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A new intelligent controller: a combination of expert control and neurocontrol

T. Wang

Department of Automation, Chongqing University, Chongqing, 630044, P.R. China

Abstract

Expert control and neurocontrol are two important approaches in intelligent control, but they are quite different in mechanism. Expert control imitates the reasoning aspect of human thinking, whereas neurocontrol simulates the imagination aspect of human thinking. This paper presents a new approach to intelligent control by means of combining neurocontrol with expert control. It not only overcomes the difficulties of representing and updating knowledge in expert control, but also solves the problems in neurocontrol that learning speed is rather slow and that control quality is not good enough during the learning process. Simulations show that this new intelligent controller possesses better control quality than either expert control or neurocontrol.

1 Introduction

Conventional control theory has played an important role in industrial control. It is, however, faced with a challenge imposed by the higher requirements of modern industrial control. This is because designing a controller using the conventional control theory is based on known mathematical models of plants, whereas, in fact, amongst industrial installations or devices, plants to be controlled possess time-varying, non-linearity, and a variety of uncertainties, except in a few simple cases. Due to these factors, traditional control techniques cannot ensure good control quality, and may even fail sometimes. In the light of previous control practice and experience, intelligent control is expected to provide more effective control strategies to rise to the challenge.

The kernel of intelligent control is human-imitation or intelligence-imitation, that is, the purpose is to try to achieve human-like performance in control. Its main focus of attention is on the controller[1]. Thus, the dependence of control system design on a mathematical model of the plant is greatly decreased. This helps to increase the control capability and adaptability to time-varying, non-linearity and uncertainty of plants.

There are currently two approaches to human-imitation in intelligent control: one is from the aspect of micro function of human configuration such as the functioning of the human brain and methods of neural networks; another is from the aspect of the macro function of human behaviour such as expert control (or rule-based control) and fuzzy control etc. These two approaches have already been applied to industrial control and met with a certain degree of success. Both, however, have some drawbacks. In this paper, we explore and propose a new intelligent control method which combines together above two approaches. The new method, on the one hand, utilizes expert control to monitor and supervise the learning process of neural networks so that the learning process is speeded up. On the other hand, it rectifies expert rules and updates the expert knowledge base via neural networks on the completion of the learning process. Simulation results will be presented to show its better control quality and adaptability than those of either expert control or neurocontrol.

2 Principles of Expert Control and Neurocontrol

Expert control is a sort of control mode constructed on the basis of expert systems. A knowledge base and an inference engine are therefore the key parts of the system. The knowledge base is used to store control rules, such as relevant control knowledge, experience, methods, etc. The structure of the knowledge base may be layered, usually including a layer of correction knowledge and a layer of control knowledge. The role of the correction mechanism is to supplement or to amend the content of the control knowledge layer, according to the output of the system, so as to enhance the correctness and raise control capability and reliability. The function of the inference engine is to utilize the knowledge to solve the problem, that is, following some control strategies, it utilizes the knowledge in the knowledge base and the information related to the expected control target, carries on logical or non-logical reasoning, and comes to a conclusion (i.e. a control output).

Expert controllers are based on knowledge models. Knowledge representation is generally in the form of production rule to express existing theoretical knowledge as well as human experience obtained in practice. The combination of qualitative and quantitative analysis can solve some problems proved to be difficult for traditional control theory based on analytic models.

Neurocontrol is a newly developed intelligent control approach based on neural networks[2,3]. Research on artificial neural networks is based on ideas about the functioning of the human brian, or our present understanding of biological nervous systems. It is well known that the human body is a most effective control system, of which the brain is a control centre. The brain is composed of millions of simple functional neurons, while its overall function is extremely complicated and rich, capable of dealing with a variety of complex problems. So the research on neural networks which attempts to achieve human-like performance in application is followed with great interest by researchers in the field of automatic control.

