The Application of Multi-sensors Fusion in Vehicle Transmission System Fault Diagnosis

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Abstract

Multi-sensors fusion technology is adopted for fault diagnosis of vehicle transmission system. By using hybrid pattern fusion based on artificial neural networks (ANN), the robustness of the diagnosing system is improved greatly. This hybrid fusion pattern avoids working with a great deal of original data from sensors, while it has the advantage of less information lost. At the same time, the diagnosis effect is improved by using feature-level and decision-level vibration data and original-level lube data.

Keywords: information fusion, artificial neural network, hybrid structure, fault diagnosis, vehicle transmission system

1. Introduction

The transmission system is the faults mostly occurring part of vehicle. There often happen some new and/or synthetic faults with the transmission system. To recognize these new or synthetic faults, the present methods are not good enough. We adopt a hybrid mode based on ANN to recognize the faults with data from different sensors and some minor results. The hybrid mode can improve the robustness of the whole ANN by fusing the data of vibration on decision level and other original data such as the viscidity of lube and diameter of dirty in the lube. It also avoids processing lots of original vibration data and lost few information. It is a signal for the hybrid data fusion based ANN mode to be used in online fault diagnosis with these advantages in the future. The testing result has shown the hybrid one has a better answer.

2. Information fusion

Information fusion is also known as multi-sensors fusion. Usually, the process is called information fusion when we make use of data from multi-sensors, analyze them and get a decision. There are different kinds of information fusion [1]. According to the feature of the data that we used in vehicle transmission system fault diagnosis, we fuse them at original-level, feature-level or decision-level.

2.1. Original-level information fusion

Original-level data fusion is based on the original data from the sensors. The advantage is it contains more details compared with other-leveled fusion, but its disadvantage is time cost for the large amount of data. Besides, the original data from sensors will be affected greatly by the environment and thus have bad stability. Original-level data fusion requires the data from the same types of sensors. This will limit its application area.

2.2 Feature-level information fusion

Feature-level information fusion is based on the vectors which we extract from original data, such as the shape, outline, direction, region, distance and so on. To fuse the vectors before decision has the advantage of condensing the data greatly but keeping enough detailed information. Feature-level information fusion is widely used in pattern recognition, image analysis, and computer vision.

2.3. Decision-level information fusion

Decision-level information fusion is based on the decisions of individual sub-modules. The final decision is made according to the fusion on this level. Decision-level fusion has a better error acceptance. This means that,

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once there has a mistake decision from a sub-module, the whole system can overcome it and get a right decision after fusing all the decisions from other sub-modules. Decision-level information fusion has an advantage that it can contain different data from different types of sensors. It has also a disadvantage of greater information loss compared with other-leveled fusion. Table 1 shows the dis/advantages of these three fusion processes.

Table 1. **The dis/advantages of the three levels of fusion**

	Original level	Feature level	Decision level
Quantum of data	Large	Medium	Small
Quantum of computation	Small	Medium	Large
Error acceptance	Bad	Medium	Good
Dependency on sensor	Large	Medium	Small
Difficulty of fusion	Difficult	Medium	Easy
Domain of usage	Small	Medium	Large
Loss of information	Small	Medium	Large

3. Application of ANN in fault diagnosis

As a technology to process information, ANN can work with the support of a database which contains different information patterns rather than to pre-judge which data are important. ANN is a parallel-distribution-process system which is driven by the data. Its knowledge comes from the studying of samples. ANN has self-learning ability. All its advantages make it a good tool to solve the problems without pre-knowledge in fault diagnosis. ANN is also a non-linear system which has a good error acceptance and can work with noise and deformed input data. This feature is very useful to the fault diagnosis of vehicle transmission systems.

Figure 1 shows the structure of the ANN used in our fault diagnosis of transmission system.

