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Application of Multi-sensor Information Fusion in the Fault Diagnosis of Hydraulic System

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Abstract: Aiming at the problem of incomplete information and uncertainties in the diagnosis of complex system by using single parameter, a new method of multi-sensor information fusion fault diagnosis based on BP neural network and D-S evidence theory is proposed. In order to simplify the structure of BP neural network, two parallel BP neural networks are used to diagnose the fault data at first; and then, using the evidence theory to fuse the local diagnostic results, the accurate inference of the inaccurate information is realized, and the accurate diagnosis result is obtained. The method is applied to the fault diagnosis of the hydraulic driven servo system (HDSS) in a certain type of rocket launcher, which realizes the fault location and diagnosis of the main components of the hydraulic driven servo system, and effectively improves the reliability of the system.

Keywords: information fusion; D-S evidence theory; BP neural network; fault diagnosis; hydraulic system

1 Introduction

Hydraulic transmission technology is one of the key technologies to realize modern transmission and control. Due to its unique advantages such as good reliability, high control precision and small volume, it has been widely used in various fields. Especially in the requirements of the complex to adapt to the work environment of military equipment, hydraulic technology has become an indispensable basic technology. A type of rocket is military to

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fight against the enemy's long-range goal of an important weapon system, which has great power and combat capability. The hydraulically driven servo system (HDSS) is the key equipment of the rockets to play combat effectiveness. As the equipment often work in harsh conditions, the use of the process will be a variety of fault phenomena, resulting in functional decline or loss, or even cause serious accidents. Because of hydraulic system fault has hidden point of failure, fault causal complex, there are many uncertain factors in the actual diagnosis process, only a single fault characteristics and diagnostic method do not give reliable conclusions, the credibility of diagnostic results is low. In order to ensure the safe and reliable operation of HDSS, fault location and diagnosis are required timely and accurately. In the diagnosis process, the traditional single sensor-based fault diagnosis method is difficult to ensure the correctness of diagnosis results, difficult to complete the task of fault diagnosis and positioning, must use multi-sensor collaborative work to achieve fault detection and location.

2 Fault diagnosis model of hydraulic system

The new diagnostic system combines BP neural network and D-S evidential theory method, by absorbing the strong self-learning, adaptive and fault-tolerant ability of the neural network, which has stronger robustness in the fusion of uncertain information. On the basis of this, two BP neural networks are constructed to deal with the iron spectrum data and pressure, flow rate, temperature (YLW) data respectively, using two parallel BP neural networks to HDSS in partial diagnosis, then the D-S evidence theory is used to diagnose the diagnosis of the two BP neural networks.

The diagnosis system avoids the single neural network diagnosis system of complex structure, long training time, and the adverse effects of a sensor failure or data source error for the diagnosis system. By trial and error method, the number of hidden layer nodes are determined, and the training time and the number of training are reduced, the diagnostic accuracy is improved. In addition, when the multiple faults of hydraulic system occur at the same time, through the demerging of the BP network output results, and then fused with the corresponding array, simultaneous multiple faults of hydraulic system are effectively diagnosed.

The new diagnostic system is divided into three modules: data preprocessing module, the local diagnosis module of BP neural network and global diagnosis module of D-S evidence theory. The diagnostic system structure is shown in Figure 1.