Artificial neural networks consist of many simple neuron-like computational elements (nodes) connected by links with variable weights. Neural network models are specified by the network topology, node characteristics, and training or learning algorithms. The node characteristic is an input-output property of a node usually specified by the type of non-linearity with an internal threshold. A learning algorithm, for example, the back propagation, refers to rules which specify an initial sets of weights and indicate how weights should be adapted during use to improve performance. The learning of a network is a process of adaptation of connection weights. And the knowledge and information are implicitly represented in the network via these distributed connection weights.

There are currently two ways to apply neural networks in the field of control [4]. First, neural networks are used as a controller. Via supervision or training, the controller automatically sums up control rules and exerts the control. Second, the use of neural networks is combined with conventional control theory, or neural networks are used as a part of the control system to realize some control algorithms. Researchers have done much significant work on these ways of controlling nonlinear or complicated plants and achieved some success [2,3,4,5,7].

3 The Combination of Expert Control and Neurocontrol

It is obvious that expert control and neurocontrol are quite different control techniques. The former is good at interpretative inference, imitating the coarse-grained reasoning aspect of human thinking, whereas the latter is skilled at reflective reasoning, simulating the fine-grained imagination aspect of human thinking. The advantages of expert control are: there is no need to input a lot of data; the expert knowledge can be transplanted; production rules can be adapted as events change; and it is easy to modularize programs. However, it is difficult to represent, to summarise and to update knowledge. Besides, the number of rules increases with the complexity of a problem so that the process of inference is slowed down. It is therefore not suitable for on-line control of large and complex systems.

The potential benefits of neural networks are: the capability of massive parallel distributed processing is suitable for multi-dimensional data or information; a greater degree of robustness, or fault tolerance, is provided so that a damage to a few nodes or links need not impair overall performance significantly; the

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associative store and access enables neural networks to learn, to adapt and to induce; and the theoretical ability of non-linear mapping provides brilliant prospects for non-linear control and system problems. Neural networks obtain knowledge from training samples, adapt to variations in the environment gradually, and exert control rapidly and correctly on the completion of training. But the process of learning is rather long and during this process the control quality is not as good as expected. In addition, when abnormal phenomena occur, they are hard to deal with.

In view of the above discussion, if we can combine these two approaches together to make use of their respective advantages and avoid their shortcomings, it will improve the performance of human-imitation, or intelligence-imitation, and therefore achieve better control quality.

Figure 1 shows the framework of a control principle based on this idea. The system employs expert control as a controller at the first instance. At the same time, it trains the neural network so that its learning traces the output of the expert controller, i.e. u_1.

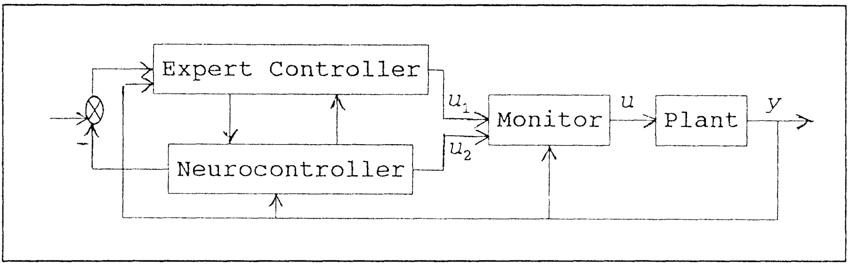

Figure 1 The Overall Structure of the New Intelligent Control System

Once the output of the neurocontroller equals the output of the expert controller, i.e. $u_1=u_2$, and the expert control achieves a certain accuracy, the monitor will switch from the expert controller u_1 to the neurocontroller u_2, i.e. let the output of the controller $u=u_2$. That means the neural network becomes the controller.

