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Research Article

Condition monitoring and fault diagnosis strategy of railway point machines using vibration signals

Yongkui Sun [1], Yuan Cao [1], Haitao Liu [2], Weifeng Yang [2,*] and Shuai Su [3]

[1]National Engineering Research Center of Rail Transportation Operation and Control System, Beijing Jiaotong University, Beijing 100044, China;
[2]CRRC Zhuzhou Institute Co Ltd, Zhuzhou 412001, Hunan, China;
[3]Frontiers Science Center for Smart High-speed Railway System, Beijing Jiaotong University, Beijing 100044, China.
*Corresponding author. E-mail: yangwf@csrzic.com

Abstract

Condition monitoring of railway point machines is important for train operation safety and effectiveness. Referring to the fields of mechanical equipment fault detection, this paper proposes a fault detection and identification strategy of railway point machines via vibration signals. A comprehensive feature distilling approach by combining variational mode decomposition (VMD) energy entropy and time- and frequency-domain statistical features is presented, which is more effective than single type of feature. The optimal set of features was selected with ReliefF, which helps improve the diagnosis accuracy. Support vector machine (SVM), which is suitable for a small sample, is adopted to realize diagnosis. The diagnosis accuracy of the proposed method reaches 100%, and its effectiveness is verified by experiment comparisons. In this paper, vibration signals are creatively adopted for fault diagnosis of railway point machines. The presented method can help guide field maintenance staff and also provide reference for fault diagnosis of other equipment.

Keywords: railway point machines, condition monitoring, variational mode decomposition (VMD) energy entropy, statistical features

1. Introduction

Railway has been developing rapidly in recent years [1–3]. Health state monitoring for vital devices and equipment has become increasingly popular around various fields [4–9]. Especially, railways such as heavy haul railway and high-speed railway in China have been developing rapidly, and have become the main force of cargo and passenger transportation [10–15]. The railway system is a critical and complex system to keep transportation tasks safe and efficient. To reach the goal, condition monitoring for core devices has become a hot issue [16–20]. Now, maintenance for railway signalling devices mainly means regular maintenance (time-based maintenance), which costs a lot of human resources. Therefore, it is necessary to use intelligent technology to realize fault diagnosis of key railway signalling equipment.

Railway point machines are one of the principal railway signalling devices to provide a required route for the train. Owing to severe outdoor circumstances, failures of railway point machines account for over 40% of all failures of railway signalling systems [21,22]. Railway point machines have a significant influence on the operation safety and efficiency of the railway system. If the turnout is not switched in place or is unlocked when the train passes, there may be a major threat for train operation. Besides, it will also influence the transportation efficiency. Thus it is necessary to exploit an intelligent and effective fault diagnosis method for railway point machines.

At present, most fault detection and condition monitoring strategies for railway point machines are developed by analysing current curves. These methods are listed as follows:

1) Threshold-based method: deviation detection is a commonly used measure to detect whether the system fails. Euclidean distance is usually utilized to evaluate data deviation [23]. However, since the time of switching process may be different, the data length of current curves may be different, meaning Euclidean distance cannot be used directly. Dynamic time warping can evaluate the similarity between two samples with different lengths. Thus dynamic time warping has been used to realize fault detection for railway point machines [24,25]. However, fault sources location cannot be realized using dynamic time warping.
2) Expert system: this enables the computer to diagnose faults by inputting expert knowledge and reasoning rules to it [26]. It was applied to the condition monitoring of the railway point machine [27]. Though it has some intelligence, its application is limited because a lot of expert experience is needed.
3) Model-based method: the main idea is to develop a mathematical model for the railway point machine according to its switching mechanism. Then, the parameter estimation [28,29] method can be applied to realize fault detection and diagnosis. There are only a few model-based studies about railway point machines [30]. However, the railway point machine is a very complex electromechanical system, so its switching process is hard to describe. Besides, model parameters are difficult to acquire.
4) Signal processing-based method: at present, the approach used most for fault detection and condition monitoring of railway point machines is signal analysis, such as current