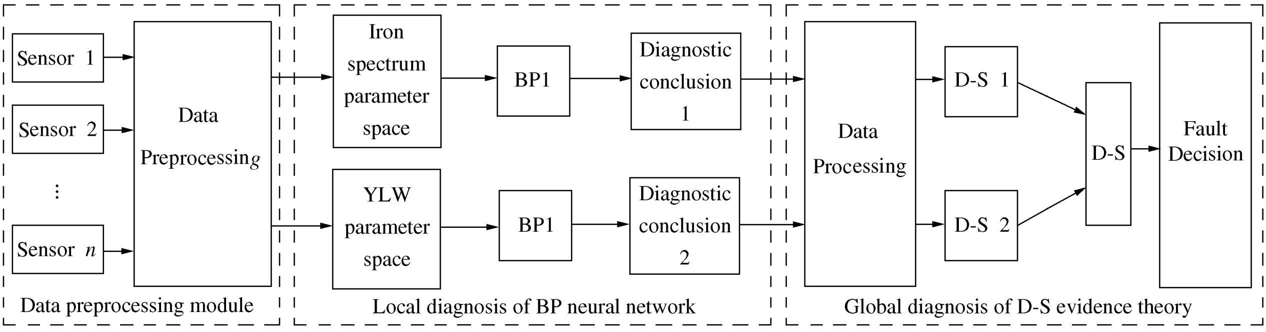

Figure 1 Structural diagram of hydraulic system fault diagnosis

2.1 D-S evidence theory

D-S evidence theory can be used to fuse consistent proposition from multiple sources (sensor), and assign to the consistent of these intersection (conjunction) propositions of basic belief assignment function corresponding proposition. In order to describe and deal with the uncertainty, the probability distribution function, the trust function and the likelihood function and so on are introduced[5-6].

1) The probability distribution function

Set Ω for the sample space, the field of propositions are represented by a subset of Ω, the probability distribution function is defined as follows.

Set function m: $2^{\Omega} \rightarrow [0,1]$, and it meets: $m(\varnothing) = 0$, $\sum_{A \subseteq D} m(A) = 1$, then m is the probability distribution function of the 2^{Ω}, $m(A)$ is the basic probability function of A.

2) Orthogonal sum of probability distribution functions

When the same evidence has two or more different probability distribution functions, it is necessary to make a combination of them, namely the orthogonal sum of probability distribution functions. M_1, M_2, $\cdots$, M_n are the probability distribution function, and the orthogonal sum is as follow:

$$\begin{cases} m(A) = 0 & A = \varnothing \\ m(A) = \dfrac{1}{1-K} \sum\limits_{\cap A_i = A} \prod\limits_{1 \leqslant i \leqslant n} m_i(A_i) & A \neq \varnothing \end{cases} \tag{1}$$

$$K = \sum_{\cap A_i = \varnothing} \prod_{1 \leqslant i \leqslant n} m_i(A_i) \tag{2}$$

If $K=0$, the orthogonal sum m is a probability distribution function; If $K \neq 0$, then there is no orthogonal sum, m_1 and m_2 are called contradictory.

2.2 BP neural network

1) Structure of BP neural network. BP network is a kind of multilayer feed-forward network with unidirectional propagation which uses the error back propagation algorithm. BP network has obvious input, hidden and output layer; hidden layer can have multilayer, adjacent layer adopts full interconnection mode connection, there is no connection between the nodes in the same layer and no direct contact between the input layer and output layer[2-3].

2) The algorithm principle of BP neural network. The principle of the standard BP algorithm: the incoming sample inputs from the input layer, and then transmit them to the output layer after hidden layer treatment. If the actual output of the output layer is not in conformity with the desired output, the output error is calculated and transmitted back through the hidden layer to the input layer in some form. The error is allocated to all the units of each layer, so as to get the error signal of each layer unit, and the error signal is used as the basis to correct the weight of each unit. Go round and begin again, the weight should be adjusted constantly, until the network output error is reduced to an acceptable level.

Because the standard BP algorithm according to the gradient descent direction of t moment constantly adjust the weights, without considering the gradient direction of t moments ago, which makes the training process of oscillating, slow convergence, and sometimes appear error gradient local minimum, can not lead to convergence. In order to avoid the disadvantages of the standard BP algorithm, this paper adopts a BP algorithm with momentum term, its principle is to add a momentum term alpha in [0, 1]. When $\alpha=0$, a weight correction is only related to the current negative gradient; when the $\alpha=1$, a weight correction totally depends on the negative gradient of the last cycle. The momentum term added to this method is essentially equivalent to the damping term, which reduces the oscillation tendency of the learning process and improves the convergence property. The correction formula of the weight:

$$w_{ij}(k+1) = w_{ij}(k) + \eta[(1-\alpha)D(k) + \alpha D(k-1)] \tag{3}$$

Where: $D(k)$ is the negative gradient of k time; $D(k-1)$ is the negative gradient of $k-1$ time; η is the learning rate.