During the control process, the switch mode of the monitor is as follows:

$$u=\begin{cases} u_1, & |e|<\delta_1 \ and \ |\dot{e}|<Q_1 \\ u_2, & others \end{cases}$$

where e is the error, $\dot{e}$ is the error change rate, and δ_1 and Q_1 are pre-designed parameters. The monitor can also supervise and control the stability of the overall system. When an unstable tendency occurs, it can adopt corresponding measures. The relevant details are in [7].

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The expert controller, as shown in Figure 1, is of a layered structure, i.e., the knowledge base consists of a set of control rules and a set of correction rules used for rectifying the control rules. Here the control rule set contains the following basic rules:

1. *If* $|e|>e_0$, *then* $u_n=Sgn(e)\ u_{\max}$
2. *If* $|e|<e_1$ *and* $|\dot{e}|<\dot{e}_1$, *then* $u_n=u_{n-1}$
3. *If* $|e|\in(e_0,e_1)$ *and* $|\dot{e}|\in(\dot{e}_0,\dot{e}_1)$, *then* $u_n=sk_pe+k_d\dot{e}$

where u_n, u_{n-1} are the current and previous output of the controller, e_0, e_1 are the thresholds of the error, and $\dot{e}_0$, $\dot{e}_1$ are the thresholds of the error change rate. The correction set includes the following rules:

1. *If* $e\dot{e}<0$ *and* $|e|\in(e_1,e_0)$,
   then $k_p=k_{p_1}+k_{p_1}k_1$, $k_d=k_{d_1}$, $s=1$
2. *If* $e\dot{e}<0$ *and* $|e|\in(e_2,e_1)$ *and* $|\dot{e}|>\dot{e}_2$,
   then $k_p=k_{p_1}+k_{p_1}k_2$, $k_d=k_{d_1}$ $s=-1$
3. *If* $e\dot{e}<0$ *and* $|e|\in(e_3,e_2)$ *and* $|\dot{e}|>\dot{e}_2$,
   then $k_p=k_{p_1}+k_{p_1}k_3$, $k_d=k_d+k_dk_3$, $s=-1$
4. *If* $e\dot{e}<0$ *and* $|e|\in(e_4,e_3)$ *and* $|\dot{e}|\in(\dot{e}_3,\dot{e}_2)$,
   then $k_p=k_{p_1}+k_{p_1}k_4$, $k_d=k_{d_2}+k_{d_2}k_4$, $s=-1$
5. *If* $-e\dot{e}<0$ *and* $|e|\in(e_4,e_3)$ *and* $|\dot{e}|\in(\dot{e}_4,\dot{e}_3)$,
   then $K_p=k_{p_1}+k_{p_1}k_5$, $k_d=k_{d_1}+k_{d_1}k_5$, $s=-1$
6. *If* $e\dot{e}>0$ *and* $e>0$ *and* $|e|<e_4$ *and* $|\dot{e}|\in(\dot{e}_4,\dot{e}_3)$,
   then $k_p=k_{p_1}+k_{p_1}k_6$, $k_d=k_{d_1}+k_{d_1}k_6$, $s=1$

where k_p, k_{p_1} are proportional gains, k_d, k_{d_1}, k_{d_2} are differential gains, k_i $(i=1,2,...,6)$ are the changeable coefficients of proportional differential gains, e_i $(i=0,1,...,4)$ are the thresholds promised by the error, and $\dot{e}_i\ (i=0,1,...,4)$ are the thresholds allowed by the error change rate.

Due to the limited number of rules, the inference can be carried out by seeking a rule on a one by one basis. Because there always exists a rule corresponding to a state in input space, an appropriate rule will always be found.

The topology of the neural network used in this paper is shown in Figure 2. The corresponding controller is a sort of adjuster with the variable proportion:

$$u_k = \frac{d_{k+1} - \hat{f}_1(y_k, w(k)) - \hat{f}_2(y_{k-1}, w(k))}{\hat{b}(k)}$$

where d_{k+1} is the target value. The system is thereby configured as Figure 3 [5].