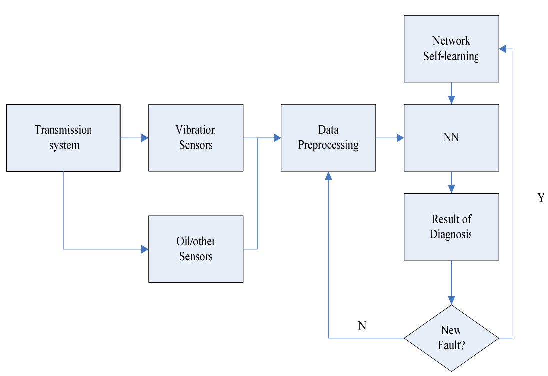

Fig. 1 **The structure of ANN used in transmission system of vehicle**

4. Application of information fusion based on ANN in fault diagnosis of vehicle transmission systems

4.1. Hybrid fusion structure

In fault diagnosis of vehicle transmission systems, data come from vibration sensors, spectrum analyzer of lube, dirty measure, and viscidity measure. Any single-leveled data fusion is not good enough for the fault diagnosis of transmission system of vehicle because the system is very complex and there often happens some synthetic faults with it. The quantum of the data from vibration sensors is great while the data from lube is small. The simple fusion may lead to the losing of some useful information. We use a hybrid fusion method which avoids large computation and has small information lost. This method fuses the original data from lube with the vectors extracted from vibration sensors. We firstly get the original data from vibration sensors. Then, we extract the eigenvectors from these original data. The eigenvectors include mean square values, wave indexes, impulse indexes, kurtosises, gradients, average square frequencies, spectral barycenters, and peak values.

We use this hybrid fusion method in “CA10B gear box wearing and tearing test” to process the data. At first, we train the ANN by each individual kind of data which include the vectors of the data from vibration sensors, the original data from spectral analysis meter, the viscidity meter, and particulate measurer. In them, the data from particulate measurer has the error of 0.3 after 10000 cycles of training and can not converge further. It says that the ANN has a local minimum value with this kind of data. While using hybrid data, the ANN converges rapidly. Figure 2 shows the structure of data fusion based ANN used in our transmission system diagnosis of vehicle test.

Table 2 is the result after fusion of the data from lube.

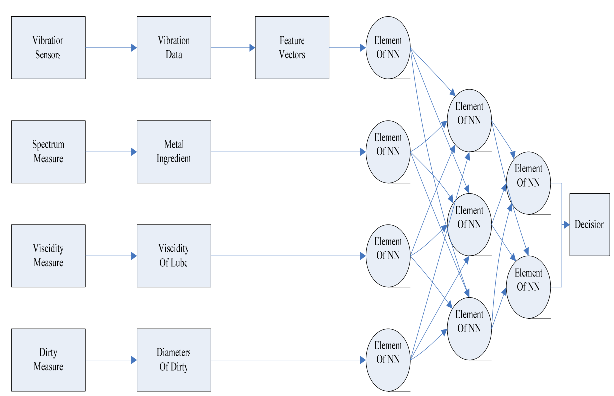

Fig. 2 **The structure of data fusion based ANN in the CA10B fault diagnosis test**

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It seems that there is a group of data which has a larger error.

Table 2. **The result of fusing data from lube.**

	Fault 1	Fault 2	Fault 3	Fault 4	Fault 5
Target	1	0	0	0	0
Output	0.99951	0.00011	0.00435	0.03118	0.00003
Target	0	1	0	0	0
Output	0.05043	0.27420	0.00168	0.02241	0.00845
Target	0	0	1	0	0
Output	0.00687	0.00032	0.97295	0.00028	0.00879
target	0	0	0	1	0
Output	0.06340	0.00000	0.00108	0.98384	0.00513
Target	0	0	0	0	1
Output	0.00000	0.00005	0.00939	0.11892	0.99350

When the vibration data is added into the hybrid structure, the result is shown in tables 3 and 4.

When we use only the data from lube, the precision of the ANN is 84%. After analyzing the original data from lube, we find there is a crude value in spectral analysis meter. The volume of ferrous material in the lube changes from 16.14 ppm to 5.377 ppm suddenly. It is abnormal. The crude datum affects the whole ANN greatly. After using the hybrid fusion ANN, which is more robust with different kinds of information, the result is good enough. Table 3 shows the result of hybrid fusion ANN. The reason why the hybrid fusion ANN has a better diagnosis result is that it takes different kinds of data from different sensors into account. Thus all the data join in the decision. When part of the data is abnormal, others make up the errors arisen by the abnormal ones. The whole ANN keep robust.

