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Information

ESKD—A New Structure of Expert System Based on Knowledge Discovery

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Abstract: A new structure of ESKD (expert system based on knowledge discovery system KD (D&K)) is first presented on the basis of KD (D&K)— a synthesized knowledge discovery system based on double-base (database and knowledge base) cooperating mechanism. With all new features, ESKD may form a new research direction and provide a great probability for solving the wealth of knowledge in the knowledge base. The general structural frame of ESKD and some sub-systems among ESKD have been described, and the dynamic knowledge base based on double-base cooperating mechanism has been emphased on. According to the result of demonstrative experiment, the structure of ESKD is effective and feasible.

Key words: knowledge discovery; expert system; dynamic knowledge base; double-base cooperating mechanism

1 Introduction

Since the first expert system, DENDRAL was developed by F. A. Feigenbaum, expert system has developed rapidly and has been used in many domains. The CASSIOPEE system in manufacture trade has been applied for diagnosis and prediction in the process of manufacturing BOING plane; FALCON system for fraud in bank and commerce can gain some features of fraud by summarizing the relation between normal and fraudulent action and then warn the decision man; Opportunity Explorer system for commodity analyzing in marketing can analyze the causes of commodity selling abnormity. These systems have improved on explanation mechanism, knowledge acquisition technology,uncertainly reasoning technology *etc*. But their structure is similar with traditional expert system, their reasoning technology is monotonous and the ability of auto-study is poor. These form a new "bottleneck" — insufficient knowledge. In addition, they are not versatility. The tendency of new generation of expert system is high intellectualization with many features, such as multi-knowledge expression, synthesized knowledge base, self-organization, cooperating, automatic knowledge acquisition *etc*.

In accordance with the above question, the article presents expert system based on knowledge discovery (ESKD). That is KD (D&K) — synthesized knowledge discovery system based on double-base (database and knowledge base) cooperating mechanism. It produces a very abundant dynamic knowledge base and corresponding integrated inference mechanism under many knowledge resources, kinds of knowledge fusion, multiple-abstract levels and different knowledge layers. Therefore, it especially fits for complicated big system and provides a valid path to produce the kernel technology on the structure of expert system. This system primarily improves the practical function of expert system.

2 Expert System Based On Knowledge Discovery (ESKD) Overall Structure Diagram

In this case, the fault diagnosis expert system is taken as an example (shown in **figure 1**).

It mainly includes the following six modules.

(1) Dynamic knowledge base sub-system based on knowledge base. Essentially, it is a knowledge discovery system based on double-base (database and knowledge base) cooperating mechanism. Dynamic knowledge base experiences the promotion process of basis — derivation — integration — expansion, which continuously expands knowledge directly constructed by expert experience and book knowledge. These form the knowledge base sub-system, which has the character of dynamic expansion and develops to manage fuzzy uncertainty, random uncertainty and qualitative information. It is the key of this system.

(2) Knowledge training sub-system. The system can be trained not only by professionals, but also from data by examples. It can find and learn the professional knowledge so as to meet the needs of different users.

(3) Grade diagnosis and decision sub-system. Fault tree is used to put the whole facility to a set of tests to be determined whether there is a fault or not. These

