Novel Hybrid Approach for Fault Diagnosis in 3-DOF Flight Simulator Based on BP Neural Network and Ant Colony Algorithm

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Abstract - In the 3-DOF(degree-of-freedom) flight simulator system, the relations between observed information and fault causes are very complicated. Based on the description of the basic principle of the ant colony algorithm, a novel hybrid approach for fault diagnosis in 3-DOF flight simulator is proposed in this paper, which is based on BP(back propagation) neural network and ant colony algorithm. Combining with rough set theory, ant colony algorithm is used to compute the reductions of the decision table. Then, the condition attributes of decision table are regarded as the input nodes of BP neural network and the decision attributes are regarded as the output nodes of BP neural network correspondingly. Experiments demonstrate that the proposed hybrid approach could achieve a fairly good performance, yield good prediction accuracy of the prediction errors.

I. INTRODUCTION

3-DOF(degree-of-freedom) flight simulator is a kind of important high precision instrument and a typical high performance servo system, which is widely used in the hardware-in-the-loop simulation of flight control system. It can be used to simulate the dynamic characteristics and various motion postures of aeroplane, satellite and spaceship in the laboratory environment [1]. The performance of 3-DOF flight simulator has direct effects on the reality and credibility of simulation experiments. There-fore, much more stringent requirements for the 3-DOF flight simulator are put for-ward. The fault diagnosis strategy is very important for the performance of the 3-DOF flight simulator.

BP(back propagation) neural network has shown great promise in dealing with complex mode, association, deduce and memory[2, 3]. But the endless training time is the inherent disadvantage of BP neural network, which restricts its practicality.

Ant colony algorithm is a meta-heuristic algorithm for the approximate solution of combinatorial optimization problems that has been inspired by the foraging behavior of real ant colonies[4]. In ant colony algorithm, the computational resources are allocated to a set of relatively simple agents that exploit a form of indirect communication mediated by the environment to construct solutions to the finding the shortest path from ant nest to a considered problem. By now, ant colony algorithm has been applied to combinatorial optimization problems such as the TSP(traveling salesman problem), JSP(job-shop problem), QAP(quadratic assignment problem), VRP(vehicle routing problem), GCP(graph coloring problem), and so on.

This paper presents a novel hybrid approach for fault diagnosis in 3-DOF flight simulator based on BP neural network and ant colony algorithm. The rest of this paper is organized as follows: the basic principle of the ant colony algorithm is outlined in Section 2. In Section 3, we describe the basic system structure of the 3-DOF flight simulator, followed by the novel hybrid approach for fault diagnosis in 3-DOF flight simulator based on BP neural network and ant colony algorithm in Section 4. Then, in Section 5, we conduct series experiments by using the novel hybrid fault diagnosis approach. Our concluding remarks are contained in Section 6.

II. PRINCIPLE OF ANT COLONY ALGORITHM

The natural metaphor on which ant colony algorithm is based is that of ant colonies. Real ants are capable of finding the shortest path from a food source to their nest, without using visual cues by exploiting pheromone information. While walking, ants deposit pheromone on the ground, and follow, in probability, pheromone previously deposited by other ants[5]. A way ants exploit pheromone to find a shortest path between two points is shown in Fig. 1.



Fig. 1. How real ants find a shortest path

The above behavior of real ants has inspired ant colony algorithm, an algorithm in which a set of artificial ants cooperate to the solution of a problem by exchanging information via pheromone deposited on graph edges. This process is thus characterized by a positive feedback loop, where the probability with which an ant chooses a path increases with the number of ants that previously chose the same path. With the above positive feedback mechanism, all ants will choose the shorter path in the end.

The ant colony algorithm mathematical model has first been applied to the TSP[6]. The aim of the TSP is to find the shortest path that traverses all cities in the problem exactly once, returning to the starting city.

