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Using ENN-1 for fault recognition of automotive engine

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ABSTRACT

In the automotive factory, various types of engines are assembled and dispatched. An engine fault not only damages the engine itself but also causes a break in the automobile system. Engine fault diagnosis can produce significant cost saving by scheduling preventive maintenance and preventing extensive downtime periods caused by extensive failure. Therefore, this paper presents a novel diagnosis method based on the extension neural network type-1(ENN-1) and applies it in the fault diagnosis of engine malfunction. The proposed ENN-1 has a very simple structure and permits fast adaptive processes for new training data. Moreover, the learning speed of the proposed ENN-1 is shown to be faster than the previous approaches. The proposed method has been tested on practical diagnostic records and compared with the multilayer neural networks (MNN) and *k*-means classification methods. The test results show that the proposed method is suitable for detecting vibration fault of automotive engine, and it is efficient in dealing with noise in the data.

1. Introduction

Along with the popularizing of car, the car has become an important tool in human life. Since the first car invents in this word, the traffic accident has also become a part of human life. There are many kinds of the reasons in traffic accident, sometime because of the drivers but most of the time because of the failure of car engine. Security is a most important subject in automotive engineering, the changed amount of fuel injection and the fuel combustible completely or not directly influences the thickness of exhaust in engine, the condition of an operating engine changes will increase vibration of this engine. Therefore, it is important to recognize incipient faults in engines, so that maintenance engineers can regulate them safety and improve the reliability of automobile systems. Components module will generate natural loss and improper maintenance, all will make the engine oil consumption to gradually increase, the thickness of exhaust will be increased, and cylinder vibration and the temperature of engine exhaust will come to abnormal situation, this type of fault is due to the gradual formation, so it is difficult to perceive. However, with the day after day operation of the engine, the fault will increase day by day, and this will not only influence the performance of engine seriously but also cause the engine to stop functioning, thereby resulting in traffic accident or something dangerous. So how to detect engine fault signs early and how to immediately repair or remove them is very necessary.

The diagnosis technique is essentially a process of pattern recognition in the changes of fault signals. In the past, various fault diagnosis techniques have been proposed, including the recently expert systems (Osborne, 1988; Styvaktakis, 2007), neural networks (Kerezsi & Howard, 1995), *k*-means method (Duda & Hart, 1973), and fuzzy logic approaches (Zhang, Sun, Qu, Hu, & Zhou, 2001). The expert system and fuzzy logic approaches involve human expertise and have been successfully applied in this field. However, there are some intrinsic shortcomings such as the difficulty of acquiring knowledge and maintaining of a database. Traditional neural networks (NN) can directly acquire experience from the training data, and overcome some of the shortcomings of the expert system. However, traditional neural networks present strategic difficulties in deciding upon the number of neurons in hidden layers and are time-consuming in training (Rumelhart, & Meclelland, 1986).

In this paper, a novel neural network topology, called the extension neural network type-1 (ENN-1) is proposed for fault diagnosis in an automotive engine. The ENN-1 introduced by the author (Wang, 2005; Wang & Chen, 2001; Wang & Hung, 2003), is a new pattern classification system based on concepts form neural networks and extension theory (Cai, 1983). The proposed ENN uses a new extension distance to measure the similarity between instances and cluster center of the fault types, so that the fault type of the test an automotive engine can be identified by the ENN-1 diagnosis system. The proposed ENN-1-based fault diagnosis method (EBFDM) permits fast adaptive processes for accessed significant and new information, and gives shorter learning times than previous approaches. Moreover, this EBFDM has shown

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higher accuracy, less memory consumption, and better noise rejection abilities in application.

2. Extension neural network type-1 (ENN-1)

The schematic structure of the ENN-1 is depicted in Fig. 1. It comprises both the input layer and the output layer. The nodes in the input layer receive an input feature pattern and use a set of weighted parameters to generate an image of the input pattern. In this network, there are two connection values (weights) between input nodes and output nodes; one connection represents the low bound, and the other connection represents the upper bound for this classical domain of the input features. The connections between the jth input node and the kth output node are w_{kj}^L and w_{kj}^U. This image is further enhanced in the process characterized by the output layer. The output layer (called the extension distance layer) is a strong lateral inhibition network; only one output node in the output layer remains active to indicate a classification of the input pattern. The operation mode of the proposed ENN-1 can be separated into the learning phase and the operation phase. The learning algorithm of the ENN-1 is discussed in the next section.