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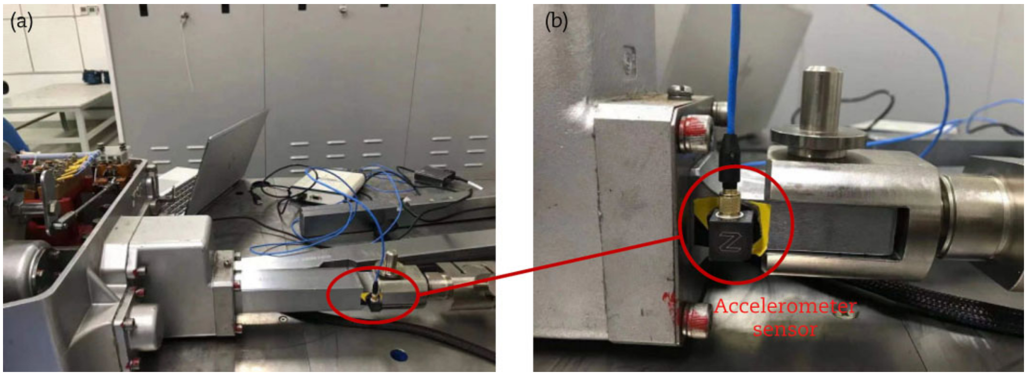

Fig. 1. Experiment setup: (a) data collection platform; (b) sensor installation.

signal [31–33]. Especially, sound signal has been applied in the fault detection and condition monitoring of railway point machines [34,35], which is a new idea. Though it is a contactless fault diagnosis method, it is easily affected by environmental noises.

Vibration signals were extensively applied in fault detection and idetification fields, such as wind turbine [36], gear [37] and motor [38]. Inspired by the application of sound signals in railway point machines and the application of vibration signals in other fields, this paper adopts vibration signals to realize the fault detection and identification of railway point machines. The advantage of vibration signals is that they are not easily disturbed by environmental noise. Besides, developed signal processing technology can provide technical support.

Though vibration signals have not been applied in the fault diagnosis of railway point machines, studies of other fields can provide references, for instance statistic features of time-domain [39], statistic features of frequency-domain [40] and features of time-frequency domain [41]. The mechanical vibration signal is usually nonlinear and non-stationary. For the convenience of analysis, it is usually necessary to be stabilized. The commonly used method is empirical mode decomposition (EMD), which can decompose the raw complex signal into several intrinsic mode functions [42]. However, mode mixing exists in EMD. Some improved versions (ensemble EMD [43] and complementary ensemble EMD [44]) are proposed to address this problem. Though EMD, including its evolutionary versions, is extensively utilized in various fields, it is not strictly based on mathematical derivation. It is worth noting that variational mode decomposition (VMD), proposed in 2014, is a preferable tool for processing nonlinear and non-stationary signals, and has a complete mathematical foundation [45].

For feature extraction, energy information is widely used as the fault feature, which is often combined with entropy, such as EMD energy entropy [46] or wavelet entropy [47]. Besides, time-domain statistical features, such as peak-peak value or mean value, and frequency-domain statistical features, such as gravity frequency or standard deviation frequency, have also been widely used due to their simplicity and high extraction efficiency [48,49]. However, a single type of feature cannot completely reflect the fault features, which may result in failure for achieving the best diagnostic results. Thus, this paper aims to integrate different types of features to realize high-accuracy fault diagnosis.

Feature selection is also a principal part of fault diagnosis because high-dimensional features usually contain lots of redundant information, which can reduce the fault diagnosis accuracy. The feature selection approaches are mainly of two types: filter and wrapper. The filter feature selection method is suitable for fast fault location due to its high efficiency. The wrapper feature selection method is time-consuming due to the iterative process. Considering the real-time requirement of fault diagnosis of railway point machines, the filter method is used in this paper. As one of the preferable filter feature selection methods, ReliefF has been widely used in feature selection and obtains good effects [50]. Therefore, ReliefF is adopted in this paper.

