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DSmT-based three-layer method using multi-classifier to detect faults in hydraulic systems

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ABSTRACT

Fault identification in hydraulic valves is essential in maintaining the reliability and security of hydraulic systems. Due to the nonlinear characteristics of hydraulic systems under noisy working conditions, it is difficult to extract fault features from vibration signals collected from the surface of the valve body. Therefore, a DSmT-based three-layer method using multi-classifier is proposed to detect multiple faults occurred in hydraulic valves. Firstly, the raw signals are personalized to construct the training samples and the unknown testing samples. Secondly, a three-layer structure of the hybrid model called the layered hybrid model is constructed, which is suitable for hydraulic valves to detect the faults of different fault groups (including coil fatigue in the actuator and the abrasion inside the valve) and improve the diagnosis accuracy obviously. Finally, classification methods are selected to classify fault groups in the first two layers, and then the fault types are identified in the third layer by the fusion results using the Dezert-Smarandache Theory (DSmT). Experimental investigations are performed to validate the performance of the present method using a hydraulic valve (solenoid controlled pilot operated directional valve) controlled the hydraulic test rig. The results show that the average accuracy of detecting twelve types of faults is about 98.1%, which are better than those using other methods. It is expected that the present DSmT-based three-layer method using multi-classifier can be applied to more complex hydraulic systems.

1. Introduction

Hydraulic valves act as the mechanical (or electrical) to fluid interface in hydraulic systems, therefore, their performance should be under scrutiny, especially when hydraulic system difficulties occur. Under execrable working conditions, a permanent damage in performance and/or failure caused by contaminated oil is almost impossible to avoid. In addition, as the spool moving direction frequently reverses or oil temperature increases, the surface abrasion caused by the spool and the sleeve seizing can also lead to hydraulic valves failure. Although some researchers have provided literature on the fault classification of hydraulic valves [1,2], effective and reliable solutions to diagnose these faults have not been revealed. The main reason is that the construction of hydraulic valve itself is a complex and closed structure, and its volume is not big. If the sensors (pressure sensors, displacement sensors) are integrated into the valve, the cost will be greatly increased and the performance of the hydraulic valve may be reduced. It is also very difficult to diagnose

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internal faults of the hydraulic valve by using external sensors. Therefore, it is very necessary that more effective fault identification methods are explored to detect the fault type of hydraulic valves, and even accurately locate the fault source.

In the field of the fault identification specifically for the hydraulic system, the engineering judgment is a conventional method. However, in the complicated cases the judgment is most difficult. This is because some important fault information is usually hidden in the vibration signal from the valve body surface. Therefore, modern common fault identification methods are that usually analysis surface vibration signals containing fault information to detect the faults, which can be ground into three broad categories [3,4]. The first is a model-based identification method, which compares real outputs with predicted ones of the modeled system to obtain residual vectors in order to monitor dynamic states. In this direction, several researchers have done intensive works towards modeling state observers. For example, Wei et al. [5] proposed an estimator constructed by extended Kalman filter to overcome nonlinear and stick–slip distortion in hydraulic systems. Bahrami et al. [6] established an adaptive-gain super-twisting sliding mode observer used in the fault reconstruction of electro-hydraulic servo systems. This mode observer addressed the chattering effect and conservatism of observer gains of hydraulic system faults. The model-based identification method is useful when the system is describable by linear equations in a certain range. However, it may become invalid for solving the nonlinear system [7,8].

The second type is considered as a signal processing technology, which can extract fault features from the measured vibration signal, even if the signal is polluted by noise. This fault identification method has been successfully applied in the bearing fault diagnosis [9–12]. Inspired by the bearing fault diagnosis, Goharrizi et al. [13] proposed a wavelet transform (WT) used to decompose pressure signals, which can detect feature patterns of the internal leakage in the hydraulic system. Jiang et al. [14] applied the improved adaptive multiscale morphology analysis (IAMMA) to demodulate fault signals of the hydraulic pump. In addition, the Hilbert-Huang transform was also applied in detecting hydraulic actuator leakage [15]. In these schemes, reference features are necessary to match faults type. Unfortunately, there is no a complete fault feature library of hydraulic systems or hydraulic components [16]. Moreover, there are more transient processes in the hydraulic acting (especially reversing motions of the directional valve), the transient impulse signal can easily cover up the fault feature signal, so that the method is limited in extracting fault features of hydraulic valves.

The third type method is the intelligent fault identification, which can spontaneously learn fault features. Many researches about the intelligent fault identification have been done and applied in hydraulic system fault diagnosis [17–19]. For example, Jegadeeshwaran et al. [20] proposed a machine learning method used in monitoring the condition of the hydraulic brake. In the method, descriptive feature characteristics were obtained as well as selected features were classified by using a machine learning algorithm named Support Vector Machine (SVM). W. Zhao et al. [21] proposed a hybrid method consisting of Empirical Mode Decomposition (EMD) and time–frequency methods to realize the feature extraction. These features were eventually classified by the training and the testing in the SVM. Similarly, the Extreme Learning Machine (ELM) was employed to learn and detect these fault features [22], which is applied in the slipper abrasion of the axial piston pump. Although the intelligent fault diagnosis method can automatically learn fault features, it usually relies on the signal processing technology to do the preliminary work (extracting sensitive fault characteristics) to ensure high identification accuracy.

In existing intelligent fault diagnosis methods, rarely fault identification of hydraulic valves is involved. Multiple faults occurring can be a more challenge for using general diagnostic schemes, but the phenomenon is very common in hydraulic valves. Therefore, the purpose of this paper is to design an effective intelligent identification method to detect multiple different types of faults occurred in hydraulic valves, including the location and severity of the fault. To achieve this purpose, there are two major challenges:

(1) Several intelligent classification strategies are combined in order to diagnose different fault types. For example, Andreas and Theissler [23] proposed that mixture of Gaussians, Naive Bayes classifier, random forest (RF) and SVM worked together to form a recognition/regression result as a new ensemble learning method. Inspired by the bagging and boosting ideas, Amozegar et al. [24] developed three ensemble methods. However, there is only one training sample set in the common ensemble learning, so that the accuracy of the fault diagnosis is largely affected by the information redundancy if different fault information is scattered in different segments in a signal sequence. Therefore, to develop a layered classification model is one solution. Meng et al. [25] used the deep belief networks (DBNs) to construct a novel layered diagnosis network. Adams et al. [26] used multiple classifiers acting together in the layered model to achieve better diagnostic effect compared with using only a single classifier.

