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Using a GA-based Extension Recognized Method for Fault Diagnosis in Car Engines

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Abstract: Due to the passenger's security, the recognized hidden faults in car engines are the most important work for a maintain engineer, so they can regulate the engines to be safety and improve the reliability of automobile systems. In this paper, we will present a novel fault recognized method based on the genetic algorithm (GA) and the extension theory, and also applies this method in the fault recognition of a practical car engine. The proposed recognized method has been tested on the practical tested records of the Nissan CEFIRO 2.0 engine and also compared with other traditional classified methods. Experimental results are of great effective for the hidden faulting recognition of car engine, the proposed method also suits application in other industrial apparatus.

Keywords: genetic algorithm (GA), extension theory, fault diagnosis, pattern recognition.

1. INTRODUCTION

Car is an important tool in human life currently, and the traffic accident has become a part of human life. An engine fault not only damages the engine itself but also causes a break in the car system. Usually, the component module of the engine generates natural loss and improper maintenance that will make the engine oil consumption to increase gradually and let the thickness of exhaust to be increased. The cylinder vibration and the temperature of engine exhaust will come to abnormal situation. The type of the hidden defect is due to the gradual formation, so it is difficult to recognize in the normal inspection. So how to detect engine fault signs early, and to immediately repair or remove them, is very necessary.

In the past, various pattern clustering techniques, including, expert systems (ES) [1], fuzzy clustering [2] and neural networks (NN) [3] have been extensively used in pattern recognition. Combinations of personal computers (PC), expert and fuzzy systems bring up possibilities of automating recognition. However, it is hard to use these rule-based methods to acquire pictorial knowledge and hard to maintain the database of decision rules. A limitation of the MNN approach is the inability to produce linguistic output, because it is difficult to understand the content of network memory.

To overcome the limitations of the ES and MNN mentioned above, a new recognition method, based on the GA and extension theory, is presented for fault diagnosis of car engine in this paper. The extension theory concept was first proposed by Cai in 1983 [4]. Now extension theory has been used in the research field of artificial intelligence (AI) and its relevant sciences. Experimental results show that the GA-based extension recognized method not only has a high accuracy and much suitable as a practical solution of diagnosis problem [5].

2. SUMMARY OF EXTENSION THEORY

There are two main points in extension theory that are matter-element model and extension set [6]. The hard core of extension theory is two theoretical pillars that include matter-element theory and the theory of extension set.

2.1 Matter-element theory

In extension theory, a matter-element uses an ordered triad as the basic element for describing things as follows:

$$R = (N, c, v) \tag{1}$$

Where N represents the matter, c the characteristics; v is N's measure of the characteristics c, where v can be a value or an interval. A multi-dimensional matter-element is defined as follows:

$$R = (N, C, V) = \begin{bmatrix} R_1 \\ R_2 \\ \cdots \\ R_n \end{bmatrix} = \begin{bmatrix} N, c_1, v_1 \\ \quad c_2, v_2 \\ \quad \cdots \cdots \\ \quad c_n, v_n \end{bmatrix} \tag{2}$$

2.2 Summary of extension set

Definition1.Let U be a space of objects and x a generic element of U, then an extension set $\tilde{E}$ in U is defined as a set of ordered pairs as follows:

$$\tilde{E} = \left\{ (x, y) \middle| x \in U, y = K(x) \in (-\infty, \infty) \right\} \tag{3}$$

Where $y = K(x)$ is called the correlation function for extension set $\tilde{E}$. The $K(x)$ maps each element of U to a membership grade between $-\infty$ and ∞. The extended membership function is shown in Fig.1. When $K(x) > 0$, it indicates the degrees to which x belongs to

x_0. When $K(x)<0$ it describes the degree to which x does not belong to x_0. When $-1<K(x)<0$, it is called the extension domain, which means that the element x still has a chance to become part of the set if conditions change.

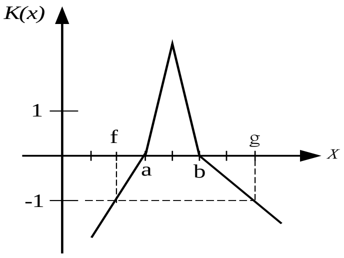

Fig. 1. The extended membership function

2.3 The basic theory of genetic algorithm

The best-known evolutionary algorithm (EA) is the genetic algorithm (GA), which transposed the notion of evolution in Nature to computers and imitates natural evolution and selection [8,9].The genetic algorithm generally includes the following five parts:

1. Gene coding:
   Combining all genes into a chromosome of sequence 0 and 1.
2. Fitness function:
   It describes the capability of a certain individual gene to reproduce and is usually equal to the proportion of the individual's genes in all genes of the next generation.
3. Selection mechanism:
   It is the intentional manipulation by chromosome of the fitness of individuals in a population to produce a desired evolutionary response.
4. Crossover:
   A process in which chromosomes exchange genes through the breakage and reunion of two chromosomes.
5. Mutation:
   A change in a gene resulting in new or rearranged hereditary determinants, mutations are rare, random events in which the base sequence of the gene is changed.