Reviewing the above-mentioned literature, this paper proposes a vibration signal-based fault detection and condition monitoring strategy of railway point machines. Firstly, VMD is utilized to preprocess the raw vibration signal, and a series of modes can be obtained. Secondly, VMD energy entropy and time- and frequency-domain statistical features are distilled, which can more comprehensively characterize the fault features compared with single type of feature. Then, ReliefF is applied to reduce the feature dimension and elect the optimal features by reducing the redundant information among the feature points. Finally, a support vector machine is applied for fault identification, which is optimized using particle swarm optimization. Experiment comparison shows the superiority of the presented fault detection approach.

The framework of the paper is as follows: Section 2 shows the setup and vibration signal description. Section 3 presents the developed fault detection strategy. Section 4 shows the results and analysis. Section 5 gives the conclusions.

2. Setup and vibration signal description

This section introduces the experiment setup and collected vibration signals under different fault conditions. The vibration signals were acquired from a laboratory in Xi'an Railway Signal Co., Ltd. The research object is a ZDJ9 railway point machine, which is widely applied in railway infrastructure, in China. The accelerometer sensor PCB 356A16_K with sampling frequency of 5.12 kHz was installed on the throw rod. The experimental device is shown in Fig. 1.

The vibration signals of eight conditions were collected using an accelerometer sensor. Their time-domain waveforms and working condition descriptions are given in Fig. 2 (the y-axis represents the vibration acceleration amplitude with a unit of gravitational acceleration) and Table 1, respectively.

The collected fault types are commonly faults. The switching resistance may be caused by untimely maintenance, such as a shortage of lubricant on the slide plate, which will increase the switching resistance. When there are obstacles between the stock rail and the blade, the blade cannot closely attach to the stock

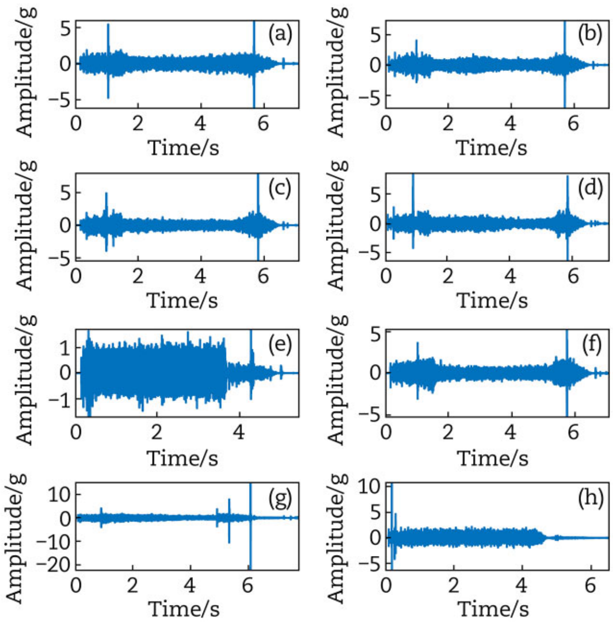

Fig. 2. Waveforms of vibration signals of different conditions: (a) condition-a; (b) condition-b; (c) condition-c; (d) condition-d; (e) condition-e; (f) condition-f; (g) condition-g; (h) condition-h.

Table 1. Vibration signal description.

Condition	Description	Length range/s
a	The load is smaller than nominal load (3 kN)	6.84–8.20
b	Nominal load (4 kN)	6.75–7.29
c	The load is larger than nominal load due to switching resistance (I) (5 kN)	6.84–8.20
d	The load is much larger than nominal load due to switching resistance (II) (6 kN)	6.95–9.18
e	The railway point machine slips due to obstacles	3.91–7.85
f	Indication circuit cannot be connected due to improper gap	6.64–7.13
g	No load (broken throw rod)	7.28–7.81
h	The railway point machine slips due to insufficient friction of frictional clutch	5.19–8.79

rail, leading to railway point machine slipping. The throw rod is utilized to transmit the conversion force to the blade. When the throw rod is broken due to train impact, the blade cannot be switched. The friction of the frictional clutch should be adjusted properly so that the switching process can be finished smoothly. If the friction is insufficient, the output conversion force cannot drive the moving blade.