(2) To improve the accuracy and reliability of results from the preliminary decision in the layered model, several information fusion theories have been developed, such as the voting. Dempster-Shafer (DS) theory and Dezert-Smarandache Theory (DSmT) are adapted at handling uncertain or conflict problems widely used in information decision process. For example, Airouche et al. [27] proposed that the final decision made by fusing several normalized measured values from different sensors in terms of DSmT should be more accurate (used to predict the pedestrian when tracking).

About these two major challenges, we have done some preliminary work [28]. In the preliminary work, three basic classifiers were selected as experts to analysis faults and acquire initial diagnostic results, and then DS theory as an arbiter was used to fuse initial results of the each classifier and finally obtain the final result. This method has been proved to be effective for the diagnosis of the same fault group, but unfortunately it has little effect on the fault diagnosis in different fault groups.

Hydraulic valve connects the electronic and hydro-mechanical portions of a system, so some faults of electronics and magnetics as well as mechanics may occur in such valves. These faults, mainly referring to the coil fatigue in the actuator and the abrasion inside the valve, have different fault mechanism and characteristics, as demonstrated by the fault information distributed in different time periods or different frequency periods of the collected signals. Moreover, if all samples are constructed into a single fault set, information redundancy and mutual interference of different types of fault signals will occur, which will reduce the diagnostic accuracy. Therefore, to detect hybrid faults from different fault groups, this paper proposes the idea of the layering diagnosis and personalized sample setting applied in hydraulic valves.

A DSmT-based three-layer method using multi-classifier is proposed to detect multiple faults from different fault groups in hydraulic valves. In this method, a three-layer structure of layered hybrid model is constructed to break the fault identification into three sub-tasks arranged in a hierarchy, where multiple efficient classifiers are combined in every layer. Moreover, to solve the redundancy problem of multiple fault information, personalized sample sets for different faults are contained in the layered model. Based on the classification information obtained by layered model, DSmT is employed as an arbiter of this information to make the final decision to detect faults in hydraulic valve. Experimental investigation shows that the DSmT-based three-layer method using multi-classifier is effective and better than other one-step intelligent diagnostic methods. Therefore, the primary contributions of the new DSmT-based three-layer method using multi-classifier are summarized as follows:

(1) A layered fusion model characterized by three-layer structure is designed to significantly reduce the difficulty of detecting multiple faults from different fault groups and greatly improve the accuracy of diagnosis.
(2) Personalized sample sets for different faults are contained in the layered model in order to solve the redundancy problem of multiple fault information.
(3) Aiming at the problem that BPA function (equivalent probability) of DSmT theory is difficult to obtain, many researchers use various methods to normalize the data of multiple sensors to construct BPA function. However, in this paper, probabilities caused by multiple classifiers can construct BPA function easily.
(4) Most of the existing methods use the statistical methods of voting and averaging or summation to fuse the decision of each classifier to get the final decision. However, in this paper, DSmT as an arbiter is introduced into the proposed method to fuse the decision of multiple classifiers.

The remainder of this paper is organized as follows. Section 2 provides the theoretical background. Section 3 the DSmT-based three-layer method using multi-classifier is introduced in details. Concreteness of the proposed method in application and experimental results are presented in Section 4. Brief conclusions are drawn in Section 5.

2. Background of the methodology

For solving multiple faults identification, several classifiers are combined together to be used in the proposed layered hybrid model to avoid the disadvantage of a single classifier. In this paper, convolutional neural network (CNN), long short-term memory networks (LSTM) and random forest (RF) are selected in terms of the sensitivity of different classifiers to different faults occurred in the hydraulic valve.

2.1. Classifiers in the layered hybrid model

CNN, as the intelligent method, has applied in various fault diagnosis fields. CNN has three main layers, including the input layer, the hidden layer and the output layer [29]. The hidden layer has a distinctive architecture named a convolutional layer (CL) and a subsampling layer (SL) [30]. Actually, CNN is a typical feed forward network, of which the information is directly transmitted from front to back by SL following CL. Numerous deep network models, such as GoogleNet, AlexNet and ResNet, have applied in CL structures. They are all called CNN. The CNN structure used in this paper is proposed by LeCun [31], which has become a standard structure for deep learning.

LSTM network has many repeating LSTM units, which is a special kind of recurrent neural network. The input parameters are performed cyclically between LSTM units, which are very different from typical feed forward neural network (transferred backward directly). When the neural information of the current layer is input to one LSTM unit, the input information is calculated in the LSTM unit to respectively generate the input gate, the output gate and the forget gate. A cellular state is generated by the combination of these gates generated by the previous LSTM unit, so that the output information is obtained by the cellular state under the action of the output gate. Consequently, it is transmitted to the next LSTM unit and repeated the above steps [32,33].

RF is an ensemble learning method, several individual decision trees are combined by bagging rules. RF is briefly introduced in two parts here [34,35]. For the first part, a training set of size N is fed into the RF model which has M decision trees ($N \geqslant M$). The M independent random decision tree vectorsΘ_1,$\Theta_2 \ldots \Theta_M$are generated by each decision tree. And then a classifier $h(x, \Theta_M)$($x \in N$, an input vector) is generated. For the other part, the M decision trees vote for the most popular class. The two part procedures are called RF.

2.2. Dezert-Smarandache theory

To improve the accuracy and reliability of preliminary results of multiple classifiers, several information fusion theories are applied. DSmT as an information fusion method is applied in this paper because it can deal with uncertain or conflict problems well. It is analogous that these classifiers are regarded as various experts who make their own decisions for specific problems and the DSmT is regarded as an arbiter of these preliminary decisions.

2.2.1. Basic model

DSmT can be interpreted as an extension of Bayesian theory which introduces the notion of hyper-power set$D^\Theta$to make the result are not only just "true" or "false" [36]. For example, temperature in Bayesian theory is described only as cold or hot, but can be described as cold, cool, warm and hot in DSmT. If only two propositionsθ_1,θ_2 are made the simplest finite set. These simplest finite sets are expressed as in Bayesian theory and DSmT, respectively:

$$\Theta = \{\theta_1, \theta_2, \Phi\}, D^\Theta = \{\theta_1, \theta_2, \theta_1 \cup \theta_2, \theta_1 \cap \theta_2, \Phi\} \tag{1}$$

WhereΘrepresents the set of propositions in probability theory, $D^\Theta$is the hyper-power set in DSmT, and the$\Phi$is the empty set.