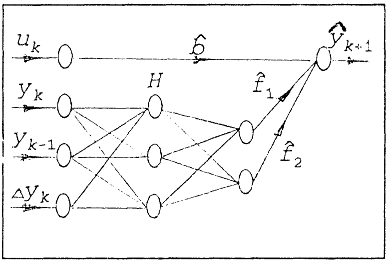

Figure 2 A Neural Network for Control

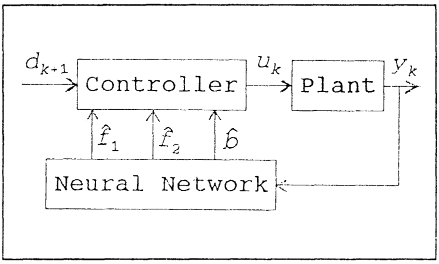

Figure 3 The Structure of Neurocontrol

The learning algorithm is the back propagation. The error energy function is

$$E_k = \frac{1}{2} e_{k+1}^2 = \frac{1}{2}(d_{k+1} - y_{k+1})^2$$

The gradient descent method adjusts $\hat{w}(k)$ and $\hat{b}(k)$ to decrease the error energy function E_k. The partial derivative of E_k with respect to $\hat{b}(k)$ is

$$\frac{\partial E_k}{\partial \hat{b}(k)} = \frac{b_0}{\hat{b}(k)} \left[\frac{d_{k+1} - \hat{f}_1(y_k, w(k)) - \hat{f}_2(y_{k-1}, w(k))}{\hat{b}(k)} \right] e_{k+1} = \frac{b_0}{\hat{b}(k)} u_k e_{k+1}$$

So the update rule of $\hat{b}(k)$ is

$$\hat{b}(k+1) = \hat{b}(k) - \eta_k \frac{M}{\hat{b}(k)} u_k e_{k+1}$$

The partial derivative of E_k with respect to $\hat{w}(k)$ is

$$\frac{\partial E_k}{\partial \hat{w}^i(k)} = \frac{b_0}{\hat{b}(k)} \frac{\partial [\hat{f}_1(y_k, w(k)) + \hat{f}_2(y_{k-1}, w(k))]}{\partial \hat{w}^i(k)} e_{k+1}, \quad \forall \hat{w}^i(k) \in w(k)$$

Therefore the adjustment equation of weight $\hat{w}(k)$ is

$$\hat{w}^i(k+1) = \hat{w}^i(k) - \epsilon_k \frac{M}{\hat{b}(k)} \frac{\partial [\hat{f}_1(y_k, w(k)) + \hat{f}_2(y_{k-1}, w(k))]}{\partial \hat{w}^i(k)} e_{k+1}, \forall \hat{w}^i(k) \in w(k)$$

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where η_k and ε_k are the learning rates at the kth step, M is the initial value of b_0. According to the back propagation algorithm, the partial derivatives can be determined from the layer of $\hat{f}_1(\bullet)$ and $\hat{f}_2(\bullet)$ to the input layer backwards, and the weights are thereby adjusted.

4 Simulations

Example 1. Suppose the transfer function of a plant is

$$G_1(s)=\frac{1}{(5s+1)(2s+1)}$$

The simulation results are shown in Figure 4 which includes: 1. the first epoch of a response curve controlled by the neural network exclusively; 2. the response curve controlled by the expert controller (i.e. the first epoch controlled by the new intelligent controller presented in this paper); and 3. the second epoch controlled by the new intelligent controller.

It is obvious that the new intelligent control approach not only overcomes the usual poor control quality of neurocontrol, but also improves the performance of expert control after a certain period of control.

