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The Research of Improved BP Neural Network in Automobile Sensor Fault Diagnosis

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Abstract

Fault control diagnosis object of automobile sensor has the problems of big space dimension of fault sample data and poor real-time capability of fault diagnosis, etc, in order to solve these problems, this text introduces static fuzzy control method to diagnose automobile fault based on BP neural network, first finding fault node by static fuzzy self-learning method and classifying and diagnosing intelligently by BP network. Experiments show that method in this paper improves the accuracy of automobile sensor fault diagnosis and reduces diagnosis error, thus improves the recognition and decision-making ability of diagnosis.

Keywords: *BP Neural Network; Sensor Fault*

1. Introduction

With the improvements of people's living standards, automobile has become the important part of people's life. But with the appearance of automobile's own faults, automobile fault study has become the focus of people's research. Literature [1] points out computer and information technology should be widely used in automobile, among which sensor should be gradually used in automobile control as it can perceive, collect, convert and process the automobile information, and convert perceived information to output other required information. Automobile sensor is the component of automobile electronic control and hardcore of automobile electronic technology. Literature [2-3] points out the soft closed-loop fault control method of multi-model sensor driven by data. Carry out the research of common sensor faults as sticking, constant gain, and constant deviation in nonlinear system. Literature [4] points out at present sensor control are mainly for the bottom part of scale body to accomplish signal output of fault sensor by sensor output. But it's easy to deviate from the center and influence the accuracy. Literature [5] points out digital weighting sensor can realize uninterrupted operation and obtain fault signal in a short period of time, but the shortcoming is expensive. Literature [6-7] points out we can carry out the fault diagnosis of array sensor by improved mode filtering method based on structure vibration response characteristics. Literature [8] points out the Bayesian network fault diagnosis based on multi-sensor information fusion, and tests show that the improved diagnosis accuracy has better application value. Literature [9] points out a sensor fault diagnosis expert system based on neural network fusion, test sensor fault by using BP neural network. Research results show that this sensor fault expert system has the characteristics of high accuracy and diagnosis speed. Literature [10] points out the sensor fault diagnosis system formed by SVM forecasting model and RBFN forecasting model, as SVM determines whether sensor fault exists and RBFN model locates fault sensor and reconstruct its information by using information redundancy within each sensor.

The paper mainly introduces static fuzzy control based on BP neural network to classify automobile sensor control fault effectively and correctly. Diagnose and recover the automobile sensor fault accurately to effectively ensure normal operation of automobile sensor.

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2. Car Sensor Control Fault Model

The output signal is mainly automotive sensor voltage signal, when the wiring between automotive sensors and ECU (sensor and the engine control unit) have open circuit, the voltage signal will be beyond the normal range and thus causes a malfunction. Usually we set the car's normal range of the sensor output signal voltage is $(U_{\min}, U_{\max})$, if the actual input signal voltage is greater than $U_{\max}$ or less than $U_{\min}$, it is considered that the signal is not reliable, which means that the sensor is faulty. Only after the sensor signal lasts some time, a fault in ECU is judged. Assuming the number of sensors in the vehicle sensor network nodes is J, each node in the data acquisition sampling process samples for n times, the data length of a single node is n. Data collected as a single node in the column of the matrix, the network data may be represented as

$$\boldsymbol{X}_{2D} = \begin{pmatrix} x_{11} & \cdots & x_{1J} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nJ} \end{pmatrix}$$

For ease of presentation, data in each node will be converged, and network data can be written in vector form

$$\begin{aligned} \boldsymbol{X} &= vec(\boldsymbol{X}_{2D}) \\ &= (x_{11},..., x_{1n}, x_{12},..., x_{n2}, x_{1J},..., x_{nJ})^T = (x(1), x(2),...x(N))^T \end{aligned} \quad (1)$$

Wherein $\boldsymbol{X} \in R^N$, $N = J \times n$.

Before compressing and sensing measurements of the data, we use discrete cosine transform (Discrete Cosine Transform, DCT) for converting the sparse voltage signal

$$\boldsymbol{X} = \boldsymbol{\Psi s} = \sum_{i=1}^{N} \psi_i s_i = \sum_{k=1}^{K} \psi_k s_k \,, \quad s_k \neq 0 \quad (2)$$