2.2.2. Combination rules

There are many basic belief assignment rules of the basic theory, such as classic Dezert-Smarandache (DSm) rule, hybrid DSm rule, and Proportional Conflict Redistribution1 ~ 6 (PCR1 ~ 6) rules, etc [37,38].

Here, the PCR6 rule is used in this study, and the equations can be expressed as:

$$m_{PCR6} = m_\wedge(X) + \sum_{i=1}^{s} m_i(X)^2 \sum_{\substack{C_1 \\ C_2}} \frac{\prod_{j=1}^{s} m_{\sigma_{i(j)}}(Y_{\sigma_{i(j)}})}{m_i(X) + \sum_{j=1}^{s-1} m_{\sigma_{i(j)}}(Y_{\sigma_{i(j)}})} \tag{2}$$

Where $m_{1.2\ldots s}(\cdot)$ is the conjunctive consensus rule, and$m_\wedge(\cdot)$corresponds to the conjunctive consensus:

$$m_\wedge(X) = \sum_{\substack{Y_1 \cap \ldots \cap Y_s = X \\ Y_{1,\ldots,Y_s \in P(\Theta)}}} \prod_{i=1}^{s} m_i(Y_i) \tag{3}$$

Where$\sigma_i$counts from 1 to s except i, is defined as

$$\begin{cases} \sigma_i(j) = j & if\, j < i, \\ \sigma_i(j) = j + 1 & if\, j \geqslant i, \end{cases} \tag{4}$$

Where the s is the number of information sources, and the $C_{1.2}$ is defined as:

$$\begin{gathered} C_1 = \cap_{k=1}^{s-1} Y_{\sigma_{i(k)}}(k) \cap X = \Phi \\ C_2 = Y_1, \ldots, Y_S \in P(\Theta) \end{gathered} \tag{5}$$

Where the$P(\Theta)$is the set of subset of Θ.

3. DSMT-based three-layer method using multi-classifier

DSmT-based three-layer method using multi-classifier is shown in Fig. 1. Actually, this is a layering approach to diagnosis. In the method, a three-layer structure of the hybrid model is designed to detect multiple faults of a hydraulic valve. In terms of the preliminary results in the layered model, DSmT is applied to obtain the final decision of multiple faults identification.

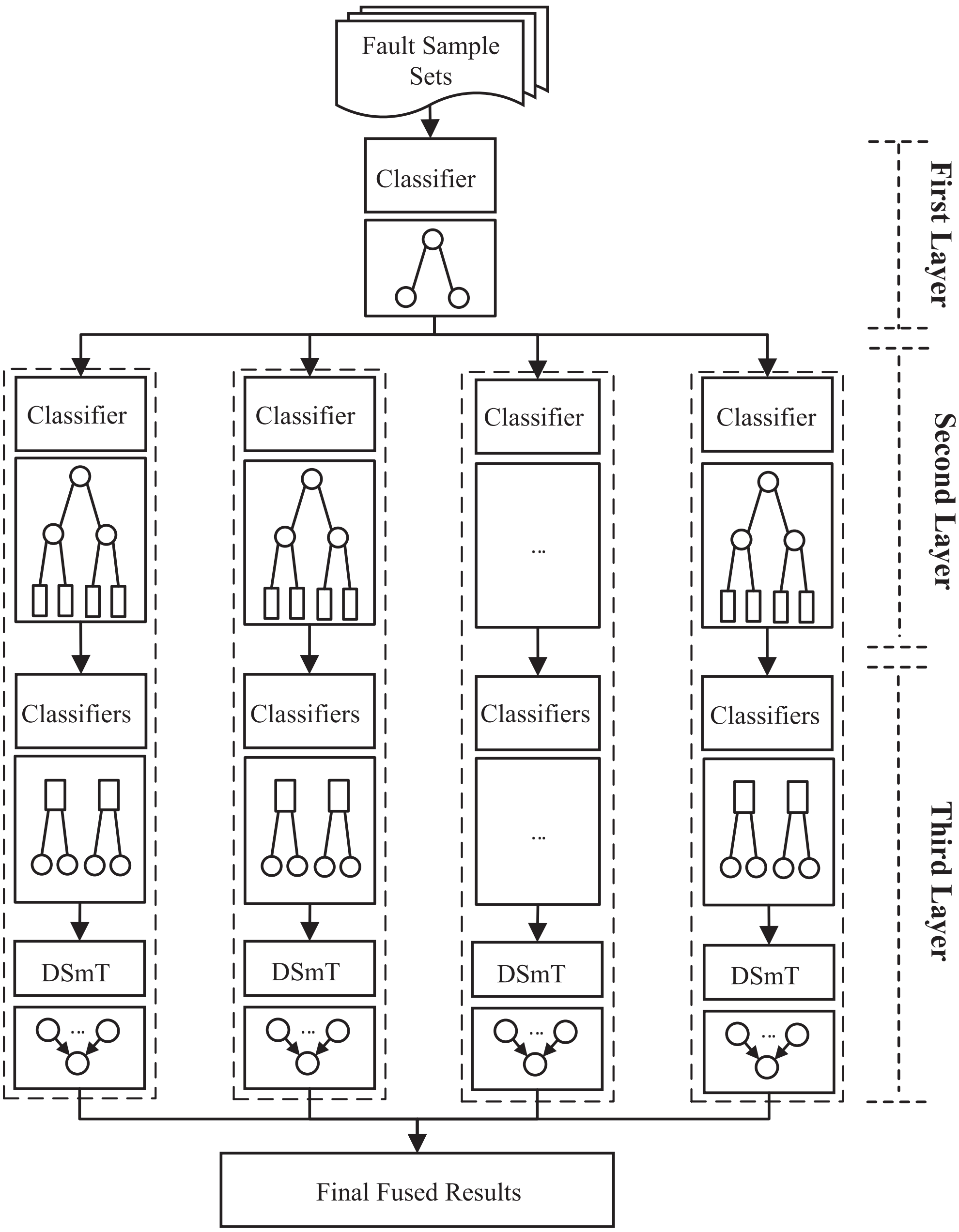

Fig. 1. DSmT-based three-layer method using multi-classifier.