3) BP neural network hidden layer node number. In BP network, the role of the hidden layer nodes is to extract and store the inherent law from the samples, each node has a number of weights, and each weight is a parameter to enhance the ability of network mapping. If the node number is too small, the ability of information obtained from the sample is poor, the training set of sample law is not enough to summarize and reflect; When the number of nodes is too much, the network is likely to grasp the irregular content of the sample, which appears to be "over fit", reduces the generalization ability and increases the training time[4].

The number of hidden layer nodes depends on the number of training samples, the size of the sample noise, and the complexity of implication law in the sample. To determine the number of nodes, a common method called trial and error method is used to determine the final number of hidden layer nodes by the empirical formula of the number of hidden layer nodes as the initial value of the trial and error method. Commonly used empirical formula in the number of hidden layer nodes:

$$m = \sqrt{n+1} + c \tag{4}$$

Where: m is the number of hidden layer nodes; n is the number of input nodes; l is the number of output nodes; c is a constant, which is between 1 and 10.

3 Diagnosis example

In this paper, the HDSS including steering hydraulic system, adjustable height hydraulic system has adjustable gun, tracking and precise targeting function. The HDSS principle diagram is shown in Figure 2.

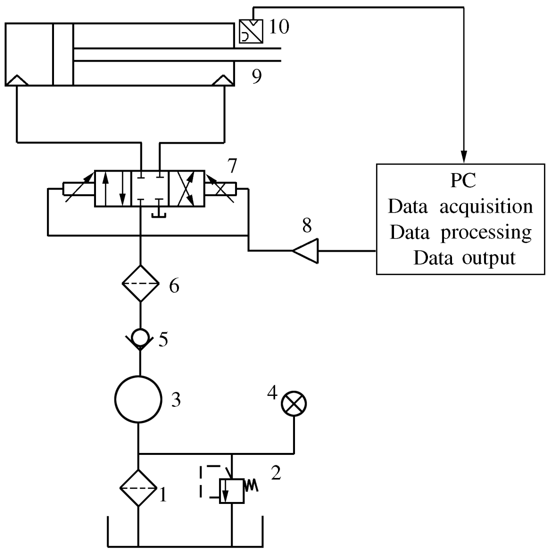

Figure 2 Principle diagram of the hydraulic driven rocket launcher servo system

The HDSS structure is mainly composed of oil filters 1 and 6, overflow valve 2, hydraulic pump 3, pressure gauge 4, one-way valve 5, electro-hydraulic proportional valve 7 (supporting the amplifier 8), hydraulic cylinder 9, displacement sensor 10, the computer is antrolled by data acquisition card and industrial.

3.1 Local diagnosis of BP neural network

1) Determination of feature vector

Determination of input and output characteristic vectors. The iron spectrum analysis method separates the abrasive particles and the pollutant particles from the oil. Through quantitatively and qualitatively analyzing abrasive particles of the composition, concentration, size characteristics and other pollution particles of the material and chemical composition, so as to identify the exact location of abrasion and failure, as well as the causes of failure. So the 4 parameters are used as the feature vector of the input layer in the BP neural network 1. According to frequently appeared fault phenomenon of the HDSS in the practical work, the hydraulic oil temperature, hydraulic pump outlet pressure, hydraulic cylinder(11, 12) oil inlet pressure, the hydraulic cylinder (11, 12) oil outlet pressure, hydraulic pump outlet flow and hydraulic cylinder (11, 12) oil outlet flow, 9 parameters are selected as the input feature vector of the BP neural network 2. According to the common fault types of the system, the oil filter clogging(F_1), the hydraulic pump fault(F_2), the hydraulic cylinder leakage(F_3), the control valve group fault(F_4), the hydraulic cylinder crawl(F_5) —— 5 kinds of fault types are selected as the output layer of the 5 node output.