Wherein $\boldsymbol{\Psi}$ is $N \times N$ dimensional DCT transform matrix; in N dimensional sparse coefficient vector s_k contains K（$K << N$） nonzero elements. Measurement data measured by the matrix is generated by the local node, denoted node j（$j \in 1,2,..., J$） generated the measurement matrix as $\boldsymbol{\Phi}_j$, the matrix of dimension is $m \times n$（$m << n$）. The resulting measured value of each node is written as a vector form

$$\begin{aligned} \boldsymbol{Y} &= (y_{11},..., y_{1m}, y_{12},..., y_{m2}, y_{1J},..., y_{mJ})^T \\ &= (y(1), y(2),...y(M))^T \end{aligned} \quad (3)$$

The measurement process of network data matrix can be expressed in vector form as follows:

$$\boldsymbol{Y} = \boldsymbol{\Theta X} = \boldsymbol{\Phi \Psi s}$$

wherein $\boldsymbol{Y} \in R^M$, $M = J \times m$, Measurement matrix

$$\boldsymbol{\Phi} = \begin{pmatrix} \Phi_1 & 0 & \cdots & 0 \\ 0 & \Phi_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \Phi_J \end{pmatrix} \in R^{M \times N} 。 \quad (4)$$

In order to find the vehicle sensor control nodes data timely and accurately, we need to use known measured value Y and under restoring matrix $\boldsymbol{\Theta}$ conditions to reconstruct sparse coefficients matrix vector. As the vehicle sensor data sparse coefficient vector control node sparse degree changes with node mobility , this paper will propose a new method to solve the fault diagnosis for this problem.

3. Automotive Sensor Diagnostic Control Based on Dynamic Fuzzy and BP Neural Network Algorithm

3.1. Energy Self-Learning Based on Dynamic Fuzzy Function

Automotive sensor network failure has some randomness, and it is a typical nonlinear structure; whereas dynamic fussy function may well find death nodes in sensor fault. Dynamic fuzzy basis function is constructed as follows:

$$F_n(x) = \frac{\prod_{i=1}^{n} T_i(x)}{\sum_{i=1..n} \prod_{i=1}^{n} T_i(x)} = \frac{ruq\left[\sum_{i=1,j=1}^{n} \left(\frac{x_i - \overline{x_j}}{\varpi_{ij}}\right)^2\right]}{\sum_{i=1,j=1..n} ruq\left[-\sum_{i=1,j=1}^{n} \left(\frac{x_i - \overline{x_j}}{\varpi_{ij}}\right)^2\right]} \quad (5)$$

Through setting car sensor nodes energy (set as w_i), we enter it into the formula (5) to give the corresponding node energy improvements as follows:

$$Y = \sum_{i=1}^{k} F_i(x) w_i \quad (6)$$

In the formula (6) , in which k represents the number of sensor nodes. By constructing dynamic functions in fuzzy function as follows:

$$if \;\; x_i \in T(x) \;\; then$$

$$Y = \sum_{i=1}^{N} \frac{u_i}{y_i} \quad (7)$$

In equation (7), x_i as fuzzy variable, $T(x)$ means REFERENCES fuzzy variables. Wherein u_i is set as real numbers between 0 and 1, $\frac{u_i}{y_i}$ Indicates the possibility of y_i is u_i ; meaning : when x_i reaches $T(x)$, the likelihood of y_i is u_i . Assuming $T(x)=\{u_1 \cdots u_n\}$ contains n specifications, we set $T^{'}$ represented by mamdani implication, by $T_1^{'} \cdots T_n^{'}$ using mamdani to infer $T^{'} = (\alpha_1 u_1 \cdots\cdots \alpha_n u_n)$. Using Equation (8) to conduct self-learning $T^{'}$ and we obtain $T^{''}$, whose precision is much larger than $T^{'}$.

$$T^{''} = \frac{\sum_{i=1}^{N} Y_i \alpha_i u_i}{\sum_{i=1}^{N} \alpha_i u_i} \quad (8)$$

We combine three Equation (6), (7) and (8) to obtain a self-learning ability to dynamically control functions for automotive sensor nodes, thereby enabling rapid judgment on automotive sensor nodes energy loss .

3.2. BP Neural Network

BP neural network is a one-way transmission network, usually consists by the input layer, hidden layer and output layer. It spread signal in forward and reverse transmission. In reverse transmission, weights are adjusted by Delta learning rule. In forward transmission, we sequentially according to formula (9) in the input and output of each layer until the output layer . When the output layer is not expected, it conducts reverse transmission according to the error adjustment weights and thresholds between expectations and actual output. See formula (10) for adjustment formula weights.

$$W_i = \sum_j w_{ij} x_j + \theta_i$$

$$y_i = f(W_i) \qquad (9)$$

In the formula (1) , W_i is the activation value of the i-th layer node, θ_i is the threshold value, x_j is the input signal, w_{ij} is the connection weights coefficient of the first node and the second node, and y_i is the output value of the node i.

$$w_{ij}(t+1) = w_{ij}(t) + \frac{\partial E}{\partial w_{ij}} \qquad (10)$$

In formula (10), $\frac{\partial E}{\partial w_{ij}}$ is the error between the desired output of neural network and the actual output .