We define the transition probability from city i to city j for the k-th ant as

$$p_{ij}^{k}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{\substack{k \in allowed_{k}}} [\tau_{ik}(t)]^{\alpha}[\eta_{ik}]^{\beta}} & if \quad j \in allowed_{k} \\ 0 & otherwise \end{cases}$$
(1)

Where *allowed*_k={N-tabu_k}, α and β are parameters that control the relative importance of trail versus visibility,

 $\eta_{ij} = 1/d_{ij}$ where d_{ij} is the distance between city *i* and city *j*,

 τ_{ii} is the amount of pheromone trail on edge (i, j). After the

ants in the algorithm ended their tours, the pheromone trail τ_{ij}

values of every edge (i, j) are updated according to the following formula

$$\tau_{ij}(t+n) = \rho \cdot \tau_{ij}(t) + \Delta \tau_{ij} \tag{2}$$

Where ρ is the local pheromone decay parameter, and $\rho \subset (0,1)$. Then, $1 - \rho$ represents the evaporation of trail between time *t* and *t*+*n*.

$$\Delta \tau_{ij} = \sum_{k=1}^{m} \Delta \tau_{ij}^{k} \tag{3}$$

Where $\Delta \tau_{ij}^k$ is the quantity of per unit length of pheromone trail laid on edge (i, j) by the *k*-th ant between time *t* and *t*+*n*. In the popular ant-cycle model, it is given by

$$\Delta \tau_{ij}^{k} = \begin{cases} \frac{Q}{L_{k}} & \text{if } k-\text{th ant uses } (i,j) & \text{in its tour } (4) \\ 0 & \text{otherwise} \end{cases}$$

Where Q is a constant, and L_k is the tour length of the *k*-th ant.

This iteration process goes on until a certain termination condition: a certain number of iterations have been achieved, a fixed amount of CPU time has elapsed, or solution quality has been achieved.

III. BASIC SYSTEM STRUCTURE OF 3-DOF FLIGHT SIMULATOR

The basic system structure of 3-DOF flight simulator is studied in this section so as to illuminate the application of rough set theory, ant colony algorithm and artificial neural network in fault diagnosis for the flight simulator. The 3-DOF flight simulator studied is driven by using three direct driven electric motors, which have three rotating parts, namely roll axis including simulation object, pitch axis including roll motor, and yaw axis including pitch motor. This 3-DOF flight simulator system can be decomposed into three controlling feedback loops, which are current loop, tachometer generator feedback loop[7, 8].

The current loop can effectively enhance the response speed, and the power amplifier is of PWM type. In order to avoid mechanical failure or system malfunctioning, it is essential in all engineering situations to safeguard against the occurrence of large initial transient overshoots. An action of tachometer generator feedback loop can solve this problem effectively. Photo-electric encoder has high resolution, its pulse signals are sent to EXE650, which can enhance the digital position feedback resolution by fifty times. Then, the modulated digital position signals are sent to IPC(industrial personal computer) through digital I/O. The IPC is the key processing unit in the control system, and the core control algorithms are conducted in this unit. Above all, it can provide a friendly interface. The basic system structure of the 3-DOF flight simulator is shown in Fig. 2.



Fig. 2 Basic system structure of the 3-DOF flight simulator

IV. HYBRID FAULT DIAGNOSIS STRATEGY BASED ON BP NEURAL NETWORK AND ANT COLONY ALGORITHM

3-DOF flight simulator is used in the hardware-in-the-loop simulation of flight control system in the laboratory environment. According to the records of testing and maintaining for the 3-DOF flight simulator, its faults have obvious accuracy and illegibility. The basic idea of fault diagnosis strategy based on rough set theory, ant colony algorithm and artificial neural network is as follows.

At first, set up an information (attribute-decision) table according to the specific domain knowledge[9]. Then, the condition attributes real-value discretization must be implemented before the reduction of the decision table.

In this section, a method based on the equal interrupt time is used to discretize continuous real-valued attributes. It is a simple and effective unsupervised discretization algorithm. After this, ant colony algorithm is used to compute the reductions of the decision table. Subsequently, the condition attributes of decision table are regarded as the input nodes of BP neural network, and the decision attributes are regarded as the output nodes of artificial neural network correspondingly. Finally, choose proper hidden layer and nerve cells, set up a back propagation neural network so as to accomplish the online fault diagnosis of the 3-DOF flight simulator.

The detailed steps of maximal generalized decision rules based on ant colony algorithm are as follows:

Step 1. Compute the core based on indiscernibility relation.

Step 2. The main aim of this step is to set parameters and initialize pheromone trails. Let ant colony algorithm be working with a fixed number of iterations.

Step 3. For each ant, we compute its transition probability given by Eq. (1). This step is named construction step.