2) Selection of hidden layer nodes

In the BP1 network, the number of hidden layer nodes(m) is obtained by using the formula (3), $m \in [4,13]$. By using the method of trial and error, the network training process is a process of constant revision of weights and thresholds, which can achieve the best performance and meet the needs of practical application. After the training and learning of the variable hidden layer neuron, the running results are shown in Table 1. After 2000 times of training, when the number of hidden neurons is 12, the BP network error is the smallest, the classification of the fault mode is best. In this paper, the number of hidden layer nodes in BP1 is selected as 12, the network structure is 4×12×5. By the same method, the number of hidden layer nodes in BP2 is selected as 14, so the structure of BP2 is 9×14×5.

Table 1 BP1 network training error

Number of neurons	4	5	6	7	8
Network error	0.098 2	0.118 5	0.099 8	0.112 3	0.104 1
Number of neurons	9	10	11	12	13
Network error	0.114 4	0.097 9	0.099 5	0.079 4	0.110 2

3) Output result

The hydraulic oil overheating failure of the hydraulic pump is selected to simulate the test. The test data of samples are input to two BP networks which have been trained well. After the network learning, the outputs of the two networks are Y and Z, respectively:

$$X = [-0.1457 \quad 1.1328 \quad -0.1057 \quad 0.3132 \quad 0.0791]$$

$$Y = [-0.1278 \quad 2.0671 \quad -0.0954 \quad 0.5387 \quad -0.0943]$$

3.2 Global integration of D-S evidence theory

The output of the two networks is processed by the D-S evidence theory. The training error of the neural network is as uncertain factors $m(\theta)$, which calculation formula is as follows:

$$m(\theta) = \frac{1}{2}\sum (t_{ij} - y_{ij}) \tag{5}$$

In the formula, t_{ij}, y_{ij} respectively is the jth neurons of the desired output and the actual output values.

The output of the neural network nodes is normalized, as the basic probability values of the focal elements, the calculation formula is as follows:

$$m(F_i) = \frac{y(F_i)}{\sum_{i=1}^{k} y(F_i)} \tag{6}$$

Where $m(F_i)$ is the basic probability of each focal element; F_i is the ith kind of failure mode.

According to the formula (1), formula (5) and formula (6), the output results of X and Y are processed, the reliability of the diagnostic target is obtained, and Table 2 is the reliability allocation of the two BP networks.

Table 2 The diagnostic results of two BP networks and the synthesis of evidence theory

BP	$m(F_1)$	$m(F_2)$	$m(F_3)$	$m(F_4)$	$m(F_5)$	$m(\Omega)$	Diagnostic conclusion
BP1	0.032 9	0.611 3	0.008 7	0.285 6	0.230 8	0.15	Uncertain
BP2	0.009 1	0.704 3	0.103 4	0.270 4	0.025 3	0.08	Hydraulic pump fault
BP1&BP2	0.023 0	0.867 3	0.011 0	0.191 6	0.064 7	0.003 8	Hydraulic pump fault

If $m(F_2) = 0.452\ 1$ and $m(F_4) = 0.394\ 6$ are selected as the fusion criterion, it can be drawn from table 2, confidence interval before BP network fusion and reliability allocation of uncertaintym(Ω) are relatively large, the diagnostic conclusions are not necessarily identified; but after the fusion process, the confidence interval of the fault state is obviously prominent, the reliability allocation of uncertainty $m(\Omega)$ is also decreased, the HDSS fault type is hydraulic pump fault and is consistent with the actual fault simulation.

4 Conclusion

In this paper, the data fusion method based on BP neural network and D-S evidence theory is introduced into the fault diagnosis, which can effectively overcome the defects of the single BP network diagnosis. By fusing the output of BP network, the uncertainty of fault classification is reduced, and the reliability of the diagnosis system is improved. At the same time, a simulation experiment was carried out by the fault type of HDSS, the feasibility of applying this method to the fault diagnosis of HDSS is verified. This study provides an effective way for the study of servo system fault diagnosis.

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