It can be intuitively seen that the waveforms of the last four conditions are obviously different from those of other conditions, while the waveforms of the first four conditions are very similar. Thus, to exploit effective fault detection, an identification strategy to achieve accurate fault recognition is essential.

3. Proposed fault diagnosis method

This section presents the given identification method for the railway point machine. Some basic theory and methods are introduced. Then, the framework and flow of the developed fault detection strategy are shown.

3.1 VMD energy entropy

Dragomiretskiy et al. [45] proposed a completely non-recursive VMD in 2014, which can extract the decomposed modes at the same time. The algorithm searches a set of modes and the corresponding centre frequencies, so that these modes can reconstruct the input signal together. Besides, each mode becomes smooth after it is demodulated to the corresponding baseband. The essence of the algorithm is to extend the classical Wiener filter to multiple adaptive bands, which provides a solid theoretical foundation and is easy to be understood. To effectively optimize the variational model, the alternating direction multiplier method is adopted, which makes the model more robust to sampling noise. VMD can decompose the original signal into k modes with different centre frequency bandwidth, and take the minimum sum of all modes' estimation bandwidth as the optimization object. The optimization object is

$$\min\{\sum_{k=1}^{K}||\partial_t[(\delta(t)+\frac{j}{\pi t})*u_k(t)]e^{-jw_k t}||_2^2\}$$

$$\text{s.t.}\ \sum_{k=1}^{K}u_k = f(t) \tag{1}$$

where, $f(t)$ is the raw signal, u_k represent the modes, w_k represent the corresponding centre frequencies of u_k, and $\delta(t)$ is the Dirac distribution function.

Then, the augmented Lagrange function is applied to the above-mentioned optimal problem, as

$$lL(\{u_k\},\{w_k\},\lambda) = ||f(t)-\sum_{k=1}^{K}u_k(t)||_2^2 + \alpha\sum_{k=1}^{K}||\delta(t)[(\delta(t)+\frac{j}{\pi t})*u_k(t)]e^{-jw_k t}||_2^2 + \left\langle \lambda(t), f(t)-\sum_{k=1}^{K}u_k(t)\right\rangle \tag{2}$$

where, α presents the quadratic penalty factor and λ represents the Lagrange multiplier.

The alternating direction multiplier approach is introduced and applied to handle the optimal issue, as

$$\widehat{u}_k^{n+1}(w) = \frac{\widehat{f}(w)+\sum_{i\neq k}\widehat{u}_i^{n}(w)+\frac{\widehat{\lambda}^{n}(w)}{2}}{1+2\alpha(w-w_k{}^{n})^2}$$

$$w_k^{n+1} = \frac{\int_0^\infty w|\widehat{u}_k^{n+1}(w)|^2 dw}{\int_0^\infty |\widehat{u}_k^{n+1}(w)|^2 dw}$$

$$\widehat{\lambda}^{n+1}(w) = \widehat{\lambda}^{n}(w)+\tau(\widehat{f}(w)-\sum_{k=1}^{K}\widehat{u}_k^{n+1}(w)) \tag{3}$$

where, $\widehat{f}(w)$, $\widehat{u}_k^n(w)$, $\widehat{u}_i^{n}(w)$ and $\widehat{\lambda}^{n}(w)$ are the Fourier transform of $f(t)$, $u_k^n(t)$, $u_i^n(t)$ and $\lambda^n(t)$, respectively.

Finally, the raw signal is decomposed as

$$f(t) = \sum_{k=1}^{K}u_k(t) \tag{4}$$

The procedures of VMD energy entropy are given as follows:

Table 2 Time- and frequency-domain statistical features.