Step 4. We incrementally build a solution and a local pheromone updating rule according to Eq. (2)~Eq. (4) until all ants have built a complete solution and we record the best solution found by now.

Step 5. If the termination condition isn't met, return to step 3. Otherwise, go on to Step 6.

Step 6. Remove redundant condition attribute values in the reduced table, and this step is repeated until every condition of the rule has been tested.

Step 7. Generation of maximal generalized decision rules, which is the reductions of the decision table.

V. EXPERIMENTAL RESULTS

In order to investigate the feasibility and effectiveness of the novel hybrid fault diagnosis approach, series experiments are conducted in this section. Combining with ant colony algorithm, rough set theory is used to compute the reduction of the decision table. Then, the reduced diagnosis rules of the 3-DOF flight simulator are obtained. In addition, these rules are used to diagnose the preprocessed testing samples to validate their diagnosis accuracy. In fact, the fault symptoms of the 3-DOF flight simulator mainly include 86 types. The reductions of the decision table are given in table 1.

TABLE 1. THE REDUCTION OF DECISION TABLE

No.	Reduction	Support	Length
1	{PosError, RealPos, SpdError}	76	3
2	{FeedbackPos, PosError,	84	3
	SpdError}		
3	{PosError, RealPos, Vc}	93	3
4	{FeedbackPos, Ia, PosError}	87	3
5	{FeedbackPos, PosError,	90	3
	RealPos}		
6	{FeedbackPos, PosError,	71	3
	RealSpd}		
7	{Ia, PosError, RealPos}	79	3

Where PosError denotes the digital position feedback error of three axis(roll axis, pitch axis and yaw axis), RealPos denotes the digital position feedback of the three axis, SpdError denotes the exact tachometer generator feedback error of the three axis, Vc denotes the control voltage of the three axis, Ia denotes the current of power amplifier.

It can be seen that after reduction of decision attributes with ant colony algorithm and rough set theory, it only needs very few typical symptoms for the network training of BP neural network. It is obvious that the BP neural network only need 5 input nodes, which are {FeedbackPos, PosError, RealPos, Vc, Ia}, for the fault diagnosis of the 3-DOF flight simulator. The number of the network hidden layer is 2, which has 25 nerve cells and 15 nerve cells respectively. In order to simplify the structure of the BP neural network, the output attribute is defined as one, and advisor learning strategy is adopted in the BP neural network training. The advisor signal training values of the BP neural network are given in table 2.

TABLE 2. THE ADVISOR SIGNAL TRAINING TABLE OF BP NEURAL NETWORK

No.	Fault symptoms	Data number	Decision attribute value
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1	No fault	40	0.15
2	Photo-electric encoder failed completely	40	0.19
3	Pulses of the photo-electric encoder missing 20%	40	0.27
4	Front turn of photo-electric encoder is normal, but reverse turn is abnormal	40	0.31
5	tachometer generator failed completely	40	0.39
6	Power amplifier monophasicly work	40	0.48
7	Current loop of the power amplifier	20	0.57
	is open		
8	Power amplifier is under voltage	40	0.70

Improved Levenberg-Marquardt algorithm is adopted in the training of the BP neural network. The testing curve of trained data by using BP neural network is shown in Fig. 3.



Fig. 3. Testing curve of trained data by using BP neural network

From the testing results, we can see that the novel hybrid approach for fault diagnosis in 3-DOF flight simulator based on ant colony algorithm and BP neural network achieves a fairly good performance, and the proposed approach has yield good prediction accuracy of the prediction errors. This hybrid approach could also reduce the number of attributes in the decision table, simplify the structure of BP neural network and improve the ability of generality. Practical application study has shown that this novel hybrid approach is practical and effective.

VI. CONCLUDING REMARKS

This work shows that it is an effective novel approach, by combining ant colony algorithm with BP neural network, to reduce the complexity of setting up the BP neural network for 3-DOF flight simulator system. As we can see from the experimental results, our novel approach reaches the precision of forecasting, and obtains higher accuracy for fault diagnosis in 3-DOF flight simulator. Practical application study has shown that this approach is practical and effective. This suggests that this hybrid fault diagnosis approach may be an efficient way for the fault diagnosis in other type of high precision simulators.

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