3.1. Personalized sample sets

Because fault information of different faults usually scattered in different sections of the collected signal, and a large amount of information collected in a long working period of the hydraulic system, information redundancy and mutual interference of different types of fault signals will reduce the detection accuracy if all fault information is constructed in a single sample set. Therefore, personalized sample sets, as training and unknown testing sample sets, are constructed by selecting different fault information from different sections of the raw signal.

3.2. Layered hybrid model

A three-layer structure of the layered hybrid model is constructed to break the fault identification into three sub-tasks arranged in a hierarchy, where multiple efficient classifiers are combined in every layer.

The first layer:

Several fault groups with obvious fault characteristics are generated in this layer. Fault samples are assigned into the corresponding fault groups using trained classifiers by personalized fault sample sets.

The second layer:

The priority combination of multiple classifiers is designed in terms of sensitivity of every classifier to fault characteristics. In this layer, faults are further subdivided.

The third layer:

The features of some faults are inevitably very weak and similar, thus selected different classifiers continue to be used in the third layer in order to distinguish such faults in fault groups. Every classifier will produce an initial decision. However, different classifiers have different 'inductive biases', so that some conflict problems of the information source may occur. The DSmT is good at handling uncertain or conflict problems widely used in information decision process. Therefore, DSmT is employed in this layer to fuse initial decision of the each classifier and then obtain the final result of multiple faults identification as an arbiter of this information.

In the DSmT-based three-layer method using multi-classifier, the layered strategy is designed to realize the identification of multiple faults in different fault groups and fuse theory is adapted to improve the accuracy and reliability of results.

4. Experimental verification

An experiment rig of a hydraulic system controlled by a hydraulic valve (solenoid controlled pilot operated directional valve) was set up, and various diagnosis experiments were carried out in this section to verify the proposed DSmT-based three-layer method using multi-classifier.

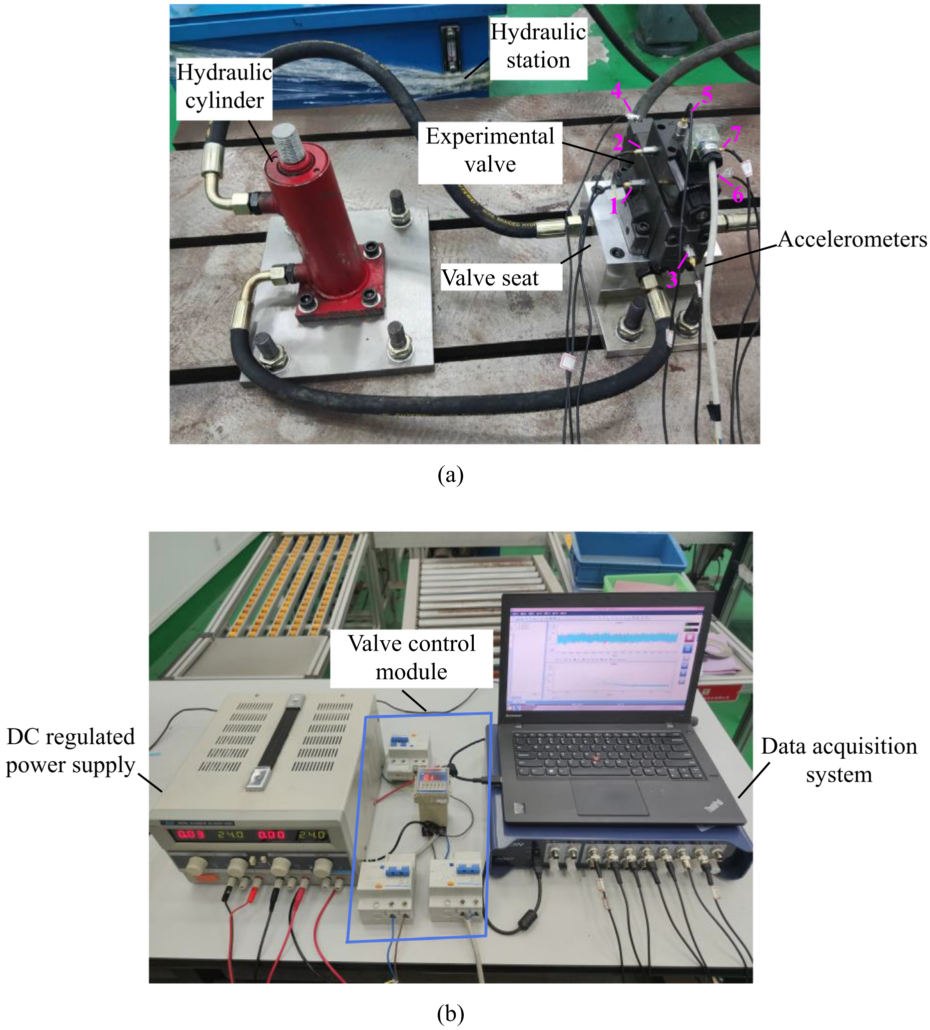

Fig. 2. Experiment rig for diagnosing hydraulic valve faults: (a) hydraulic test system, (b) data acquisition system.

4.1. Experiment rig for faults diagnosis for the hydraulic valve

4.1.1. Experimental hardware

The experiment rig for diagnosing hydraulic valve faults is illustrated in Fig. 2. Fig. 2 (a) shows a common hydraulic system consisting of the control component (hydraulic valve), hydraulic actuator (the cylinder), power supply and other auxiliaries. The hydraulic valve and the cylinder are fixed on the base to avoid the vibration interference from the hydraulic system itself during the working. In this experiment rig, hydraulic valves with different faults are considered as experimental objects. Six acceleration transducers (EA-YD series, in ECON) are symmetrically distributed on the sides of the valve body surface, and one acceleration transducer is arranged on the top of the pilot stage of the valve. The controller of the valve and the data acquisition module for vibration signals of the valve surface are show in Fig. 2 (b). All acceleration transducers signals are collected by the data acquisition module.