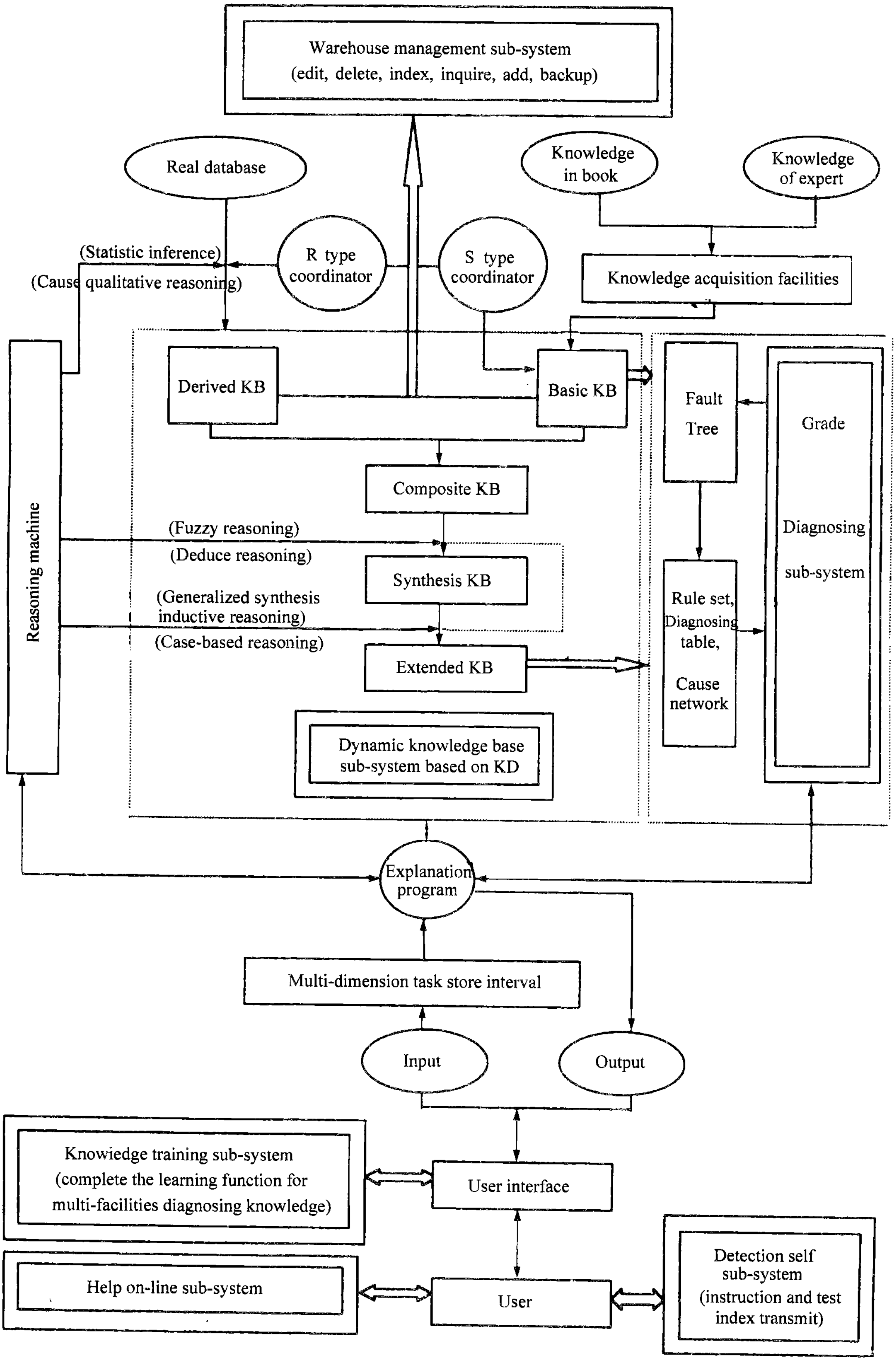

Figure 1 Block diagram of FESKD overall structure

modules will be tested one by one if there is. When one module is found fault, rule base (cause and effect network fault diagnosing table) is used to test and diagnose the internal module until the faulty point is found. Using correct resemble mechanism and knowledge in knowledge base, the system tests the facility and diagnoses whether the facility is normal or not. If the facility is not normal, the system will find the cause of the fault and provide solution according to the decision tree.

(4) Base management sub-system. It mainly manages real database, basic knowledge base and derived knowledge base. It can edit, delete, index, inquire, add and backup. It establishes good interface in Windows style. Users can expediently realize the operation of knowledge base and database.

(5)Detection self sub-system. To avoid false diagnosis caused by the fault of testing hardware itself, the expert system will check the testing hardware itself by close-loop before operation.

(6)On-line Help sub-system. This sub-system will help users use the system more effectively and get the help of corresponding information at any time.

3 Dynamic Knowledge Base System with Double-base Cooperating Mechanism

The knowledge base, which is used to resolve problem, isn't the basic knowledge base, but the extended knowledge base has been promoted. The promoted process is just as follows.

3.1 Basic knowledge base

Basic knowledge base stores expert experience and knowledge in books (take diagnosis expert system as an example). Basic knowledge base is made up of rule-base I, fault tree I, decision tree I and cases-base I, of which the rule-base includes all rules; fault tree is used to locate the basic fault and confirm its causality, influence and probability of the fault. This fault tree is structured by the method of minimum cutset, which can largely decrease the scanning space; decision tree can mine classification rule in large database by SLIQ method. When choosing a ramification of the tree, several attributes are considered at the same time to improve the yielding efficiency of the classification rule; cases-base stores previous typical cases in order that the diagnosis sub-system can directly diagnose by this rule.

3.2 Derived knowledge base

(1) Derived knowledge base stores new knowledge which is discovered by KDD*. The mining process is different between KDD (knowledge discovery based on database) and KDD*:

$$\text{KDD*} \triangleq \text{KDD} + \text{double-base cooperating mechanism}$$

i.e. KDD* structures the inner link "path" between database and basic knowledge base by double-base cooperating mechanism. Thereby it uses basic knowledge base to restrict and drive the mining process of KDD. It changes the inherent running mechanism to form an open and optimized expender in comparison to KDD on structure and function.