2.1. Learning algorithm of the ENN-1

The learning of the ENN-1 can be seen as supervised learning; the purpose of learning is to tune the weights of the ENN-1 to achieve good clustering performance or to minimize the clustering error. Before the learning, several variables have to be defined. Let training pattern set be $x \equiv \{x_1, x_2, \ldots, x_N\}$, where N_p is the total number of training patterns. The ith pattern is $x_i^p \equiv \{x_{i,1}^p, x_{i2}^p, \ldots, x_{in}^p\}$, where N_p is the total number of the features, and the category of the ith pattern is p.

To evaluate the learning performance, the error function is defined below:

$$E_t = \frac{1}{2}\sum_{i=1}^{N_p}\sum_{j=1}^{n_c}(d_{ij} - o_{ij})^2 \tag{1}$$

where d_{ij} represents the desired jth output for the ith input pattern. The detailed supervised learning algorithm can be described as follows:

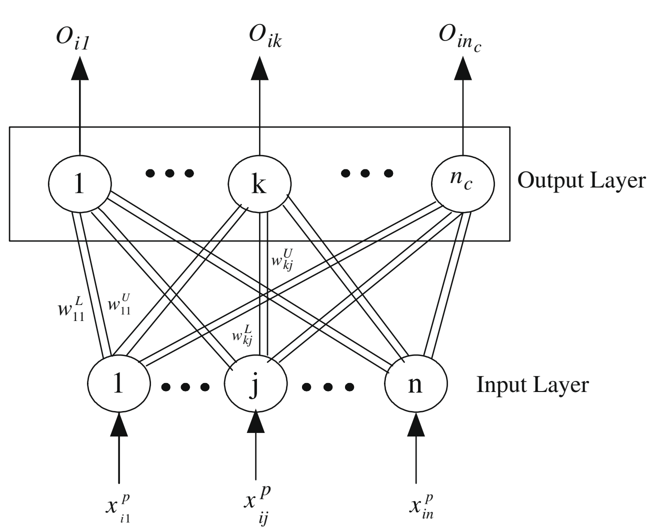

Fig. 1. The structure of extension neural network type-1.

Step 1. Set the connection weights between input nodes and output nodes by the matter–element model (Cai, 1983):

$$R_k = \begin{bmatrix} F_k, & c_1 & V_{k1} \\ & c_2, & V_{k2} \\ & \vdots & \vdots \\ & c_n, & V_{kn} \end{bmatrix} \quad k = 1, 2, \ldots, n_c \tag{2}$$

where R_k: kth cluster (matter-element); F_k: Name (or fault type) of the cluster R_k; c_j: jth characteristic (feature) of F_k; n_c: Number of clusters, $V_{ki} \le w_{ki}^L, w_{ki}^U$ is the classical domain (boundary) of the kth cluster (N_k) about the jth feature c_j. The range of classical domains can be directly obtained from previous experience, or determined from training data as follows:

$$w_{kj}^L = Min\{x_{ij}^k\} \tag{3}$$

$$w_{kj}^U = Max\{x_{ij}^k\} \tag{4}$$

It should be noted that the initial weights of the proposed ENN-1 are directly determined from training data, which is different from the traditional neural networks.

Step 2. Calculate the initial cluster center of every cluster.

$$Z_k = \{z_{k1}, z_{k2}, \ldots, z_{kn}\} \tag{5}$$

$$z_{kj} = \left(w_{kj}^L + w_{kj}^U\right)/2 \quad \text{for } k = 1, 2 \ldots n_c;\ j = 1, 2 \ldots n \tag{6}$$

Step 3. Read the ith training pattern and its cluster number P.

$$X_i^p = \{x_{i1}^p, x_{i2}^p, \ldots x_{in}^p\} \tag{7}$$

Step 4. Use the proposed extension distance (ED) to calculate the distance between the training pattern X_i^p and the kth cluster as follows:

$$ED_{ik} = \sum_{j=1}^{n}\left(\frac{|x_{ij}^p - z_{kj}| - (w_{kj}^U - w_{kj}^L)/2}{|(w_{kj}^U - w_{kj}^L)/2|} + 1\right) \quad \text{for } k = 1, 2 \ldots n_c \tag{8}$$

Step 5. Find the k^*, such that $ED_{ik^*} = Min\{ED_{ik}\}$. If $k^* = p$ then go to *Step 7*; otherwise *Step 6*.