Feature	Equation
Mean	$\bar{x}=\left[\sum_{i=1}^{N}\lvert x(i)\rvert\right]/N$
Standard deviation (STD)	$x_{std}=\sqrt{\left[\sum_{i=1}^{N}(x(i)-\bar{x})^2\right]/N}$
Skewness	$x_{ske}=\left[\sum_{i=1}^{N}(x(i)-\bar{x})^3\right]/\left[(N-1)x_{std}^3\right]$
Kurtosis	$x_{kur}=\left[\sum_{i=1}^{N}(x(i)-\bar{x})^4\right]/\left[(N-1)x_{std}^4\right]$
Peak	$x_p=\max\lvert x(i)\rvert$
Root mean square (RMS)	$x_{rms}=\sqrt{\left[\sum_{i=1}^{N}x^2(i)\right]/N}$
Crest factor (CF)	$x_{cf}=x_p/x_{rms}$
Shape factor (SF)	$x_{sf}=x_{rms}/\left[(1/N)\sum_{i=1}^{N}\lvert x(i)\rvert\right]$
Impulse factor (IF)	$x_{if}=x_p/\left[(1/N)\sum_{i=1}^{N}\lvert x(i)\rvert\right]$
Margin factor (MF)	$x_{mf}=x_p/\left[(1/N\sum_{i=1}^{N}\sqrt{\lvert x(i)\rvert})^2\right]$
Frequency center (FC)	$x_{fc}=\left[\sum_{i=1}^{K}f(i)s(i)\right]/K$
Root mean square Frequency (RMSE)	$x_{rmsf}=\sqrt{\left[\sum_{i=1}^{K}f^2(i)s(i)\right]/\sum_{i=1}^{K}s(i)}$
Standard deviation frequency (SDF)	$x_{sdf}=\sqrt{\left[\sum_{i=1}^{K}(f(i)-x_{fc})^2 s(i)\right]/\sum_{i=1}^{K}s(i)}$

Note: $s(i)$ is frequency spectrum amplitude, $f(i)$ presents the corresponding frequency of $s(i)$ and M represents the spectrum line number.

First, calculate the energy information of each mode $u_k(t)$ as

$$E_k=\lVert u_k(t)\rVert_2^2 \tag{5}$$

Then, the total energy is calculated as

$$E=\sum_{k=1}^{K}E_k \tag{6}$$

Finally, the VMD energy entropy can be acquired via the definition of Shannon entropy

$$en_k=-p_k\log(p_k),\quad p_k=\frac{E_k}{E} \tag{7}$$

3.2 Time- and frequency-domain features

Time- and frequency-domain statistical features' and parameters' distilling is efficient and simple, and has been extensively used in mechanical equipment fault diagnosis fields. Taking signal with length of N as an example, the commonly used statistical features are given in Table 2.

In order to remove the effect of dimensions, the obtained time- and frequency-domain features are standardized by

$$u=\frac{u-\mathrm{mean}(u)}{\mathrm{var}(u)} \tag{8}$$

where, mean(u) and var(u) represent the mean and variance of vector u.

3.3 ReliefF

Feature selection has a great impact on diagnosis accuracy. The basic idea of ReliefF algorithm is that it is using the capability of features to discriminate close-distance samples. First, a sample R is randomly selected from the training set D. Then, the q nearest samples H (called Near Hit) and M (called Near Miss) are determined from the same class of R and the other classes, respectively. Then, the weight update rules of each feature are stated as: if the distance of a feature between R and Near Hit is smaller than that between R and Near Miss, the corresponding feature is conducive to identify the nearest and easily confused samples of the same condition and different conditions, whose weight will be increased. If not, the weight of the corresponding feature will be reduced. After repeating m times, the average weight of each feature is finally obtained. The greater the feature weight, the stronger the feature identification ability. Otherwise, the weaker the classification ability of the feature. This approach is very efficient. The weights update rule is

$$W(A)=W(A)-\sum_{b=1}^{q}dif(A,D_i,H_b)/(mq)+\sum_{d\notin class(D_i)}\left[\frac{p(d)}{1-p(class(D_i))}\sum_{b=1}^{q}dif(A,D_i,M_b(d))\right]/(mq) \tag{9}$$

where, $p(d)$ represents the prior probability of class d, m presents iteration times and $M_b(d)$ is the bth sample with smallest distance which belongs to class d. The operator $dif(\cdot)$ is

$$dif(A,D_i,H_b)=\begin{cases}0, & D_i[A]=H_b[A]\\ 1, & D_i[A]\neq H_b[A]\end{cases} \tag{10}$$

where, $D_i[A]$ is feature A in D_i, and $H_b[A]$ is feature A in H_b.