(2) The technological realization of double-base cooperating mechanism is to construct interrupting type and heuristic type coordinator. The requirement of realizing interrupting type and heuristic type coordinator is that the large (basic) knowledge base is divided into several correlative sub-knowledge bases according to each domain; Meanwhile, the real database is divided into correlative sub-databases according to each domain. Thus the layers between knowledge nodes in knowledge base and data sub-class (structure) make a one to one mapping. The basis theory, which is proposed by us, is pan-homotopy conception and the following structure mapping theorem (details can be found in reference [1, 2]):

Theorem (Structure Mapping Theorem): Aiming at X, in the sub-database corresponding to sub-knowledge nodes, $<E, \mathcal{K}>$ of knowledge nodes and $<F, \Lambda>$ of data sub-class (structure) are identical pan-homotopic type spaces.

This theorem presents the mapping of layers between knowledge nodes in the sub-knowledge base and data sub-class in corresponding sub-database, as shown in **figure 2**.

On the basis of the research above, it can be seen that the mathematical structure of database and knowledge base in the knowledge discovery system can be essentially come down to pan-homotopy category. Namely database is pan-homotopy category combined with data sub-type (structure) set and "mining path", which is called data mining category; and knowledge base is pan-homotopy category combined with knowledge nodes set and "reasoning arc", which is called knowledge reasoning category. Additionally more result about the isomorphy and restricting mechanism of knowledge reasoning category $C_R(E)$ in $<E, \mathcal{K}>$ and data mining category $C_D(F)$ in $<F, \Lambda>$ are got, and "directional searching" and "directional mining process" are resolved.

(3) The technological realization. The main function

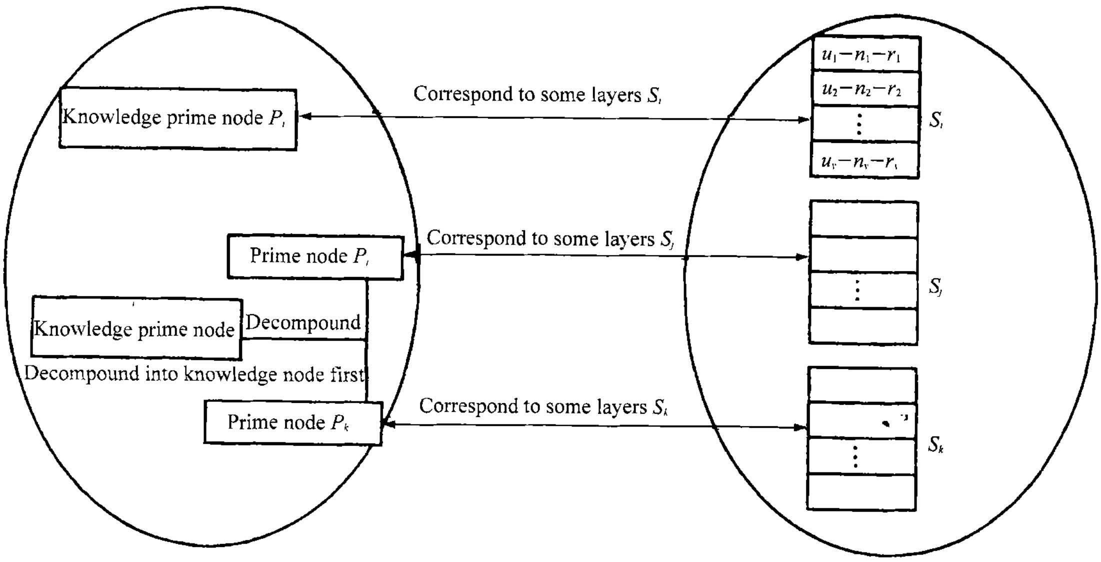

Figure 2 Corresponding graph of Structure Mapping Theorem

of R type coordinator is to "interrupt" the process of KDD and search whether there are repetition and controversy of the resulting rule in knowledge base after the rule (knowledge) is resulted from large amount of data in real database through setting focus. If there is repetition, the resulting rule is cancelled and returned to the beginning position in KDD. If there is controversy, expert will cancel the contradictory rule according to credibility & strength of the rule, or the controversy can be eliminated by such means as expanding premise. That is to say the result will be stored after evaluation. If there is neither repetition nor controversy, the process of KDD continues. Namely the result is set into knowledge base after evaluation. The main function of S type coordinator is to search irrelevant state of knowledge nodes in knowledge base under the principle of property on which knowledge base is established. Knowledge shortage is found. Data-class corresponding to real database use s heuristics and is activated to produce "directional mining process". The priority of "directional mining" is sorted according to relevant strength.