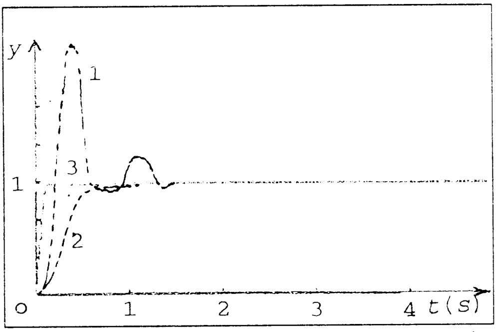

Figure 4 Simulated Control Curves: 1. the first epoch controlled by the neurocontroller; 2. controlled by the expert controller; 3. the second epoch controlled by the new intelligent controller.

Example 2. Suppose a plant has the same transfer function as example 1, with the addition of a pure time delay $e^{-0.2s}$ and a nonlinear factor *PH*. The *PH* nonlinear curve is simplified to three parts of analytic curves as shown in Figure 5. The target value is 7. This means the output should trace the *PH* signal stepped from 3 to 7. The simulation using the new intelligent controller combining neurocontrol with expert control is shown in Figure 6.

5 Concluding Remarks

Neurocontrol and expert control are two important approaches in intelligent control. With the development of intelligent control, there is a tendency to combine these two approaches together. Although the method proposed in this paper is only a primary exploration. the simulations make it clear that the method initially solves two sorts of problems. Firstly, the learning speed of

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neural networks is increased and its control quality is made better. Secondly, the performance of expert control is improved on the completion of learning of neural networks and the knowledge base becomes more accurate and perfect.

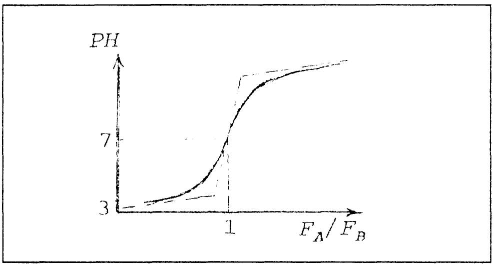

Figure 5 The PH Test Curve of Acid and Alkali

However, as the work presented in the paper is preliminary research, there exist many problems to be solved such as how to effectively combine these two approaches together, how to transfer the knowledge between them, how to optimize network topology and learning algorithms, and so on. Nevertheless, the results suggest the technique to be promising.

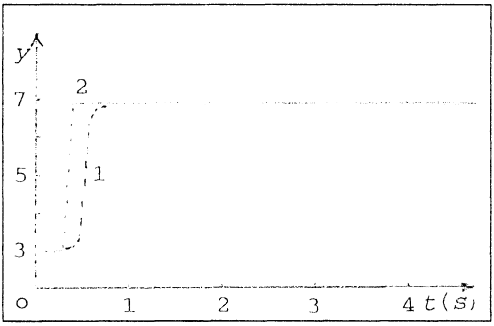

Figure 6 Simulated Control Curves: 1. controlled by the expert controller (i.e. the first epoch by the new intelligent controller); 2. controlled by the new intelligent controller

References

1. Li, Z., Research on the theory of intelligent control, *Information and Control*, 1991, 5, 27-37.
2. Werbos, P.J, Neurocontrol: where it is going and why it is crucial, pp61-68, *Artificial Neural Networks, 2. Proceedings of the 1992 Int. Conf. (ICANN-92)*, Brighton, UK, 1992, Elsevier, Amsterdam, 1992.
3. Antsaklis, P.J., Neural networks for control systems, *IEEE Trans. on Neural Networks*, 1990, 2, 242-244.
4. Huang Z. & Dai, G., Research on neurocontrollers, *Information and Control*, 1992, 6, 45-54.
5. Wang, T., et al, A neural network for the adaptive control of the second-order nonlinear system, *Journal of Chongqing University*, 1992, 5, 89-95.
6. Nguyen, D.H. & Widrow,B., Neural networks for self-learning control systems, *IEEE Control Systems Magazine*, 1988, 5, 18-23.
7. Qin, A., The monitoring of stability in a human-imitation intelligent control system, *Master Thesis of Chongqing University*, 1992.