The experimental valve is a solenoid controlled pilot operated directional valve (type is DSHG-04, in YUKEN), as show in Fig. 3. If the solenoid acts in the pilot stage, the spool will move to the right pushed by the solenoid force. The pilot oil flows into the right chamber of the main valve via pilot valve channel. Consequently, due to the pressure increases in the right valve chamber, the spool in the main valve moves to the left. When the solenoid switches off, the pilot-solenoid valve spool is held by the spring. The pilot oil flows into the left chamber of the main valve via pilot valve channel. Pressured oil acts on the left side of the main spool and pushes it to right. Along with the gain and loss of the solenoid, the reciprocating movement of the spool is realized.

4.1.2. Faults description

The faults result in potential failure effects of the valve mainly including the fatigue caused by the insulation layer damage of the solenoid [39,40] (the temperature of the solenoid increased in long-time working) and the internal leakage caused by the abrasion occurred in the spool or the sleeve (unbalance force in the reciprocating movement of the spool).

Table 1 presents 12 fault types. Here, the normal is pattern 1. The remaining 80% of the electromagnetic force is defined as pattern 2 (the solenoid fatigue will result in the decline of the electromagnetic force, which could be simulated by adjusting the power supply), 40% is pattern 3, and 20% is pattern 4 (the spool in the pilot stage have almost not work). The abrasion occurred in different shoulders of the main valve spool with different severity are defined as pattern 5 to 10. And the abrasion occurred on the internal surface of the valve body is pattern 11 (single side) and 12 (double sides).

Several faults were set artificially on a hydraulic valve to simulate the practical condition of multiple faults. Fig. 4 shows surface morphology of the valve with the abrasion at different locations or with different severity. The mild wear fault occurred in the shoulder of the main spool is shown in Fig. 4 (a). The moderate wear fault occurred in the shoulder of the

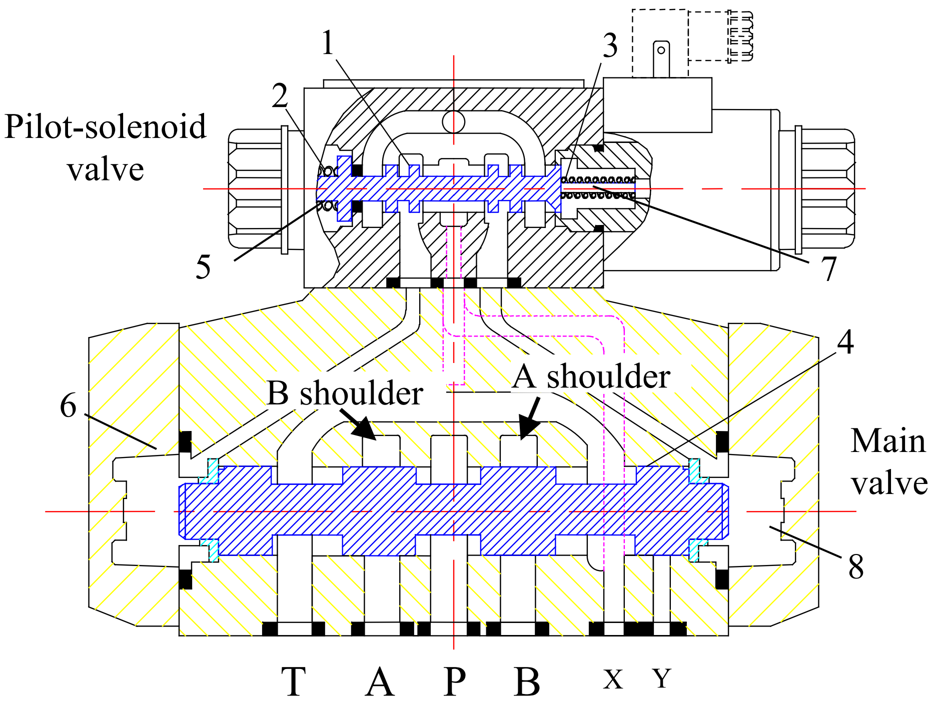

Fig. 3. Section of solenoid controlled pilot operated directional valve. 1-pilot-solenoid valve spool; 2-spring; 3-solenoid; 4-main valve spool; 5-left chamber of the pilot stage; 6-left chamber of the main valve; 7-right chamber of the pilot stage; 8-right chamber of the main valve.

Table 1
Fatigue samples description in the experiment.

Patterns	Severity	Fault Location	Fault Description
1	Normal	Normal	Normal
2		Solenoid	The remaining 80% of the electromagnetic force
3	Fatigue fault		The remaining 40% of the electromagnetic force
4			The remaining 20% of the electromagnetic force
5	Mildleakage faults	A shoulder of the main spool	Valve spool is worn but the pressure-equalizing groove is not damaged, see Fig. 4 (a).
6		B shoulder of the main spool	
7	Moderate leakage faults	A shoulder of the main spool	Valve spool is worn and the pressure-equalizing groove is also damaged, see Fig. 4 (b).
8		B shoulder of the main spool	
9	Serious leakage fault	A shoulder of the main spool	Valve spool is severely worn and accompanied by the pitting fatigue, see Fig. 4 (c).
10		B shoulder of the main spool	
11	Leakage fault on body	Valve body internal surface	Single side wears, see Fig. 4 (d).
12			Double sides wear, see Fig. 4 (e).

