A Machine Learning Based Engine Error Detection Method

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Abstract. Nowadays the fault of automobile engines climb due to the growth of automobiles. Traditional mechanical automobile testing is not efficient enough. In this paper, the Machine Learning based Engine Error Detection method (MLBED) is proposed for the complex nonlinear relation and operation parameters of automobile engine operating parameters such as large scale data, noise, fuzzy nonlinear etc. This method is a fault diagnosis and early warning method designed on the basis of self-organizing neural network, Elman neural network and probabilistic neural network. The experimental results show that MLBED has a great advantage in the current fault detection methods of automobile engine. The method improves the prediction accuracy and efficiency.

Keywords: Self-organizing neural network · Elman neural network
Probabilistic neural network · Engine fault

1 Introduction

At the moment, with the development of industry and the improvement of technology, the integration of automotive engine is very high. The most faults of automobiles is caused by the engine where the engine is the power source of an automobile. If an automobile is in a poor working condition, it is a very high possibility due to engine failure. The most common engine faults are as follows. Firstly, the fuel injection pressure of first cylinder is either too large or too small. Secondly, the needle valve of first cylinder injector is broken. Thirdly, abnormal fuel injection pressure of engine also can lead a direct impact on the engine's power efficiency, running stability and emission performance. Fourthly, oil path blockage anomaly can directly cause the engine fail. Therefore, it is necessary to monitor the working condition to avoid the failure of the engine [1, 2]. Early typical fault diagnosis methods are designed on the basis of the engine thermodynamic mathematical model [3, 4]. These methods can identify the performance loss of each component which detects multiple faults and quantifies the performance degradation of components. The fault diagnosis is to

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identify the pattern of the fault including both feature extraction and state identification. It is unnecessary to disassemble engine for measuring the shocking signal of engine cylinder. This is convenient and fast. The signal information of vibration and noise is abundant which can reflect the working condition of the engine in real-time [5, 6]. For a long time, there is still many shortcomings in the engine monitoring system such as the low frequency of engine examining and the poor reliability of data monitoring.

The rest of this paper is organized as follows. In Sect. 2, related engine fault diagnosis methods are reviewed. In Sect. 3, the proposed Machine Learning based Engine Error Detection method is introduced. The experimental results are shown in Sect. 4. And we conclude this paper and give the future research direction in the last section.

2 Related Work

There is a list of applications of Machine Learning Algorithms [7–13]. Ye et al. present a method for qualitative diagnosis of some prototype faults [7]. The Back Propagation Neural Network (BPNND) and the Probabilistic Neural Network (PNND) are applied in the qualitative diagnosis for some prototype faults of aero-engine. The proposed method solves the problem of the qualitative diagnosis of some prototype faults of aero-engine. The problem is that the collection of the measured data is not clear. This causes the further analysis cannot be taken based on data.

The adaptive fuzzy neural network is used by Ma et al. to engine fault diagnosis [8]. However, the measured parameters the authors are not collected clearly and a major process is missed to identify algorithm accurate.

Zhou et al. present a good method which obtains good results in the engine fault diagnosis [9]. The application of improved BP algorithm in engine fault diagnosis is studied while an example training process and test results are given. The shortcomings are basically caused by the structure characteristics of BP neural network. In the training of large samples and high precision, the network does not converge and easy to fall into the local optimal.

Gao et al. apply the Elman neural network in a engine performance fault identification and fault diagnosis model to prove the relationship between exhaust gas composition on engine performance [10]. However, the classification of engine operating conditions is insufficient, which is easy to cause the phenomenon of false positives.

A engine warning system is presented [11]. The patented system detects the moisture and sends out the warning signal to remind the user that the air filter is in the water and the automobile need to be stopped. The problem is the warning is only given when automobile engine is in bad condition, and there is no fault prediction.