3. GA-BASED EXTENSION RECOGNIZED METHOD

In this paper, the proposed recognized method involves a combination of the genetic algorithm (GA) and extension theory. The extension theory provides a means for distance measurement in the classification process. The genetic algorithm has the ability to search for an optimal solution within a wide space.

3.1 The training stage

The chromosomes propagate next generation of chromosomes to combine the matter-element models in the proposed method. Setting *Patterns*= {p_1, p_2,…p_n} with *i-th* as follow: p_{ij}={c_1,c_2,…,c_k}.In the patterns, *i* is the total number of genes, and *j* is the type of pattern. Using the proposed method can be simply described as follows:

Step1: Set the epoch, the crossover rate C_r, the mutation rate m_u, the tolerance of error rate E_r, and the chromosome rate R_a.

Step2: Find the gene of lower limit and upper limit value.

$$v_a^j = \min(c_{kn}^j) \tag{4}$$

$$v_b^j = \min(c_{kn}^j) \tag{5}$$

$$v^j = < v_a^j, v_b^j > \tag{6}$$

k is number of characteristic.

v_a is the upper limit, and v_b is lower limit.

Step3: Produce new gene of lower limit and upper limit value with chromosome rate. The chromosome rate is produced with random generator.

$$v_a^j - R_a \le G_L^j \le v_a^j + R_a \tag{7}$$

$$v_b^j - R_a \le G_L^j \le v_b^j + R_a \tag{8}$$

Step4: The genes make up the chromosome.

$$chrom = \{G_L^{11}, G_L^{11}, G_L^{12}, G_L^{12}, ..., G_L^{jk}\} \tag{9}$$

The amount of gene in a chromosome is calculated by the function 2*k*j.

Step5: Building the matter-element model from gene.

$$R_j = \begin{bmatrix} N, c_1, < G_L^1, G_U^1 > \\ c_2, < G_L^2, G_U^2 > \\ \vdots \quad \vdots \\ c_n, < G_L^k, G_U^k > \end{bmatrix} \quad j = 1,2,...,m \tag{10}$$

Step6: Input the training of data that is the value of gene.

$$x^j = \{c_1, c_2, ..., c_k\} \tag{11}$$

Step 7: Calculate the correlation function.

$$z^k = (G_L^k + G_U^k) \tag{12}$$

$$K_{nk} = \sum_{i=1}^{n} \left[\frac{\left| x_{nk}^j - z_{jk} \right| - (G_U^{jk} - G_L^{jk})/2}{\left| (G_U^{jk} - G_L^{jk})/2 \right|} + 1 \right] \tag{13}$$

Step8: Normalizing the value of correlation function for the matter-element model to be between 1 and -1.

Step9: Input the next training of data to repeat Step6 to Step8.

Step10: Input the next matter-element model, and repeat Step5 to Step9.

Step11: Calculate the fitness function.

$$Fitness = \frac{N_r}{N_a} \tag{14}$$

N_r is the right amounts, and N_a is the total mounts.

Step12: The selection of the parental chromosomes put into the mating pool, and the genes implement crossover mechanism.

Step13: Let the next generation of chromosomes to replace the chromosomes, and implement mutation mechanism.

Step14: Calculate the correct rate.

$$E_r = (1 - Fitness) \times 100\% \tag{15}$$

Step15: Until the training is finished. If training process is not finished; otherwise go to Step3.

4. FAULT DIAGNOSIS OF CAR ENGINE

The tested object of this research is the engine of the Nissan Cefiro2.0 as shown in Fig. 2, the engine temperature is working between *80~95*℃, and the base configuration of the engine has about 1.0mm spark-plug gap. In the experiment time, the car is parked gear when the engine is the normal condition or the fault tests condition.

Fig. 2. The engine of Nissan Cefiro 2.0

4.1 The tested configuration

The back pressure is received on digital storage oscilloscope by using pressure transmitter; the exhaust temperature was received by temperature sensor. The exhausted component was received by exhaust gas analyzer. The experimental structure is shown in Fig. 3, the signals of engine are all delivered by the sensors to the diagnosis system, and then the detailed records of signals can be easy designed by a LabView8.5 software [12], the typical windows of fault diagnostic software are also shown in Fig. 4. Here, the fault types are divided into 16 kinds (including no fault), and there are 8 characteristics to be the input data. The components of engine exhaust include HC (ppm), CO (%) and CO_2 (%), and this study separately installed the temperature sensor in T_1, T_2, T_3 and T_4, so that we can promptly monitoring the temperature for every exhaust position to speculated engine fault.