3.4 SVM

SVM is a powerful means which is widely utilized to address pattern and fault recognition with good effect. It is based on mathematical derivation, which takes the structural risk minimization as the optimization function. By introducing the kernel function, SVM can address the nonlinear classification issue, where the radial basis function is the preferable kernel function. Due to its applicability to small sample data, SVM is utilized in this paper. The hyperparameters of SVM are optimized by particle swarm optimization, which is presented in our study [16].

3.5 Proposed method

Integrating the above-mentioned methods, an intelligent fault detection and identification strategy of railway point machines is

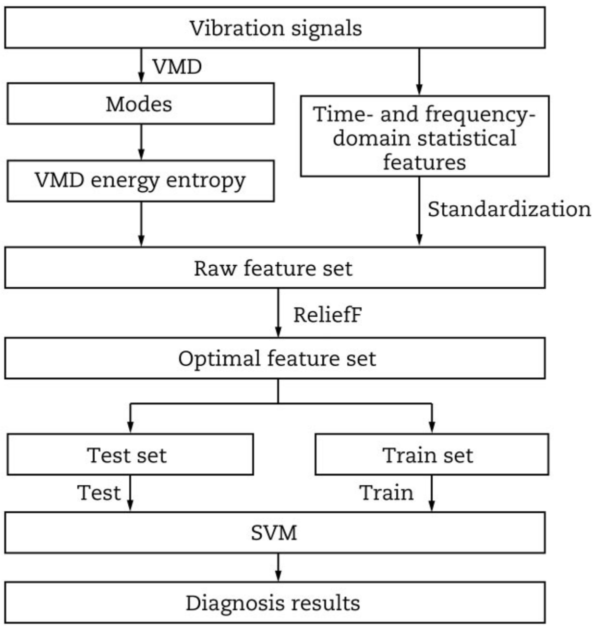

Fig. 3. Flowchart of the presented diagnosis strategy.

presented. The flowchart of the presented diagnosis strategy is given in Fig. 3.

During feature extraction, two types of feature are extracted: energy entropy and statistical features, which constitute the raw feature set. Then, ReliefF is applied to elect the optimal feature set. Finally, training samples are utilized to train the SVM classification model. Test samples are utilized to verify the effect of the presented fault detection strategy.

4. Results and analysis

4.1 Feature extraction

To extract the VMD energy entropy, VMD is utilized to disintegrate the original vibration signals during the switching of railway point machine. The time-domain waveforms of the obtained modes of a sample of condition-a are given in Fig. 4.

Fig. 4 shows the first 14 modes of a sample of condition-a. The first several modes contain high-frequency information, which will characterize the characteristics of the original vibration signal to a great extent. In this paper, the first 12 modes are selected to extract VMD energy entropy. Thus, a vector with 12 entropy features can be obtained for each sample. Then, 13-dimensional time- and frequency-domain statistical parameters and features are acquired and standardized from original vibration signals. By integrating VMD energy entropy and statistical features, a vector with 25 features for each sample is obtained.

4.2 Feature selection

In this paper, 436 samples are separated into two parts: 261 training samples and 175 test samples. The detailed data separation situation is given in Table 3.