3 Machine Learning Based Engine Error Detection

In view of the limitation and disadvantage of the automobile engine monitoring system, this paper proposes the Machine Learning based Engine Error Detection method (MLBED). Two major mechanisms are provided by MLBED methods. First, Component analysis is improved with extracting the method of feature values from the vibration signal and pressure signal parameters. The characteristic value preserves which establishes a comprehensive evaluation function. The characteristics of the comprehensive evaluation function are very related to the value of energy parameters, such as the kurtosis parameter, waveform parameters, margin parameters, pulse parameters and peak parameters. It allows the comprehensive evaluation value. The range of the experimental data obtained from the comprehensive evaluation value is from −4.78708 to 26.49655. Second, the SOM classifies operational parameter of engine and diagnoses its hitch. There are five types of faults as off-limits injection pressure of the first cylinder fuel, the broken needle valve of first cylinder injector, oil path blockage and exceeded fuel supply advance angle. Third, the Elman neural network is applied for find the characteristic value of the data to predict failure. In order to show that our results are valid and reliable, we classifies and diagnose them by using PNN and SOM. This method can predict, diagnosis and inspect of operating parameters of automobile engine.

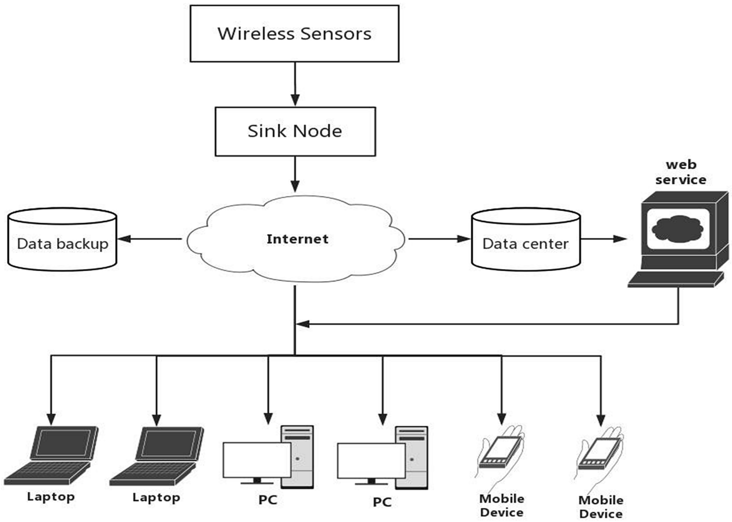

Fig. 1. Architecture module

Figure 1 is the structure of automobile engine warning system. Automobile engine early warning system includes wireless sensor device, background monitoring and early warning system. The following three components are shown.

(1) Wireless sensor data acquisition node is responsible for collecting the temperature, humidity, current, voltage, speed, torque and other data and transmit these data to the sink node.
(2) Sink node is responsible for receiving the data which sent from each monitoring sensor nodes and instantly transfer them to the monitoring background via wireless network.

(3) Wireless communication module is in charge of the whole network system. The network structure of wireless sensor network based on IEEE802.15 which can realize point to point communication between nodes in the network.

The backstage monitoring and warning system of automobile engine includes main data backup, data center (data storage), server (data pre-processing, data training and model building), feedback monitoring and early warning results.

3.1 Self-organizing Neural Network

As shown in Fig. 2, the engine analysis of Self-Organizing Neural network (SOM) structure schematic diagram can be classified into the field of artificial intelligence in unsupervised learning. Two dimensional SOM is called KFM (Feature Mapping Kohonen). The input network is a 6 dimensional vector $x = [x_1, x_2, x_3, x_4, x_5, x_6]$ of all 6 values while the output unit is two-dimensional array, the number of 6 $\times$ 6 species. The input layer and the output layer of each unit is fully connected where W indicates the connection weights. The KFM of the learning process is iterative learning of G sample vector and calculates the winning neuron. Until the change of weight W is less than a certain threshold or a certain number of iterations, the output units of the same sample vector belonging to the same class. Although KFM has a learning process, it can be seen that this kind of learning method is automatically acquired from all the samples.