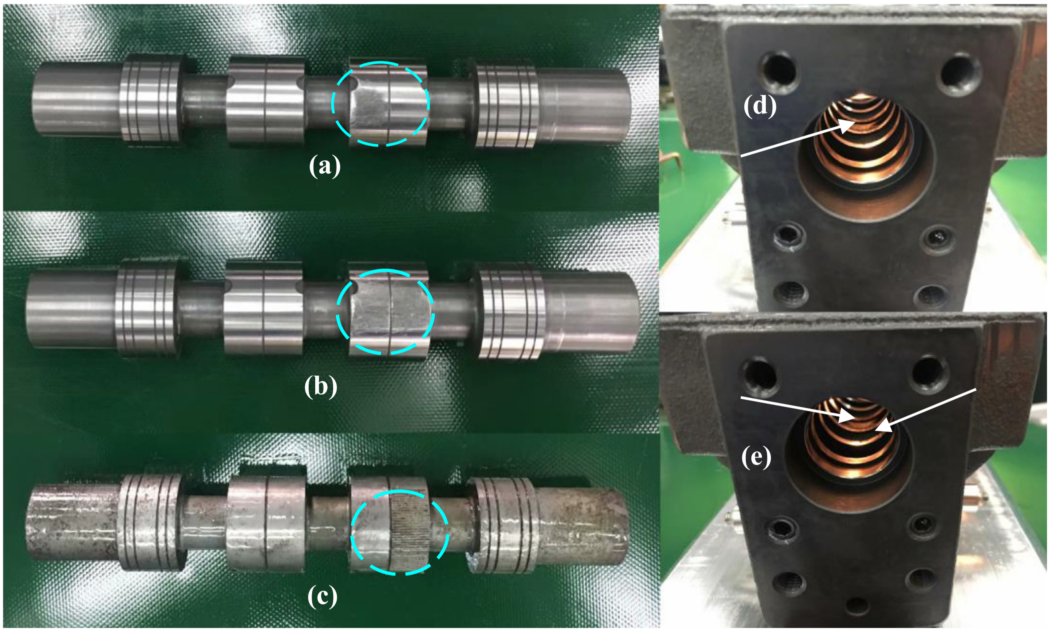

Fig. 4. Surface morphology of the valve with the abrasion at different locations or with different severity. (a) Valve spool is worn but the pressure-equalizing groove is not damaged; (b) Valve spool is worn and the pressure-equalizing groove is also damaged; (c) Valve spool is severely worn; (d) Single side wear on the valve internal surface; (e) Double sides wear on the valve internal surface.

main spool is shown in Fig. 4 (b). The surface morphology of the valve with the abrasive wear is illustrated in Fig. 4 (c). In addition, the single side wear and double sides wear on the internal surface of the valve body are respectively shown in Fig. 4 (d) and (e).

4.2. Signal acquisition and analysis

In all acceleration transducers signals, signals from the accelerometer (no. 3 and no. 4) at both ends of the main valve are more weaker compared with other signals. And other signals collected by data acquisition module are very similar to each other. Consequently, the No.1 accelerometer signals are taken as an example.

In the case study, the signal was continuously collected at a sampling frequency of 6000 Hz. Each fault pattern signal was repeated collected twice when the experimental hydraulic system with the fault valve worked. The first collected signal as an experimental group was constructed into the training sample set, and the second signal was collected as the control group to be constructed into the testing sample set. The time waveform of 30 min and single period (the period of the spool reversal is 8 s) were shown in Fig. 5.

As illustrated in Fig. 5, the period of the main spool reversal is divided into six segments, labeled as a, b, c, d, e and f, respectively. Between segment a and segment b, the movement direction of the main spool changes. The spool reverses again between segment d and segment e. Therefore, ahead of the spool reversed, there is abundant information in the section a (or d). The section after the spool reversal also contains abundant information, which is the section b (or e). The interval between the two changes in direction is the section c (or f).

The acceleration waveforms contain the interference information, such as low-frequency disturbance or unreliable information. The low-frequency disturbance appears as a random component in some samples, while the unreliable information generates due to the bigger amplitude of the shock signal beyond the linear range of the accelerometer. Because the interference information will produce the interference to analyze the signal to diagnose the fault, the information is usually eliminated or suppressed first. The processed signal is show in Fig. 6.

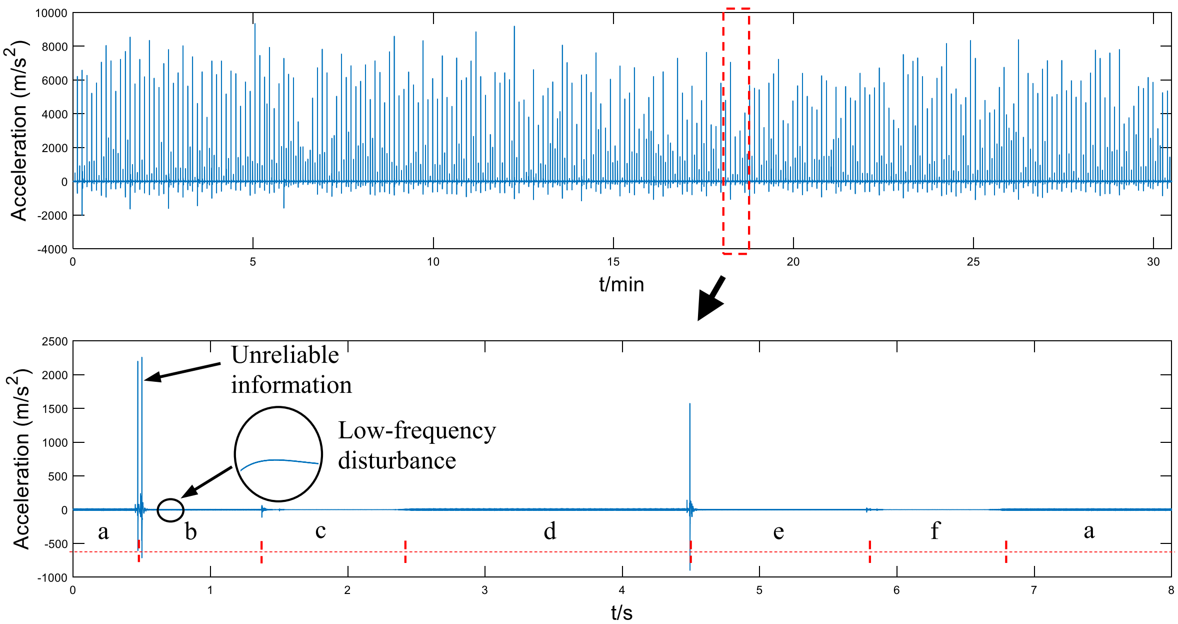

Fig. 5. Acceleration waveform of 30 min and single period.