(4) Significance. 1) Besides discovering knowledge according to the factitious "interest", we proposed the new path of automatically enlightening directional mining according to "knowledge shortage" in basic knowledge base. 2) The mechanism greatly decreases " the evaluating quantity" after discovering hypothesis rule. 3) According to the above mechanism of "structure mapping", the searching space is greatly reduced and the mining efficiency is improved. 4) The mechanism rather availably resolves the redundancy and consistency problem in knowledge after new and old knowledge synthesized. 5) During the KDD process and the wide relation with basic knowledge base, KDD regarded as an open system improves and optimizes the structure, process and running mechanism of itself.

3.3 Composite knowledge base

Composite knowledge base stores the knowledge which is composed of basic knowledge base and derived knowledge base. Its detail step is as follows. First, rule-baseII is formed by compounding the rule in derived knowledge base and in basic knowledge base. Second, fault treeII, decision treeII and cases-baseII are formed by using the rule-baseII to modify fault treeI, decision treeI and cases-baseI. This process can be shown in **figure 3**.

3.4 Synthesis knowledge base

Synthesis knowledge base stores the new knowledge which is discovered on the basis of composite knowledge base by fuzzy reasoning and deductive reasoning. Meantime, it is similar with 3.3 to modify the fault tree, decision tree and cases base.

3.5 Extended knowledge base

Extended knowledge base stores the new knowledge which is discovered through the reasoning mechanism of generalized reduce synthesis and cases-base on the basis of synthesis knowledge base. It is different with knowledge discovery based on knowledge base (KDK), so we call it KDK*. KDK*, on the one hand, stimulates interface of human-computer to "gain" knowledge by a coordinator and apply exiting knowledge for the process of knowledge discovery, on the other hand, return discovered rule to KDD to evaluate.

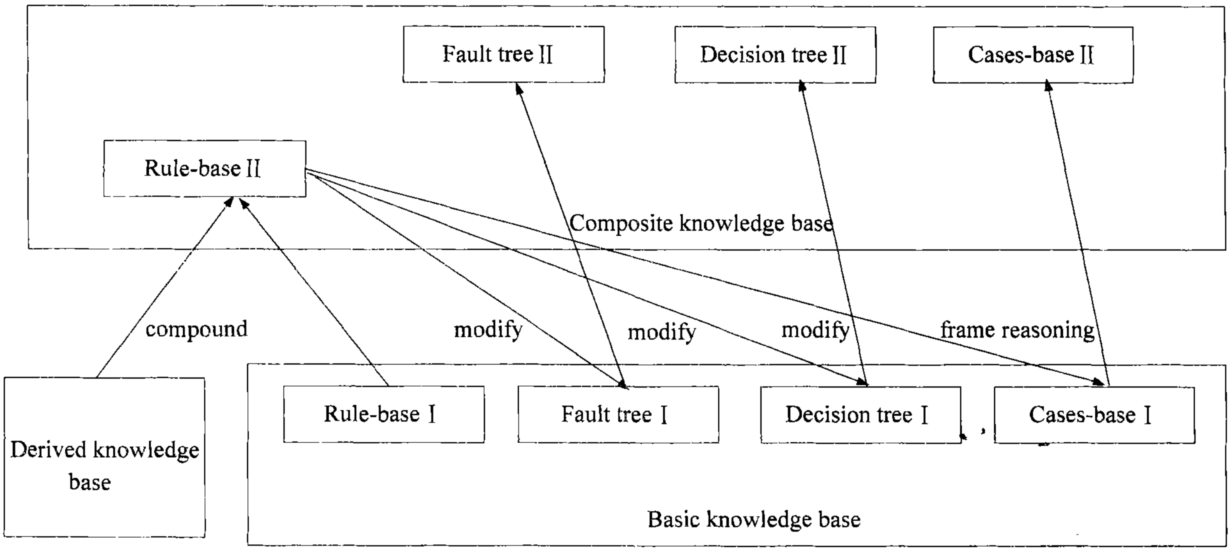

Figure 3 The process of composite knowledge base forming

It units KDD with KDK. From here it can be seen that cooperating mechanism cooperate not only database and knowledge base but also KDD and KDK.Dynamic knowledge base experiences the promotion process of basis — derivation — integration — expansion. The process only finishes the first stage of discovery, i.e. the first abstraction level. The expansion knowledge base in the first abstract level is regarded as basic knowledge base in the second abstract level. The second abstract level will be finished in a process similar to each step of discovery in the first abstract level. Things like that continue. When cognition is developed, time and space environment are changed in different stages. Knowledge will constantly be enriched and promoted and cognition will deepen.

4 Conclusions

Comparing the structure of ESKD with traditional structure of expert system, the following performance characteristics and creative idea can be found.