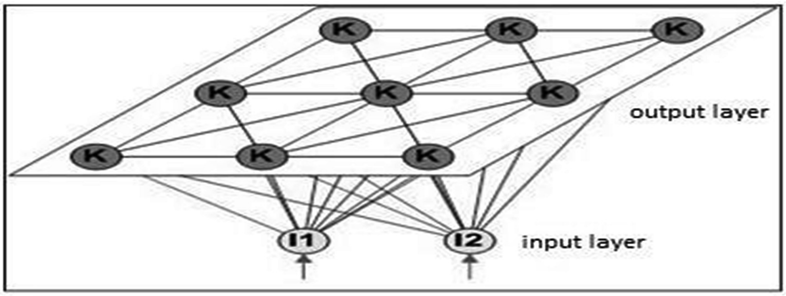

Fig. 2. SOM neural network structure

3.2 Elman Neural Network

A schematic diagram of automobile engine structure of Elman neural network is shown in Fig. 3. Elman neural network analysis can be classified into the field of artificial intelligence in supervised learning. The acquisition from operation parameters of automobile engine with 5 kinds of failure modes of vibration signal analysis of vibration waveform statistical processing including, energy parameters, kurtosis parameter, waveform parameters, margin parameters, pulse parameters and peak parameters. The prediction parameter values of the past parameters. Hence it is a problem of time series. If we want to solve problems by applying Elman neural network, one parameter is taken before this node N to predict a time node of the parameter value. The mapping function can be expressed as $x_n = f(x_{n-1}, x_{n-2}, \ldots, x_{n-N})$. The training samples and test samples are divided, and the Elman neural network is established.

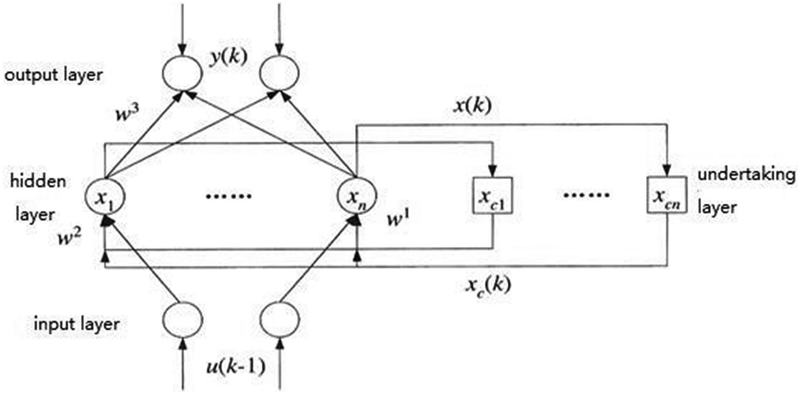

Fig. 3. Structure of Elman neural network

3.3 PNN Probabilistic Neural Network

A schematic structure of probabilistic neural network engine (PNN) is illustrated in Fig. 4. The analysis of PNN can be classified into the field of artificial intelligence in supervised learning. Acquisition of automobile engine normal operation and five kinds of failure modes of vibration signal analysis of vibration waveform statistical processing including energy parameters, kurtosis parameter, waveform parameters, margin parameters, pulse parameters and peak parameters. As a fault judgment training sample, twelve input samples, each sample is six dimensional vector $x = [x_1, x_2, x_3, x_4, x_5, x_6]$. Then the PNN is established for each of the samples, which is six dimensional vector and the classification model is six.

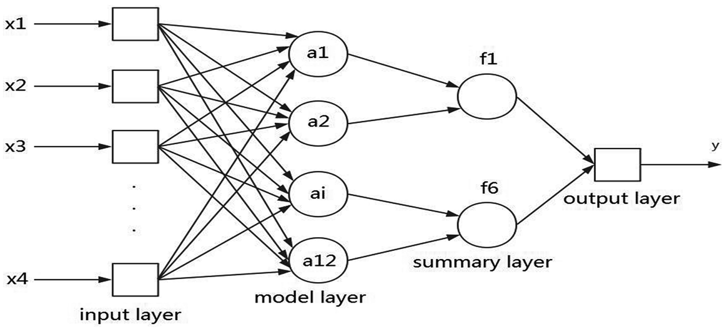

Fig. 4. Structure of PNN neural network

4 Simulation Results and Analysis

4.1 Improved Principal Component Analysis

Table 1 is SPSS results after the operation. The discriminant equation is obtained according to the coefficient of the non standardized discriminant equation:

$$D1 = 0.029 * EP + 0.05 * MP + 0.002 * PP1 + 0.009 * KP + (-0.017) * PP2 - 1.182$$

$$D2 = 0.045 * EP + (-0.029) * MP + (-0.001) * PP1 + 0.014 * KP + (-0.319) * PP2 - 0.583$$

$$D3 = 0.004 * WP + 0.012 * EP + 0.005 * MP + 0.011 * PP1 + (-0.004) * KP + 0.457 * PP2 - 2.009$$

Table 1. Canonical discriminant function coefficient

	Function		
	1	2	3
Waveform parameter (WP)	.000	.000	.004
Energy parameter (EP)	.029	.045	.012
Margin parameter (MP)	.050	−.029	.005
Peak parameters (PP1)	.002	−.001	.011
Kurtosis parameter (KP)	.009	.014	−.004
Pulse parameters (PP2)	−.017	−.319	.457
(constant)	−1.182	−.583	−2.009