3.3. Description of the Algorithm

In this paper, it uses the sparsity in a transform domain to achieve control of automotive sensors detect reconstruction algorithm. Most of the current reconstruction algorithm combine sparse vector sparse pre-specified level of prior information to support the potential size of the set, whereas the algorithm in this paper based on this method, first to determine the set of automotive sensor failures through self-study in support of the dynamic function, and then through BP neural network algorithm of fault sensor for rapid classification, thus shortening the detection time to improve the detection efficiency.

Specific steps are as follows:

Initialization: residuals $\boldsymbol{r_0} = \boldsymbol{Y}$, iterations $t=1$, potential support set iteration step $size \neq 0$, the support set potential $L = size$, segmentation number $stage = 1$, the index set $\Lambda_0 = \phi \; \Omega_0 = \phi$.

calculate the correlation coefficient between recovery matrix for each column and residuals, and select $2L$ correlation coefficient that have the largest magnitude

$$u_t = \{u_i \mid u_i = |\langle r, \Theta_i \rangle|\} \quad i = 1,2,...N \,, \quad \Omega_{t_0} = (u_t, 2L)$$

(2) update the set of index values, and introduce into the formula (5)

$$\Lambda_{t-1} = \Lambda_{t-1} \square F_n(x)$$

$$\Lambda_{t_0} = \Lambda_{t-1} \cup \Omega_t \qquad \Lambda_t = (\Lambda_{t_0}, L)$$

(3) estimated sparse coefficient vector

$$\hat{\boldsymbol{s}} = \arg \min_{i \in R^{\Lambda_t}} \|\boldsymbol{Y} - \boldsymbol{\Theta}_{\Lambda_t} \boldsymbol{s}\|_2$$

(4) Update the residuals: $\boldsymbol{r_t} = \boldsymbol{y} - \boldsymbol{\Theta}_{\Lambda_t} \hat{\boldsymbol{s}}$

(5) introduce into the formula (9) and formula (10), determines the algorithm termination condition: $\|\hat{\mathbf{s}}_{\mathbf{t-1}} \square y_i - \hat{\mathbf{s}}_{\mathbf{t}}\|_2 < \varepsilon$. If satisfied, the algorithm stops, output $\hat{\mathbf{x}} = \mathbf{\Psi}\hat{\mathbf{s}} \square w_{ij}$; if not satisfied, go to Step

(6) continue this subparagraph iteration: $t = t + 1$, to step (1).

Final solution: $\hat{\mathbf{x}} = \mathbf{\Psi}\hat{\mathbf{s}} \square w$

4. Experimental Simulation and Analysis

The paper select 200 groups of automobile fault data in Shaoxing Fenglin Garage, and divide each group into 50 sets of data, use the first 30 sets for training and rest 20 sets for test. Then classify fault samples by static fuzzy fusion, at the same time, design one BP neural network classifier to validate the self-learning usage of static fuzzy function. The comparison of diagnosis results of two BP neural network classifiers is shown as Table 1. Three groups of data chosen by impact sensor fault are shown as Table 2. Table 3 shows results processed by static fuzzy function self-learning method. Table 4 shows the actual output data of BP neural network classifier.

Table 1. Diagnosis Results Comparison

Input layer	Hidden layer	Output layer	Training frequency	Recognition rate
18	18	12	300	45/50
20	25	18	150	40/50

Table 2. Select Three Groups of Impact Fault Data

First group	Second group	Third group
0.15	0.27	0.42
0.32	0.34	0.25
0.41	0.42	0.49
0.42	0.56	0.78
0.91	0.78	0.91
0.89	0.61	0.89
0.78	0.63	0.56
0.40	0.38	0.45
0.49	0.35	0.32
0.39	0.36	0.49
0.46	0.35	0.37
0.42	0.42	0.49

Table 3. Fault Data Processed by Static Fuzzy Function

First group	Second group	Third group
1.5219	1.3568	1.6211
0.2118	0.0762	0.1849
0.3214	0.2523	0.6081
0.1725	0.0473	0.0176
0.0696	0.0156	0.1917
0.2443	0.3423	0.3551
0.2789	0.0241	0.2991
0.0464	0.0629	0.0605