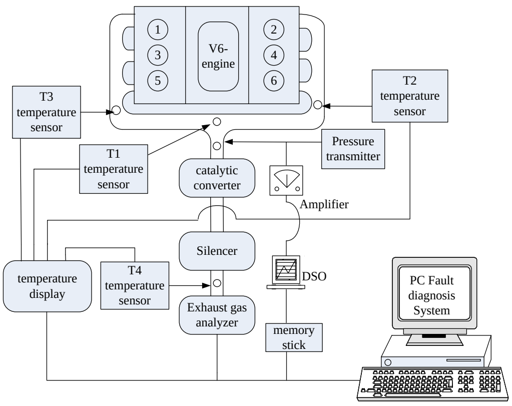

Fig. 3. The experimental structure

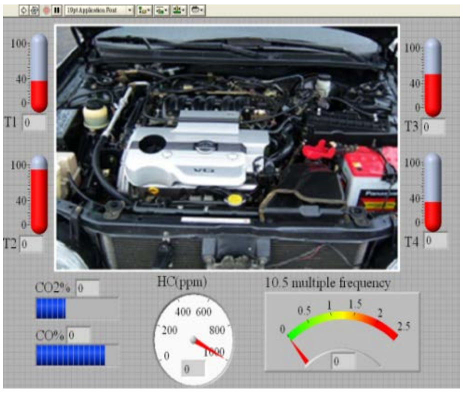

Fig. 4. The LabView recorder of the fault diagnosis system

4.2 Testing results and discussion

In this paper, we use 208 sets of tested data according to the reference [13] to test the practicability of the proposed method. In the training stage, the training data are 160 sets, and the other data (48 sets) are used to test pattern. The input data of a fault diagnosis system would unavoidably contain some uncertainties and noise. The sources of error include environmental noise, transducers, human mistakes, etc., which could lead to data uncertainties. To take the noise and uncertainties into account, 1,800 sets of testing data were created by adding ±5% to ±15% of random, uniformly distributed error to the training data to appraise the fault-tolerant abilities of the proposed method. To take into account the noise and uncertainties, and 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 reason is the input data of engine system would contain some noise and uncertainties. Table 1 shows recognition results of different methods, we can find, when using the multilayer neural network (MNN) and k-means-based method to diagnose the faults of engine, the maximum accuracy of the MNN-based method is 95% and the accuracy is 85% in k-means-based method. The accuracy of the proposed diagnostic method is 98%, and the accuracy of the proposed method is quite high and batter than the other methods. The input data of a fault diagnosis system would unavoidably contain some uncertainties and noise.

The sources of error include environmental noise, transducers, human mistakes, etc., which could lead to data uncertainties. To take the noise and uncertainties into account, 1,800 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 numbers of added errors are given in Table 2. Usually, the error-containing data indeed degrade the recognition capabilities in proportion to the number of errors added. This table shows that these methods all bear remarkable tolerance to the errors contained in the data. The proposed method shows good tolerance to the added errors, and has high accuracy rates of 65% in extreme error of ±20%.Usually, the error containing data indeed degrade the recognition capabilities in proportion to the amounts of error added.

Table 1. Diagnosis performances of method compare

Method	Training time	Accuracy rate (%)
Proposed method	1000	98%
K-means method	N/A	85%
MNN-I (8-8-16)	1000	62%
MNN-II (8-10-16)	1000	80%
MNN-III (8-15-16)	1000	95%

Table 2. Diagnosis performances of proposed method

Noise percentage (%)	Accuracy rate (%)
± 0%	98%
± 5%	95%
± 10%	87%
± 15%	77%
± 20%	65%

5. CONCLUSIONS

This paper presents a novel fault diagnosis method based on the GA and extension theory for car engine. The calculation of the proposed recognized method is fast and very simple. It can be easily implemented by PC software. When a diagnosed data input the proposed diagnosis system, the proposed recognized method will output the possibility of all fault types. It provides useful information to engine fault diagnosis and maintenance. Test results shows that the proposed method cannot only diagnose the main fault types; it can also detect useful information for future trends and multi-fault analysis by the relation degrees. Moreover, the proposed method has a significantly high degree of diagnosis accuracy and shows good tolerances to errors added.

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