4.2 Results of SOM Self Organizing Neural Network

Table 2 presents the results of Matlab operation. The application of SOM neural network presents the current operating state of the engine time node under time node from 1 to 4. The engine running state reflects the injector needle wear of first cylinder, low or high fuel injection pressure of the first cylinder, or the fuel supply advance angle before $5' \sim 6$.

Table 2. SOM output result

Time node	1	2	3	4	5
Running statement	Statement 2	Statement 1	Statement 1	Statement 2	Statement 2
Time node	6	7	8	9	10
Running statement	Statement 2	Statement 2	Statement 2	Statement 2	Statement 4
Time node	11	12	13	14	15
Running statement	Statement 4	Statement 4	Statement 2	Statement 3	Statement 4

4.3 Elman Neural Network Results

As shown in Fig. 5, the left figure is the prediction results of MLBED method, while the right figure is the prediction results by applying [11]. The prediction results are not good due to the small size of the sample, and the input dimension is high. Therefore for each input variable relative output characterization can be imprecise. However, if the sample data is large enough, the model is better.

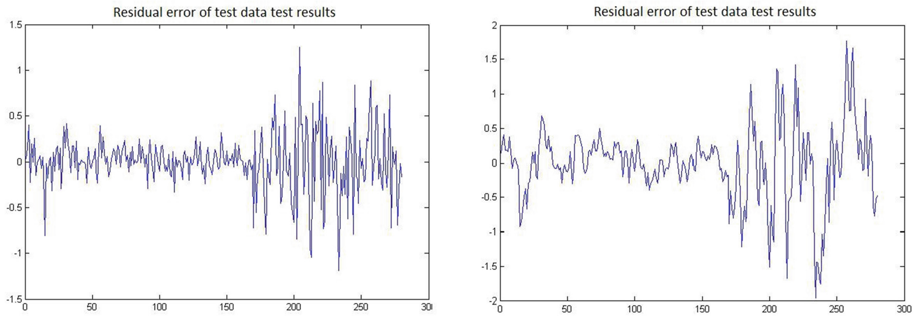

Fig. 5. Comparison of test results with other simulation results

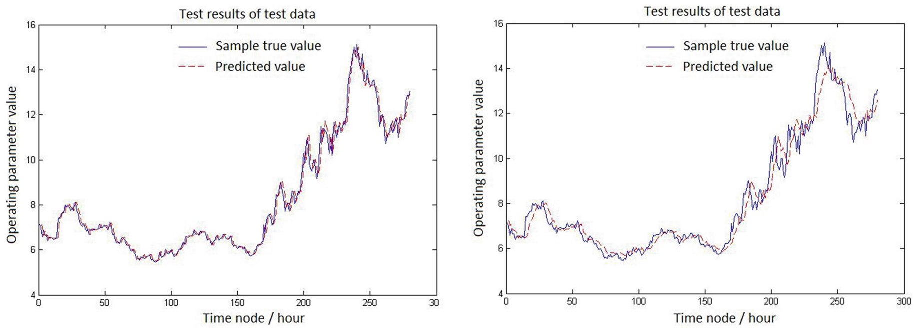

Fig. 6. Comparison of test results with other studies

As shown in Fig. 6, the left figure is the result of the MLBED method while the right figure is the residual error of applying [11]. Fine results of MLBED are shown in the vicinity of 0 of the residual fluctuations, it does not appear big deviation. However, compared to method of [11], you will find that the residuals are close to 0 near the convergence of data. If the forecast data is more than 170 of the time, the residual error appears larger fluctuations and the accuracy of the prediction is also high. Therefore the prediction of a certain range of data is still very accurate.