Step 6. Update the weights of the pth and the k^*th clusters as follows:

(a) Update the centers of the pth and the k^*th clusters:

$$z_{pj}^{new} = z_{pj}^{old} + \eta\left(x_{ij}^p - z_{pj}^{old}\right) \tag{9}$$

$$z_{k^*j}^{new} = z_{k^*j}^{old} - \eta\left(x_{ij}^p - z_{k^*j}^{old}\right) \tag{10}$$

(b) Update the weights of the pth and the k^*th clusters:

$$\begin{cases} w_{pj}^{L(new)} = w_{pj}^{L(old)} + \eta(x_{ij}^p - z_{pj}^{old}) \\ w_{pj}^{U(new)} = w_{pj}^{U(old)} + \eta(x_{ij}^p - z_{pj}^{old}) \end{cases} \tag{11}$$

$$\begin{cases} w_{k^*j}^{L(new)} = w_{k^*j}^{L(old)} - \eta(x_{ij}^p - z_{k^*j}^{old}) \\ w_{k^*j}^{U(new)} = w_{k^*j}^{U(old)} - \eta(x_{ij}^p - z_{k^*j}^{old}) \end{cases} \tag{12}$$

where η is a learning rate, it is set to 0.09 based on the learning experience in this paper. From this step, we can clearly see that the learning process is only to adjust the weights of the pth and the k^*th clusters. Therefore, the proposed ENN-1 has a speed advantage over other traditional neural networks, and can quickly adapt to new and important information.

Step 7: Repeat Step 3 to Step 6, if all patterns have been classified, then a learning epoch is finished.

Step 8: Stop, if the clustering process has converged, or the total error has arrived at a preset value, otherwise, return to Step 3.

It should be noted that the proposed ENN-1 can take human expertise before the learning, because the initial weights can directly take according to previous experience, or determined from training data; and it can also produce meaningful weights after the learning, because the classified boundaries of the features are clearly determined by both the upper and lower bounds of weights.

3. The proposed engine diagnosis method

The tested object of this research is the engine of the Nissaan CEFIRO 2.0 as shown in Fig. 2. The base configuration of the engine has about 1.0 mm spark-plug gap, and the engine temperature is working between 80 and 95 °C. When in the experiment time, however engine in normal time or in all kinds of fault tests time are all in parked gear.

3.1. The configuration of the tested system

The main specifications of the engine are shown in Table 1, the maximum power is 150 hp, and the maximum torque of this engine is 19.3 kg m. This paper uses the pressure transmitter; repeater and Digital Storage Oscilloscope (DSO) to retrieve the back pressure of the engine exhauster, and uses the analyzer of exhaust gas to get exhausted components, and uses the temperature sensor for the exhaust temperature. According to the testing report of engine fault, the items of inside fault include the fuel nozzle malfunction, the ignition malfunction, the improper size of the gaps at each spark plug, and the malfunction of oxygen sensor. The experimental structure is shown in Fig. 3. The fault types can be divided into 16 kinds (including no fault), and 8 characteristics are the input data. This study separately installed the temperature sensor in T1, T2, T3 and T4, so that we can promptly monitor the temperature of every exhaust position to speculate engine fault. The components of engine exhaust include HC (ppm), CO (%) and CO2 (%). The exhaust pressures relative to the multiple frequency of engine's rotational speed are shown as Table 2.

Fig. 2. The engine of Nissaan CEFIRO 2.0.

Table 1
The main specifications of the Nissaan CEFIRO 2.0 engine.

