takes as input **x** and the feedback error as follows :

$$u_d = \Phi^c\{\mathbf{x}, \mathbf{E}\} \tag{9}$$

where u_d represents a desired controller output (control input) produced by the inverse controller, Φ^c, using the desired output, y_d, output and input dynamic memories **y** and **u**, and feedback error **E** which is the dynamic error defined by the difference between the actual output and the desired output.

By assuming that the plant inverse, Φ, can be approximated by a neural network , the control input can be obtained from the controller, Φ^c, which is a direct copy of Φ.

From equation (3) and (9), the total control input for the diesel engine is given as follows :

$$u_c = \Phi^c\{\mathbf{x}\ \mathbf{E}\} + u_p \tag{10}$$

where u_c represents the control input to the plant and u_p represents the control input genereated by the PID controller of equation (3). The schematic configuration of the overall control system is depicted in Fig.1.

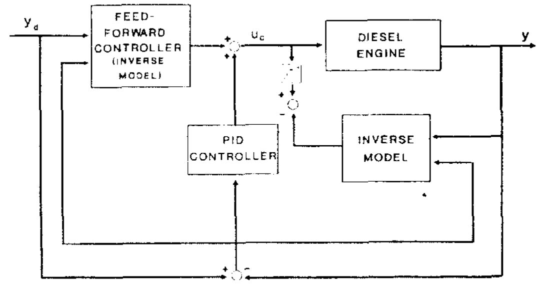

Fig. 1 Schematic configuration of control system

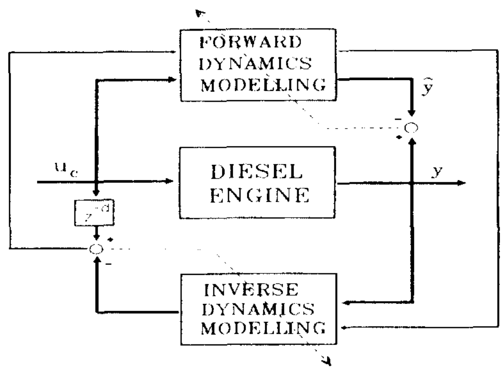

Fig. 2 Inverse and forward dynamics nodelling architecture

C. On-line Training

The neural network Φ is trained on-line to model the varying inverse dynamics of the plant. The inverse identification network Φ is placed across the plant and takes as inputs the actual output and the error between the desired output and the actual output. The forward dynamics model of the plant is also involved in training the inverse dynamics model [8]. This is because the feedback error is used as an input to the control network. Therefore, in training the inverse model of the plant, the feedback error term is generated through the forward dynamics model by taking as an input the difference between the control input and the output of the inverse modelling network. The training scheme is depicted in Fig.2

It is assumed that Φ is sufficiently complex to be able to approximate any output-input mapping of g(.) in equation (5). The recurrent backpropagation network is used to implement Φ [9]. In training the inverse network Φ, the delay term d (see Fig.2) is generally chosen to be between 1 and 3 for systems without time delays [5].

III. SIMULATION RESULTS

Simulation results for a marine diesel engine are given to illustrate the performance of the proposed control scheme. For simulation, the parameters of the diesel engine system in equation (1), $K_c = 1156.141$, $K_r = 0.0006$, $T_f = 0.4094$, $T_r = 1.7470$ were used, respectively . These parameters were obtained based on assuming that the diesel engine runs at a normal operating point with 80 r.p.m [7]. This diesel engine system in equation (2) with sampling time 0.05 seconds becomes as follows

$$y(k+1) = 1.8568y(k) - 0.8600y(k-1) + 0.00117u(k) + 0.00107u(k-1) \quad (11)$$

For the inverse and forward dynamics modelling networks, learning rate=0.02, momentum term=0.02, self feedback gains=0.8, number of hidden/state units=7 were chosen. The delay term d=1 was used and uniformly distributed random signal was used as a training input signal to the plant.

First, the step responses were obtained for the plant with only the tuned PID controller and with the proposed intelligent adaptive controller. In this case $K_p = 7.8595$, $T_i = 0.7500$ and $T_d = 0.1875$ were used. Fig.3 and Fig.4 show the step and combined sinusoid control responses for the plant. From the figures it can be observed that the responses with the adaptive controller are slightly improved. Fig.5 and Fig.6 respectively depict the training results and the recall response of the inverse dynamics modelling network after 4,000 training iterations.

Second, the step responses for the plant operating at 50 r.p.m. were obtained with only the PID controllers as shown in Fig.7. In this case, the PID gains were set with those used in the first case and with the tuned gains for the system operating at 50 r.p.m. It is observed that the response for the plant operating at 50 r.p.m. with the fixed PID controller is poor due to the improper gain settings.

Third, the proposed control system was tested for its ability to cope with plant dynamics variation. Again the step and combined sinusoid responses for the plant operating at 50 r.p.m. were obtained with only the fixed PID controller and with the intelligent adaptive control system as shown in Fig.8 and Fig.9. The training results and recall responses are shown in Fig.10 and Fig.11, respectively. In this case, the inverse dynamics modelling network was trained with 4,000 iterations. As shown in the figures, the response for the adaptive control system is much improved from that obtained with the fixed PID controller.