4.4 PNN Probabilistic Neural Network Results

Probabilistic neural network (PNN) is simple in structure and its training process. PNN model for the robust nonlinear classification capability. The fault sample space is mapped into the fault pattern space to form a fault diagnosis network system with strong fault tolerant capability and structure adaptive capability, which can improve the accuracy of fault diagnosis (Table 3).

Table 3. PNN output result

Sample	Actual	Judgement	True/False	Fault type
1	3	3	True	The broken needle valve of first cylinder
2	6	6	True	Normal
3	2	2	True	The first cylinder fuel injection pressure
4	5	5	True	Fuel supply advance angle exceeded
5	1	1	True	The first cylinder fuel injection pressure
6	4	6	True	Normal

5 Conclusion

In this paper, the early warning system is designed for automobile engine while the MLBED method is proposed on the basis of a data acquisition and machine learning method. It provides the classification of the automobile engine fault prediction. The experimental results show our proposed method provides accurate fault recognition and prediction.

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References

1. Zhou, Z.P.: Analysis and countermeasure of abnormal valve clearance of engine valve. Diesel Engine Des. Manuf. **18**(1), 52–56 (2012)
2. Saravanan, N., Siddab, S., Kumar, R.: A comparative study on classification of features by SVM and PSVM extracted using Morlet wavelet for fault diagnosis of spur bevel gear box. Expert Syst. Appl. **35**(3), 1351–1356 (2008)
3. Doel, D.L.: Temper—a gas-path analysis tool for commercial jet engines. J. Eng. Gas Turbines Power **116**(1), 82–89 (1994). J. Trans. ASME
4. Barwell, M.J.: Ground Based Engine Monitoring Program for General Application. R. SAE Technical Paper. No. 871734 (1987)
5. Shen, Z.X., Huang, X.Y., Ma, X.: Laugh EMD and support vector machine fault diagnosis of diesel engine. Vib. Test Diagn. **30**(1), 19–22 (2010)

6. Xu, Y.X., Yang, W.P., Lv, X.: Study on fault diagnosis of automobile engine based on support vector machine. Vib. Shock **32**(8), 143–146 (2013)
7. Xu, L.M., Wang, Q., Chen, J.P., Pan, Y.Z.: Prediction of debris flow average velocity based on BP neural network. Geol. Eng. Environ. Eng. **31**(2), 25–30 (2013)
8. Ye, Z.F., Sun, J.G.: Aeroengine fault diagnosis based on probabilistic neural network. J. Aeronaut. Sci. **23**(2), 155–157 (2002)
9. Ma, J.C., Si, J.P., Niu, J.H., Wang, E.M.: Engine fault diagnosis based on adaptive fuzzy neural network. Noise Vib. Control **35**(2), 165–174 (2015)
10. Qu, C.S., Lu, Y.Z., Tan, Y.: An improved empirical mode decomposition and its application in signal noise. J. Autom. **36**(1), 67–73 (2010)
11. Lian, Y., Feng, L.G., Wu, F.L., Zhao, Y.: Study on fault diagnosis of integrated navigation based on genetic PNN network. Foreign Electr. Meas. Technol. **33**(1), 120–126 (2012)
12. Xu, L., Chen, Y., Chai, K., Schormans, J., Cuthbert, L.: Self-organising cluster-based cooperative load balancing in OFDMA cellular networks. Wiley Wirel. Commun. Mob. Comput. **15**(7), 1171–1187 (2015)
13. Zhao, L., Li, Y., Meng, C., Gong, C., Tang, X.: A SVM based routing scheme in VANETs. In: 16th International Symposium on Communications and Information Technologies, Qingdao, pp. 380–383. IEEE Press (2016)
14. Xu, L., Luan, Y., Cheng, X., Xing, H., Liu, Y., Jiang, X., Chen, W., Chao, K.: Self-optimised joint traffic offloading in heterogeneous cellular networks. In: IEEE International Symposium on Communications and Information Technologies, Qingdao, pp. 263–267. IEEE Press (2016)
15. Xu, L., Chen, Y., Chai, K.K., Luan, Y., Liu, D.: Cooperative mobility load balancing in relay cellular networks. In: IEEE International Conference on Communication in China, Xi’an, pp. 141–146. IEEE Press (2013)