(1) Abundance: traditional knowledge base system only uses reasoning machine to extend knowledge in basic knowledge base. However, the dynamic knowledge base of ESKD experiences a series of promotion process of basic — derived — integrated — synthesized — extended. Both the quantity and quality of the knowledge reserve are quite abundant. Its management system is perfect and is high intellective to discover deep layer knowledge and estimate knowledge.

(2) Strong reasoning (include deduce, induce, fuzzy, qualitative, reasoning based on cases, statistics reasoning and so on) and interpretation ability.

(3) Independence: the system uses structurization system analysis method. The whole expert system is divided into independent sub-systems that can perform different function. Each sub-system can both work cooperatively and be used independently by different users.

(4) Self-learning and Self-adaptability: self-learning is improved by coordinator, learning by cases and knowledge training. New knowledge is acquired and set into dynamic knowledge base; at the same time dynamic knowledge base and database based on knowledge discovery extend in time and space. New knowledge is regenerated to fit the changing environment following the increase of abstract level. This makes the system rather self-adaptive.

(5) Versatility: ESKD adapts to quite wide field. Meanwhile, ESKD supports the cline/sever structure and different database system.

(6) Feasibility: This expert system uses mature data mining method, just like statistic induction and causal qualitative inference *etc*. The result of demo indicates its feasibility; meantime, it has important significance for theory research of expert system. Under the operating platform of Internet and Windows 95/98, we have finished the development of demonstrating program of the two important modules in ESKD with VC++5.0 and Oracle. The result is satisfactory.

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Application of Diagonal Recurrent Neural Network to DC Motor Speed Control Systems

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Abstract: A new kind of dynamic neural network—diagonal recurrent neural network (DRNN) and its learning method and architecture are presented. A direct adaptive control scheme is also developed that is applied to a DC (Direct Current) speed control system with the ability to auto-tune PI (Proportion Integral) parameters based on combining DRNN with PI controller. The simulation results of DRNN show better control performances and potential practical use in comparison with PI controller.

Key words: diagonal recurrent neural network; PI controller; DC Motor speed control system

1 Introduction

The conventional PID (Proportion Integral Differential) controllers have been widely used in DC motor speed control systems. It has many advantages, such as simple structure, good stability and high reliability. However, it has two inherent disadvantages: First, the optimal proportional, integral and derivative parameters of a PID controller are difficult to determine; Second, good performances can't be easily guaranteed when the property parameters of controlled objects change or stochastic disturbances are big even though a set of satisfactory parameters has been adjusted well.

Recently, neural networks interest the researchers of control areas for their massive parallelism,self-learning and self-organization capabilities, highly nonlinear approximation. Multilayered feedforward neural networks [1, 2] and single neuron controllers [3, 4] are widely used in control fields. But multilayered feedforward neural networks only express static nonlinear mapping and can't represent nonlinear dynamic systems. In order to apply them to control systems, time must be introduced into the network to realize time-delay of input and output with time delay operator. Dynamic recurrent neural networks have good performances in the aspect of dealing with dynamic systems or time-varying systems because of theirs inner feedback units in comparison with static networks.

In reference [5], the structure and learning method of the diagonal recurrent neural network (DRNN), *i. e.* a new kind of dynamic neural networks, have been introduced in detail. A generalized dynamic back propagation algorithm is developed and used to train DRNN. The architecture of DRNN is a modified model of the fully connected recurrent neural network with one hidden layer, and the hidden layer is comprised of self-recurrent neurons.This paper develops a direct adaptive scheme by combining DRNN [5, 6] with a conventional PI controller, and applies it to a DC motor speed control system. The simulation results of DRNN will be compared with that of conventional PI controllers.

2 Direct Adaptive Scheme Based on DRNN

The current loop is retained and the speed loop is reconstructed using DRNN. All these are to increase the speed of system response and to limit the current of DC motor armature. **Figure 1** shows the block diagram of the direct adaptive DC motor speed control system based on the DRNN. In figure 1, T_{oi} is the filtering time constant of the current loop, T_s the delaying time constant of commutation device, T_l the electromagnetic time constant, T_m the electromechanical time constant, K_s the amplifying gain of SCR device, R the global resistance of armature loop, β the current feedback coefficient, α the speed feedback coefficient, and C_e the back-EMF constant. The number of neurons in the input layer of DRNN is 3 $\{r(k),\ y(k-1),\ u(k-1)\}$, the number of neurons in the output layer is 2 $\{o_1(k), o_2(k)\}$, where $o_1(k)=K_p(k)$, $o_2(k)=K_I(k)$, and the number of neurons in the hidden layer is determined by simulation.