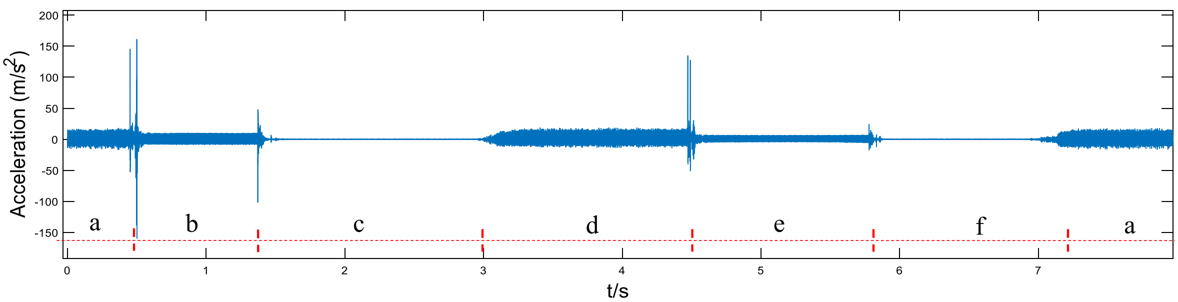

Fig. 6. The processed single period waveform.

4.3. Experimental results and discussion

The proposed three-layer method using multi-classifier is applied to detect multiple faults in hydraulic valves. The detailed diagnostic procedure is illustrated in Fig. 7.

Firstly, the processed signal is personalized to construct the training samples and the unknown testing samples for each layer. Different fault information is selected from different sections of the complete signal in terms of the characteristic of each fault type and then is personalized to construct corresponding fault samples. This process is illustrated by S1, S2, and S3 in Fig. 7. Some signal is extracted from the processed signal and recombined into the new signal sample set S1 as the fatigue fault samples. The sample set S1 is used as fatigue failure groups from the first to the third layer. The segment 'a' of signals through Fast Fourier Transformation (FFT) is constructed as the signal sample set S2, which represents the internal leakage fault group of the second layer. In addition, the signal segment 'f' is constructed as the new sample set S3 in the third layer for subdividing the internal leakage faults. The description of the personalized samples is shown in Table.2.

Then, personalized sample sets are input to the layered hybrid model, where multiple efficient classifiers are combined in every layer. Here, three classifiers RF, CNN and LSTM are selected. In the first layer, the CNN is employed to assign fault samples into corresponding fault groups, including the fatigue fault group and the internal leakage fault group. In the second layer, CNN and RF are used to detect the severity of the fatigue failure and internal leakage faults, respectively. The final types of fatigue faults are detected by CNN, and the specific locations of internal leakage faults are diagnosed by the combination of CNN, RF, and LSTM in the third layer. The fault types from 1 to 12 have been listed in Table 1.

Finally, according to probabilities generated by multiple classifiers, BPA functions are constructed in the hyper-power set. Then BPA functions are further processed in the information fusion step based on the DSmT's combination rules. As a result, DSmT as an arbiter of this information is applied to fuse the initial decisions and then make the final decision to detect internal leakage faults in the hydraulic valve.

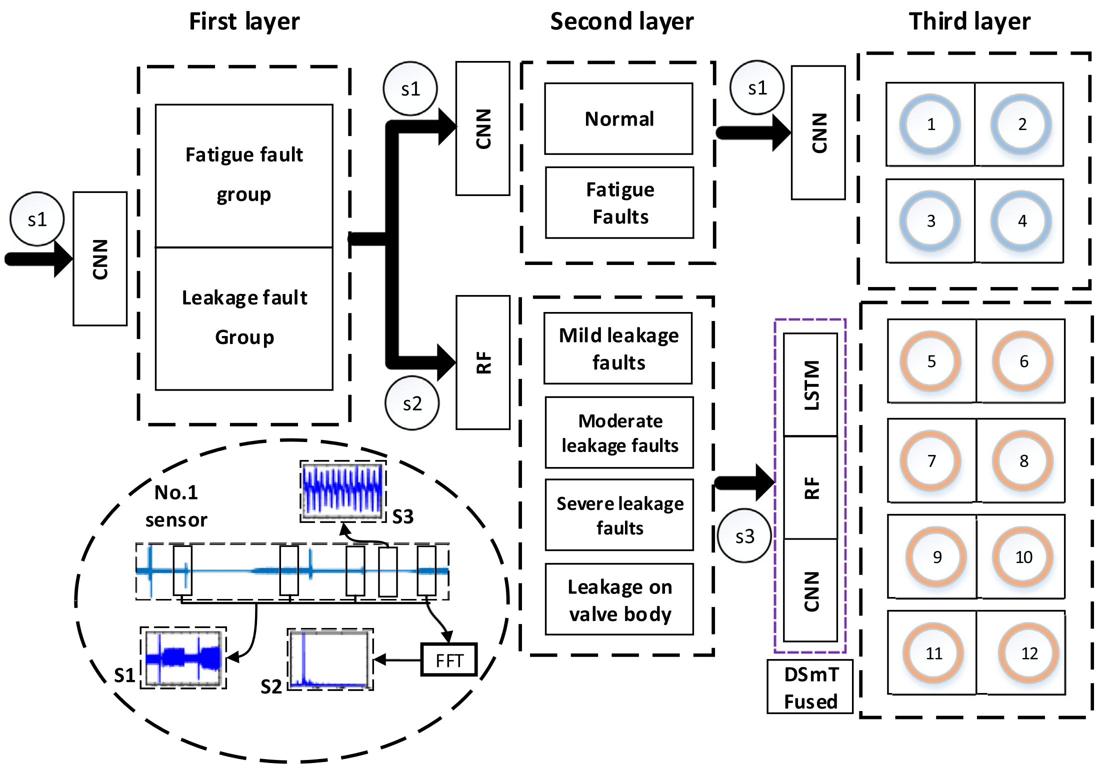

Fig. 7. The execution process of three-layer method using multi-classifier.

Table 2
Description of the personalized samples.

Sample patterns	Date point	Size of training/testing sample	Sample type
S1	16,900	2100/528(first layer),700/176	Time domain
S2	1445	1400/352	Frequency domain
S3	324	1400/352	Time domain

Table 3 displays the fault diagnosis accuracies in each layer and the final fusion results. The classification average accuracies in the first and second layers are 100%, 99.1%, and the accuracies of three classifiers (RF, CNN and LSTM) in the third layer are respectively 95.8%, 96.6%, and 96.6%. The average accuracy of the final fusion result is 98.1%. A columnar comparison of each type of fault diagnosis accuracy between the third layer and the fusion layer is shown in Fig. 8. The comparison chart illustrates that although the diagnosis accuracies have reached a high level if each classifier is used alone in the third layer, after the fusion process the diagnosis results of each type of the fault have higher accuracy and better stability.