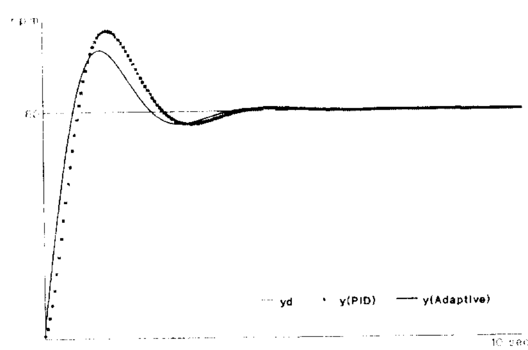

Fig. 3 Step responses with PID and adaptive controllers

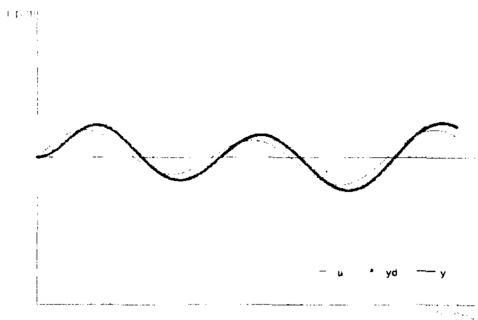

Fig. 4 Combined sinusoid responses

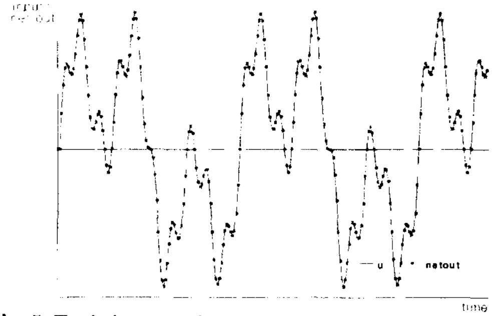

Fig. 5 Training results

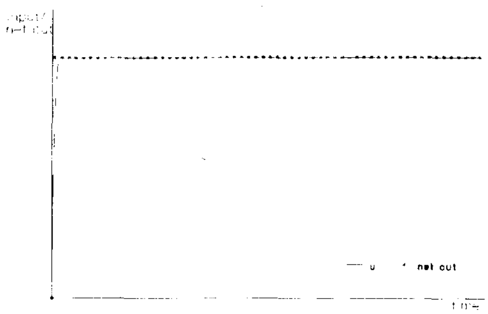

Fig. 6 Recall responses

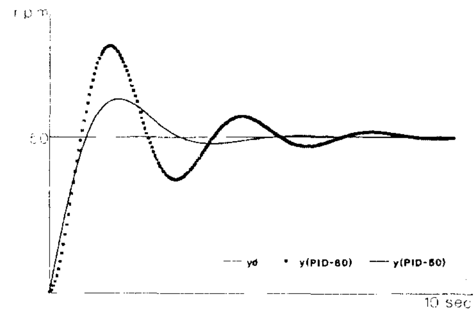

Fig. 7 Step responses with fixed and retuned PID controllers

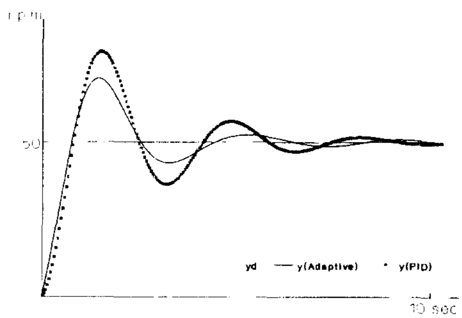

Fig. 8 Step responses with PID and adaptive controllers

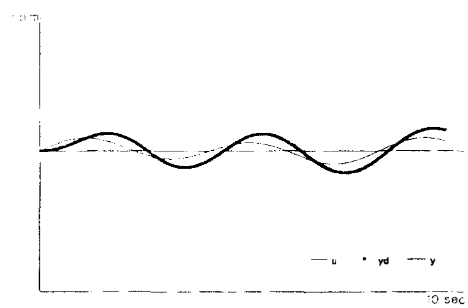

Fig. 9 Combined sinusoid responses

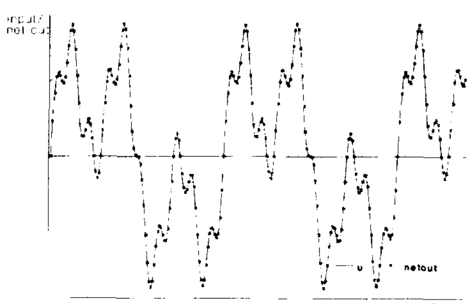

Fig.10 Training results

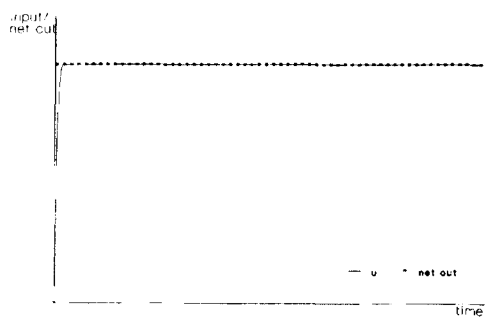

Fig.11 Recall responses

IV. CONCLUSION

This paper has presented a new intelligent adaptive control scheme for the speed control of marine diesel engines by combining PID controller with adaptive feedforward control scheme. It is assumed that the dynamics of diesel engines varies according to operating environments. The scheme employes the fixed PID controller and the neural-network-based inverse controller obtained by direct inverse learning scheme. Due to the control structure and the nature of neural networks, the proposed control scheme can easily be used in applications to speed control of marine diesel engines requiring fast and precise action. The simulation results demonstrated the applicability of the proposed method to intelligent adaptive control of diesel engines.

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