In the DBP algorithm, the derivative $\frac{\partial E}{\partial W}$ can be expanded using the chain rule. This special characteristic in updating the weights using the chain rule can be extended for hybridizing the DBP algorithm and the other conventional control algorithm. In the proposed control

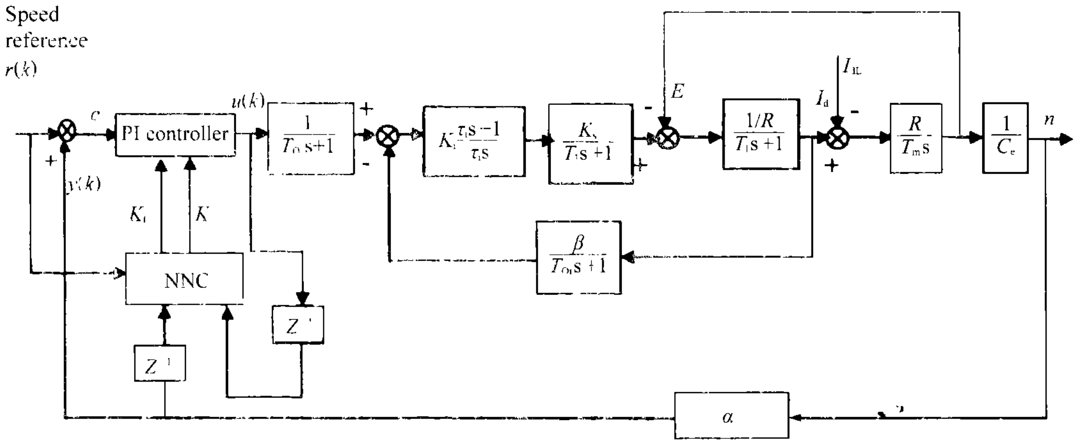

Figure 1 Block diagram of direct adaptive DC motor speed control system based on DRNN

scheme, DRNN is used as an on-line estimator. It can adjust adaptively the weights and give real-time proportional, integral parameters of the PI controller, while the conventional PI controller still gives controlled voltage. The input-output relation of the PI controller is written in the difference form as

$$u(k)=u(k-1)+K_p(k)(e(k)-e(k-1))+K_i(k)e(k) \quad e(k)=r(k)-y(k) \tag{1}$$

Because this paper uses direct adaptive scheme, must be known when adjusting weights using DBP algorithm. Nevertheless, the exact calculation of $\frac{\partial y}{\partial u}$ is difficult to determine because of the unknown plant dynamics. To overcome this problem, two methods are generally presented: first, a neural network identifier is added to obtain $\frac{\partial y}{\partial u}$, but it will result in complicated calculation and poor real-time property; second, the term $\frac{\partial y}{\partial u}$ is replaced by its sign. Researchers have proved that influences by the replacement can be compensated through selecting proper learning rate. Therefore, this paper uses the second method to obtain $\frac{\partial y}{\partial u}$.

In order to train the DRNN off-line, the cost function can be defined:

$$E=\frac{1}{2}(u_d(k)-u^*(k))^2 \tag{2}$$

where u_d represents the desired output of the PI controller, and u^* the actual output of the PI controller. Weights adjustment can be attained by equation (1) and the formulae in reference [5] using the chain rule. After training the DRNN off-line, DRNN can be used in on-line control. Weights should be adjusted in on-line to follow the given speed signal when the parameters of the controlled system change. So the performance function is defined as

$$E=\frac{1}{2}(r(k)-y(k))^2 \tag{3}$$

where $r(k)$ is the given speed signal of the kth sampling instant, $y(k)$ the speed feedback of the kth sampling instant. Weights are adjusted by equation (3) and the formulae in reference [5] using the chain rule.

3 Simulation Results

The motor used for simulation is a 220 V, 136 A, 1460 r/min DC motor. The other parameters are: $\lambda=1.5$, $T_{oi}=2$ ms, $T_l=0.03$ s, $T_m=0.18$ s. $T_s=1.7$ ms, $K_s=40$, $R=0.5\Omega$, $\beta=0.05$ V/A, $\alpha=0.007$ Vmin/r [7].