Items	Specifications
Engine from	6-cylinder/4-stroke gasoline engine
Fuel supply	Gasoline
Valve type	DOHC 24 V
Cylinder volumes	1995 cc
Compression ratio	9.5:1
Max. power	150 hp/6400 rpm
Max. torque	19.3 kg m/4000 rpm

3.2. Testing results and discussion

In this paper, we use 208 tested data according to the reference (Chen, 2006) to test the practicability of the proposed method, the partial engine data with different fault types are shown in Table 3. In the training stage, the training data are 160 sets that are 10 sets of data in each fault. In the testing stage, the other data (48 sets) are used to test pattern. In order to take into account errors and uncertainties, 48 sets of the testing data were created by adding ±5% to ±20% random uniform-distributed samples to test the robustness of diagnosis methods, the results are shown in Tables 4 and 5. We can find, when using the multilayer neural network (MNN) and *k*-means-based method to diagnose the faults of engine, the maximum accuracy rate is 97% in the MNN, and the accuracy rate is 85% in *k*-means-based method, but if we use the proposed method based on the ENN-1, the accuracy rate is 100% the accuracy rates of the proposed method are quite high with all 100% for both the training and testing sets.

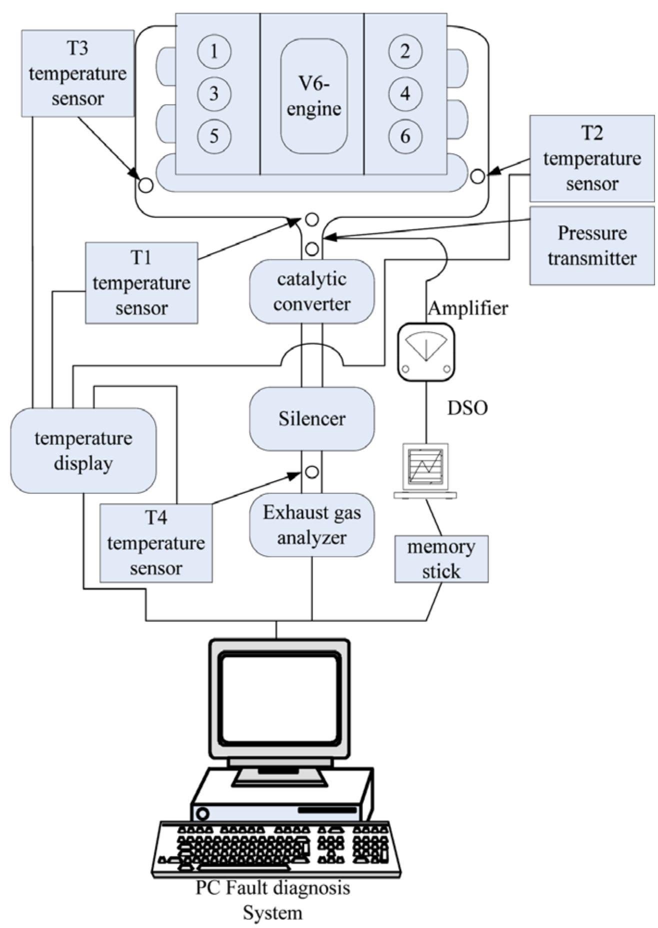

Fig. 3. The experimental structure.

Table 2
Fault types relative to the multiple frequency of the engine rotational speed.

Items	Fault types	Characteristic frequency 9.5th–12th multiple frequency
1	No fault	Nothing
2	Spark plug over 2.0 mm	Nothing
3	Spark plug under 0.2 mm	12
4	No fuel injection in the 1st cylinder	9.5, 10.5, 12
5	No fuel injection in the 2nd cylinder	9.5, 12
6	No fuel injection in the 3rd cylinder	9.5, 10.5, 12
7	No fuel injection in the 4th cylinder	9.5, 12
8	No fuel injection in the 5th cylinder	9.5, 10.5, 12
9	No fuel injection in the 6th cylinder	9.5, 12
10	No ignition in the 6th cylinder	9.5, 10.5, 12
11	No ignition in the 5th cylinder	9.5, 12
12	No ignition in the 4th cylinder	9.5, 10.5, 12
13	No ignition in the 3rd cylinder	9.5, 12
14	No ignition in the 2nd cylinder	9.5, 10.5, 12
15	No ignition in the 1st cylinder	9.5, 12
16	Oxygen sensor malfunction	12