Table 4. Comparison of Three Groups of Data

Group	Impact	stuck	offset	circle	normal
First group	0.5233	0.1875	0.0458	0.0704	0.3892

Second group	0.4815	0.0751	0.0885	0.0483	0.4524
Third group	0.6625	0.0287	0.0913	0.0472	0.3482

Found from Table 1-4, after processing fault sample data of automobile sensor by improved BP network algorithm, input layers of neural network reduces from 20 layers to 8 layers, and training frequency reduces sharply to 100 times, obviously, CPU time-consuming shortens significantly and it basically keep the same fault recognition rate. While ensure recognition rate by static fuzzy function, it simplifies BP neural network structure and improves diagnosis speed, which is an effective method to realize the improvement of fault sample classification real-time by BP neural network.

In order to further explain the advantage of algorithm in this paper, we compare it with other text algorithms in two sides of test error and test success rate. The results show as picture 1-2.

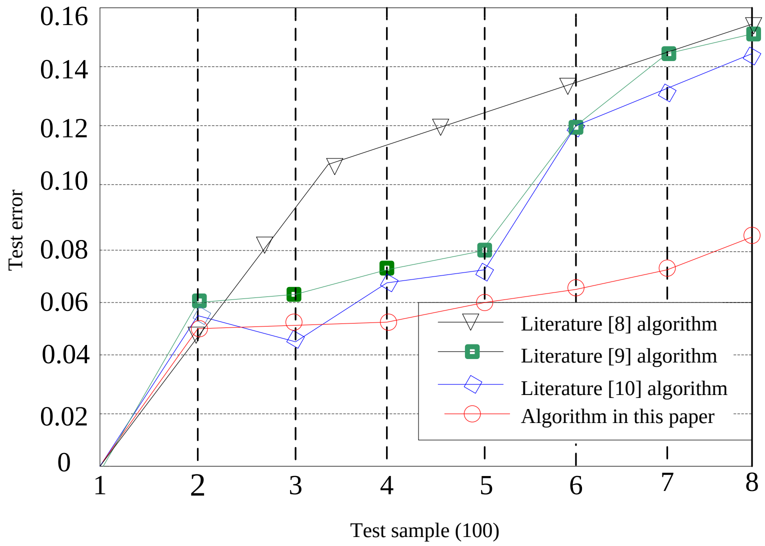

Figure 1. Test Error Comparison of Four Algorithms

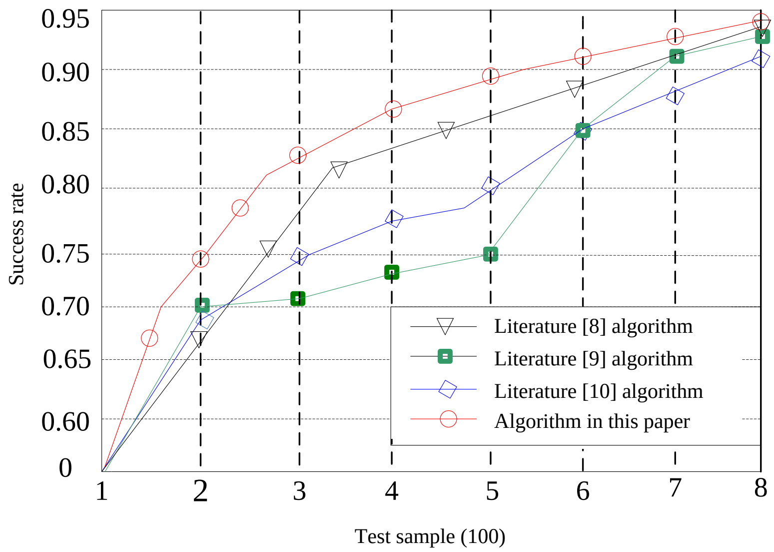

Figure 2. Test Success Rate Comparison of Four Algorithms

It shows from above pictures, algorithm in this paper is much better than that of other three algorithms in the aspect of test error, as it effectively improves the test accuracy. In addition, the test failure rate of the algorithm in this paper is lower than that of other three algorithms. In the four fault tests frequently used in automobile, algorithm in this paper is obviously better than the other three algorithms, which show algorithm in this paper has certain superiority.

5. Conclusion

For the test of fault control of automobile control, this paper points out classifying fault rapidly by introducing static fuzzy control method based on BP neural network, first collecting input data of fault sample by static fuzzy function, and then classifying data of the output results of neural network. At the same time, the experiment data shows algorithm in this paper can simplifies neural network structure while ensure fault accuracy and improve the speed of fault diagnosis.

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