The current regulator is a PI controller and its parameters are designed according to typical I system, where $K_i=1.013$, $\tau_i=0.03$ s. The numbers of input, hidden and output neurons of DRNN are respectively 3, 5 and 2, the learning rate $\eta=0.001$. The activation function of hidden layer is selected as

$$f_h=\frac{1}{1+e^{-0.1x}} \tag{4}$$

The activation functions of output layer are selected as

$$\begin{cases} O_1=30\left(\frac{1}{1+e^{-x}}-0.5\right) \\ O_2=4\left(\frac{1}{1+e^{-x}}-0.5\right) \end{cases} \tag{5}$$

The DRNN is trained off-line according to the previous section, and trained 20 times during every sampling cycle under on-line control. The armature current must be limited because of the confined overload of the DC motor. Thus the controlled voltage u of the speed loop has maximum positive and negative limited amplitude ($u_m=+10$ V). The PI controller of the conventional speed loop is designed as a typical II system in order to compare with the DRNN controller, where $K_p=11.7$,

$\tau_i = 0.087$ s. In **figure 2**, *A* shows the motor speed step response of the DRNN control system under the condition of n=1 429 r/min, initial load I_{dL} = 50 A and full load after aa instant; *B* shows the motor speed step response of the conventional PI controller under the same condition as before. In **figure 3**, *A* shows the motor speed step response of the DRNN control system under the conditions of n = 1000 r/min, full load, and with doubled global resistance; *B* shows the motor speed step response of the conventional PI controller under the same condition as before.

The simulation results show that speed overshoot, dynamic speed descent and recover time under the DRNN control are smaller than the conventional PI controller.

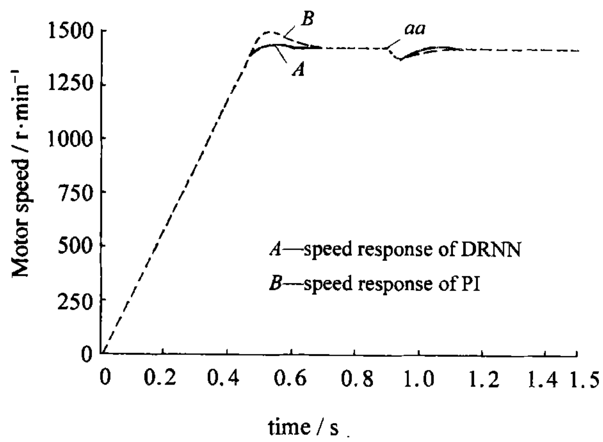

Figure 2 Motor speed response (motor start under 50 A load and then suddenly applying full load at *aa* instant)

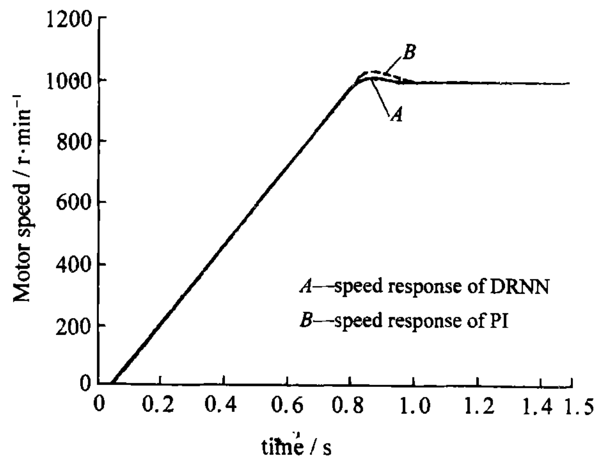

Figure 3 Motor speed response (motor start under full load and with doubled global resistance)

The ADD32, a 32-bit digital DC speed system of AVTRON company in U.S.A, is used during simulation. It has two basic loops of speed control systems: the speed loop and the current loop, and it provides good openness which allows it to be easily configured. This paper reconstructs the speed loop using the DRNN. The DRNN adjusts adaptively weights and gives suitable proportional, integral parameters of PI controller according to outer surroundings, while the control voltage is still given by the speed regulator of the ADD32. The laboratory setup of the proposed control system is shown in **figure 4**. The devices have ADD32, personal computer (Pentium 133), PC-6315