The input data of an engine recognition system would unavoidably contain some noise and uncertainties. The sources of error include environmental noise, transducers, human mistakes, etc., which could lead to data uncertainties. To take into account the noise and uncertainties, 48 sets of testing data were created by adding ±5% to ±20% of random, uniformly distributed, error to the training data to appraise the fault-tolerant abilities of the proposed method. The test results using different amounts of errors added are given in Table 5. Usually, the error containing data indeed degrade the recognition capabilities in proportion to the amounts of error added. This table shows that the proposed method can all bear remarkable tolerance to the errors contained in the data. The proposed method has a significantly higher recognition accuracy of 90% with ±5% errors added and also has accuracy rates of about 60% in extreme error of ±20%, which prove the learning efficiency of the proposed method, Fig. 4 shows the learning curves of the ENN-1 in the training stage, it shows that the training times of the proposed method is quite economical, i.e. only 20 epochs. Although the engine recognition system is trained off-line, the training time is not a critical point to be evaluated. It is an index, however, implying in some degree the efficiency of the algorithm developed, which is rather beneficial when implementing the recognition methods in a Microcomputer for a real-time detecting device or a portable instrument.

Table 4
Diagnosis performances of method compare.

Method	Training time (Epochs)	Accuracy rate (%)
Proposed ENN-1 method	20	100
K-means method	N/A	85
MNN- I (8-4-16)	1000	50
MNN-II (8-8-16)	1000	62
MNN-III (8-10-16)	1000	80
MNN-IV (8-12-16)	1000	97
MNN-V (8-15-16)	1000	95

Table 5
Diagnosis performances of errors added.

Noise percentage (%)	Accuracy rate (%)
±0	100
±5	90
±10	75
±15	67
±20	58

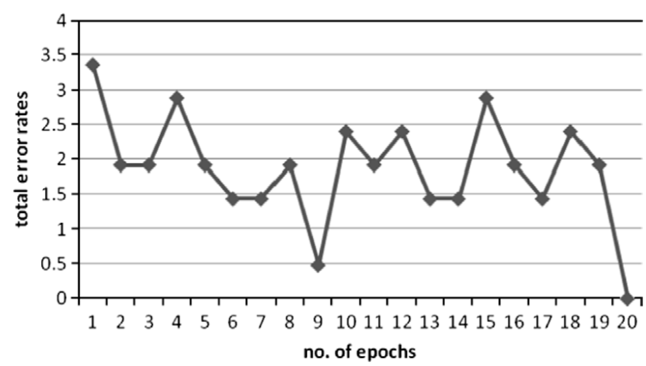

Fig. 4. The learning curve of the proposed ENN-1.

4. Conclusions

This paper presents a novel fault diagnosis method based on the ENN-1 for automotive engine. Compared with other existing methods, the structure of the proposed ENN-1 is simpler, and the learning time is the faster than other methods. Moreover, the proposed

Table 3
The engine data with different fault types (partial samples).

Cases	Temperature				Exhaust components			Features of the 10.5th frequency[a]	Fault no. number	Fault types
	T1	T2	T3	T4	CO (%)	HC (ppm)	CO_2 (%)			
1	206	280	220	81	0.35	40	14.2	2	1	No fault
25	196	283	222	78	2.04	130	13.1	2	2	Spark plug over 2.0 mm
41	244	289	233	73	1.69	440	13.05	2	3	Spark plug under 0.2 mm
56	302	302	192	143	0.03	10	14.94	1	4	No fuel injection in the 1st cylinder
67	324	280	229	117	0.02	0	12.05	2	5	No fuel injection in the 2nd cylinder
103	334	286	232	95	2.42	120	12.77	1	8	No fuel injection in the 3rd cylinder
153	381	227	250	115	2.85	180	13.46	2	12	No fuel injection in the 4th cylinder
166	362	303	193	78	3.59	540	12.29	1	13	No fuel injection in the 5th cylinder
196	254	304	233	131	0.07	40	14.45	2	16	No fuel injection in the 6th cylinder

[a] 1: the component of the engine rotational speed has 10.5th frequency; 2: the component of the engine rotational speed does not have 10.5th frequency.

ENN-1-based diagnosis method also permits fast adaptive processes for the new data, which only tune the boundaries of classified features or add a new neural node. It is feasible to implement the proposed method in a Microcomputer for portable fault detecting devices. This new approach merits more attention, because ENN-1 deserves serious consideration as a tool in diagnosis problems. This paper may be useful in promoting further investigation. We hope this paper will lead to further investigation for industrial applications.

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