The classification accuracy of RF, CNN, LSTM and the proposed method is compared, as shown in Table 4. The signal processed in a single period is constructed into a new sample set. Then the new sample set and the previously constructed sample sets S1, S2 and S3 are input into the single classifiers CNN, RNN and RF to obtain the classification results. Since a single CNN, RNN and RF can get the best accuracy with the new sample set, the accuracies under the new sample set are used to compare with the proposed method. Moreover, a finite number of tests are implemented for the single classifiers CNN, RNN and RF (by adjusting the parameters of each classifier to ensure that the classifier has good performance), these classifier models with the best accuracy are selected to compare with the proposed method in the selected finite number of tests.

As shown in Table 4, the average diagnosis accuracies of CNN, RNN, and RF only can be obtained as 73.3%, 65.5% and 69.9% respectively, while the average diagnosis accuracy of the proposed method can reach 98.1%. In addition, according to the diagnosis accuracy of each fault, the results of the single-stage classification method are not as stable as those of the proposed method.

In the experiments, the fatigue fault when the electromagnetic force can still drive the pilot valve is not as obvious as the internal leakage caused by imbalance force in the valve body. Therefore, it is difficult to detect the fatigue failure of the solenoid in the actuator when it can still work. Moreover, when the wear inside the valve has been very serious (such as the pattern 9 and 10), resulting in excessive clearance and completely changing its internal force condition, the internal leakage faults are also difficult to detect as several feature signals disappear. However, the proposed method can greatly improve the

Table 3
Fault diagnosis accuracies in each layer and the final fusion results (%).

Patterns		1	2	3	4	5	6	7	8	9	10	11	12	Average
First Layer		100						100						100
Second Layer		100		100		97.8		98.9		100		100		99.1
Third Layer	RF	97.7	100	100	100	95.5	93.2	95.5	93.2	90.9	100	93.2	90.9	95.8
	CNN	97.7	100	100	100	86.4	100	95.5	100	86.4	100	100	93.2	96.6
	LSTM	97.7	100	100	100	90.9	93.2	93.2	93.2	97.7	93.2	95.5	100	96.6
Fused results		97.7	100	100	100	90.9	97.7	95.5	100	95.5	100	100	100	98.1

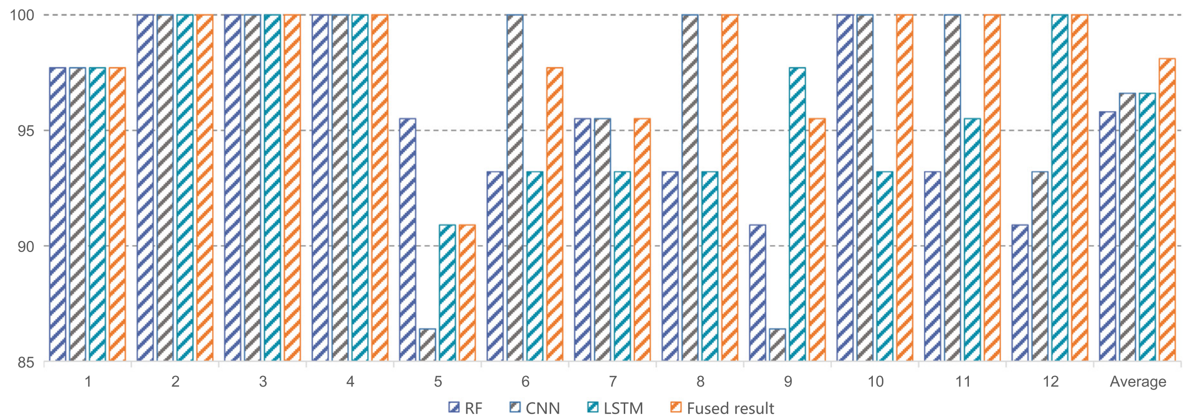

Fig. 8. Comparison chart of each type of fault diagnosis accuracy between the third layer and the fusion layer.

Table 4
Fault diagnosis accuracy of single-stage classification methods and the proposed method (%).

Patterns	1	2	3	4	5	6	7	8	9	10	11	12	Average
RF	88.6	68.2	75	100	93.2	93.2	77.3	88.6	68.2	25	27.3	75	73.3
CNN	65.6	100	90.9	100	20.5	97.7	93.2	95.5	6.8	2.3	72.7	93.2	69.9
LSTM	20.5	9.1	15.9	100	90.9	95.5	95.5	100	50	75	50	84.1	65.5
Proposed method	97.7	100	100	100	90.9	97.7	95.5	100	95.5	100	100	100	98.1

diagnostic performance because of a three-layer structure of the layered hybrid model and the personalized sample sets. Compared with single-stage classification methods, the proposed method has not only high identification accuracy but also high stability to identify multiple faults in different fault groups in hydraulic valves.

5. Conclusion

The hydraulic valve connects the electronic and hydro-mechanical portions of a system, some faults of electronics and magnetics as well as mechanics may occur in such valves, so it is often the focal point of discussion when system troubles occur. For such hybrid faults, a DSmT-based three-layer method using multi-classifier is proposed and experimentally verified. In this method, a layered hybrid model characterized by the three-layer structure is designed and established to simplify the diagnosis difficulty by breaking the diagnosis objective into several sub-tasks, and multiple efficient classifiers are selected for each sub-task in every layer for improving the diagnosis accuracy. Finally the DSmT is employed as an arbiter of this information to make the final decision to ensure higher accuracy and better stability of each fault. To verify the effectiveness of the proposed method, a hydraulic valve (solenoid controlled pilot operated directional valve) controlled hydraulic test rig is built. Twelve faults in the hydraulic valve are made to represent normal, different severity solenoid fatigues and various main valve wear fatigues. Compared with RF, CNN, LSTM, the average diagnosis accuracies of the proposed method is increased from 73.3%, 69.9%, and 65.5% to 98.1%, respectively. It is clearly that this method in effective to identify multiple faults in hydraulic valves. Moreover, the proposed method has high stability to identify multiple faults in different fault groups in hydraulic valves.

The future work will focus on the hybrid fault diagnosis methods for more complex fault groups in hydraulic system, and try to develop multi-sources signal fusion technology to improve the universality and reliability of diagnosis.

Declaration of Competing Interest

None.

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