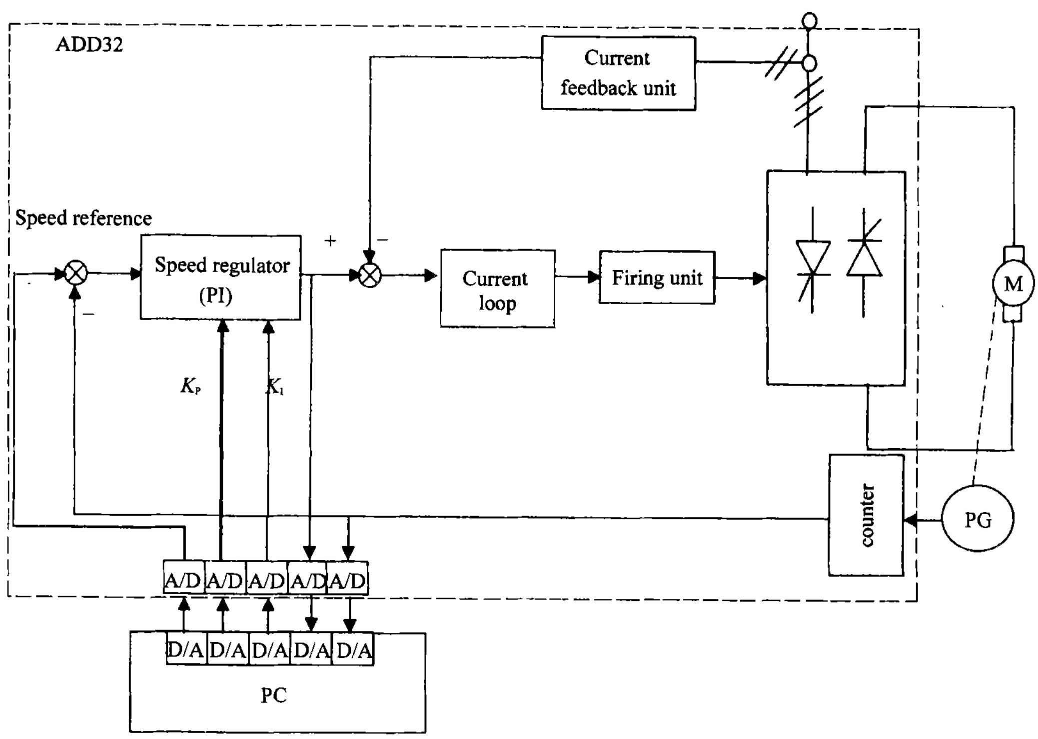

Figure 4 Laboratory setup for a DC motor speed control system based on DRNN

A/D/A card and a DC motor. Now we are trying practical application and developing neural network control block embedded in ADD32.

4 Conclusions

A new kind of dynamic neural network—DRNN and its learning method are presented, and a direct adaptive control system by combining the DRNN with a conventional PI controller is developed. The proposed control system can adjust adaptively the proportional, integral parameters to adapt to the changes of outer surroundings. The exact model of the controlled object needn't be established during the design process, and good control performances can be kept under the changes of parameters of the controlled objects. The proposed scheme provides a new way of applying intelligent control to drive systems.

References

[1] Sin Weerasooriya, Mohamed A. El-Sharkawi: *IEEE Trans on Energy Conversion*, 8 (1993). p.107.

[2] Heng-Ming Tai, Kaveh Ashenayi: *IEEE Trans on Industry Electronics*, 39 (1992). p. 504.

[3] Xiaodong Wang, Boshi Chen: *Electric Automation*, 5 (1996). p. 4.

[4] Jianyuan Hu, Longan Wu: *Electric Automation*, 1 (1993). p. 19.

[5] Jing Wang, Hui Chen: *J. of Univ. of Sci. and Tech. Beijing*, 6 (1999). p. 149.

[6] Chao-Chee Ku, Kwang Y. Lee: *IEEE Trans on Neural Network*, 6 (1995). p. 146.

[7] Boshi Chen: *Automation Control System of Electrical Drives* (Second Edition), Machinery Industry Press, Beijing, 1992.

[*continued from page* 67]

References

[1] Bingru Yang: *Journal of System Engineering and Electronics*,10 (1999), No.1. p.48.

[2] Bingru Yang: [In:] *International Symposium on Computer*, Hong Kong, 1998. p. 149.

[3] Bingru Yang: *Fuzzy Sets and System*, North Holland, 95 (1997), No.2. p. 83.

[4] Bingru Yang: *Computer Research and Development*, 34 (1997), No. 7. p. 492.

[5] Bingru Yang: *Pattern Recognition and Artificial Intelligence*, 9 (1996), No.1. p. 31.

[6] Bingru Yang: *Pattern Recognition and Artificial Intelligence*, 10 (1997), No. 4. p. 329.

[7] Gregory Piatesky Shapiro: [In:] *Proceed Second International Conference on Knowledge Discovery & Data Mining*, August2-4, 1996. p. 89.

[8] U. Fayyad, G. Piatetsky Shapiro, P. Smyth: [In:] *Proc. of KDD-96*, Menlo park, CA: AAAI Press, p. 82.

[9] S. S. Anand, D. A. Bell, J. G. Hughs: *Data & Knowledge Eng.*, 18 (1996). p. 189.

[10] R. H. Lchiang: *Data & Knowledge Engineering*, 21 (1997). p. 57.

[11] C. Li, G. Biswas: [In:] *Proceedings of the First Pacific-Asia Conference on Knowledge Discovery and Data Mining. Beijing*, 1997. p. 35.

[12] M. Metha, R. Agrawal, J. Rissanen: [In:] *Proc. 1996 Int. Conference on Extending Database Technology (EDBT'96)*, Avignon, France, March 1996.