Besides, the hybrid ANN can also recognize synthetic faults. We use the unitary data from different kinds of sensors to train the hybrid fusion ANN. The diagnosis result for "CA10B gear box typical faults test" is shown in table 4.

We can find when there is a synthetic fault, the hybrid fusion ANN also has a high precision in diagnosis. But the reliability to a simple fault pattern is less when we take the synthetic fault patterns into account. The reason is that a synthetic fault will cause a higher difficulty of classification. We can deduce that if there are some more fault patterns to be diagnose. The accurate of the ANN will fall down. To solve this problem, the structure should be modified by adding more input data and output decisions. Otherwise, the ANN can not classify the too much fault patterns well.

Table 3. **Result of data from vibration vector and from lube**

Actual fault	Result 1	Result 2	Result 3	Result 4	Result 5
Fault 1	0.97428	0.00007	0.00000	0.00057	0.00016
Fault 1	0.97266	0.00054	0.00000	0.01185	0.00005
Fault 2	0.00261	0.98422	0.00385	0.00419	0.02210
Fault 2	0.00105	0.98326	0.00334	0.00696	0.00589
Fault 3	0.00883	0.00164	0.98218	0.00000	0.02115
Fault 3	0.00811	0.00161	0.98158	0.00003	0.02121
Fault 4	0.02684	0.00018	0.00003	0.97246	0.00699
Fault 4	0.01956	0.00019	0.00033	0.98308	0.01282
Fault 5	0.00001	0.00282	0.01270	0.00001	0.98350
Fault 5	0.00001	0.00473	0.02141	0.00000	0.98570

Table 4. **CA10B gear box fault diagnosis result.**

Actual state	Normal	Fault 1	Fault 2	Fault 3	Fault 4	Fault 5	Fault 6
Normal 1	0.99983	0.00166	0.01616	0.00000	0.00032	0.00000	0.00132
Normal 2	0.99963	0.00010	0.00110	0.00000	0.00253	0.00000	0.00659
Fault 1	0.02297	0.99179	0.02418	0.00001	0.00000	0.00383	0.00018
Fault 1	0.00373	0.93412	0.00107	0.00019	0.00001	0.00532	0.00073
Fault 2	0.00043	0.03209	0.82460	0.00779	0.00072	0.01727	0.00642
Fault 2	0.00092	0.04738	0.77644	0.00900	0.00226	0.03325	0.00097
Fault 3	0.00001	0.35169	0.00231	0.94279	0.00001	0.04875	0.00091
Fault 3	0.00001	0.37297	0.02553	0.96259	0.00003	0.09996	0.00024
Fault 4	0.08611	0.00016	0.00063	0.00000	0.83797	0.05520	0.00022
Fault 4	0.09192	0.00097	0.00095	0.00002	0.89939	0.18353	0.00012
Fault 5	0.02779	0.00684	0.00003	0.00003	0.03714	0.98487	0.00010
Fault 5	0.07681	0.00638	0.00010	0.00001	0.06720	0.98133	0.00005
Fault 6	0.01079	0.00681	0.00010	0.00000	0.00000	0.00000	0.93150
Fault 6	0.01277	0.02290	0.00011	0.00000	0.00000	0.00001	0.88284
Synthetic fault	0.00000	0.99492	0.98646	0.99923	0.00149	0.99367	0.00000
Synthetic fault	0.00001	0.99595	0.99016	0.99873	0.00155	0.99529	0.00000

5. Conclusion

To fuse different kinds of data in a diagnosis system can improve the robustness of the system because the system will have a decision with all kinds of data. If part of them has problem, others will compensate the error arisen by them. But there is a big gap between different kinds of data. The simple fusion method will not work well. In fault diagnosis of vehicle transmission system, the data from vibration sensors are great while the data from other sensors are very few. To fuse these data with only a simple method has no meaning because lots of

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vibration data will submerge other data out. The whole diagnosis system is still not robust. We propose a method to fuse the vibration data on feature level and that from lube on original level. The system loses few useful information and save the time used in computing.

Synthetic faults diagnosis is a big problem because the traditional classifier is usually a linear one. With hybrid fusion ANN, the result is good enough.

6. References

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