Not all the 25 features are beneficial for fault identification. To abandon the ineffective features and reserve the optimal features, ReliefF is adopted to realize feature selection. The weights of the 25 features using ReliefF are given in Fig. 5. Besides, 25 features

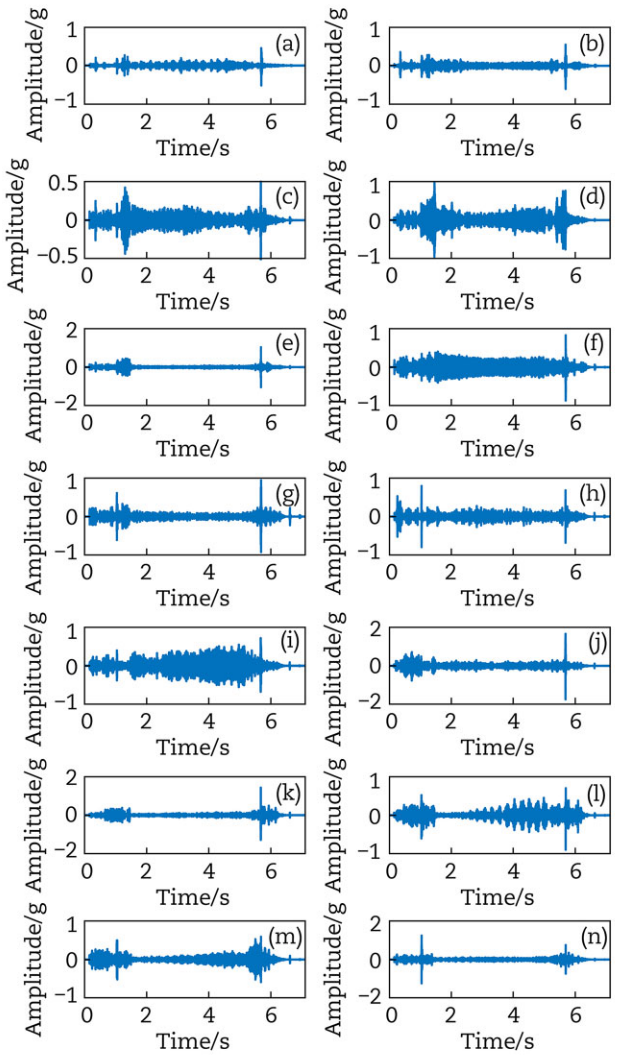

Fig. 4. VMD results of a sample of condition-a: (a) mode1; (b) mode2; (c) mode3; (d) mode4; (e) mode5; (f) mode6; (g) mode7; (h) mode8; (i) mode9; (j) mode10; (k) mode11; (l) mode12; (m) mode13; (n) mode14.

Table 3. Detailed data separation description.

Condition	a	b	c	d	e	f	g	h	Total
Training samples	36	34	36	23	24	36	36	36	261
Test samples	24	23	24	16	16	24	24	24	175

combining EMD energy entropy and statistical features are also processed using ReliefF. The corresponding weights are given in Fig. 6.

It can be concluded that the weights of VMD energy entropy are much larger than those of EMD energy entropy, indicating that the discrimination ability of VMD energy entropy is better than that of EMD energy entropy. Besides, the discrimination ability of VMD energy entropy (the first 12 features) is better than the statistical features (the last 13 features). To further verify the validity of the presented feature extraction methods, the following part will give the sort results using SVM. In this paper, the features whose weights are larger than 0 are selected as the optimal features.

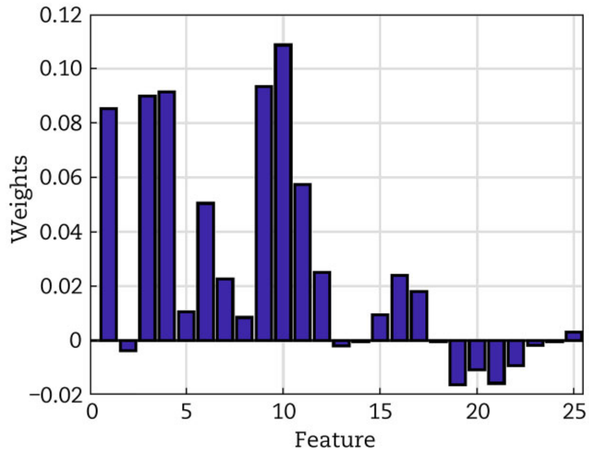

Fig. 5. Weights of the 25 features (VMD energy entropy and statistical features).

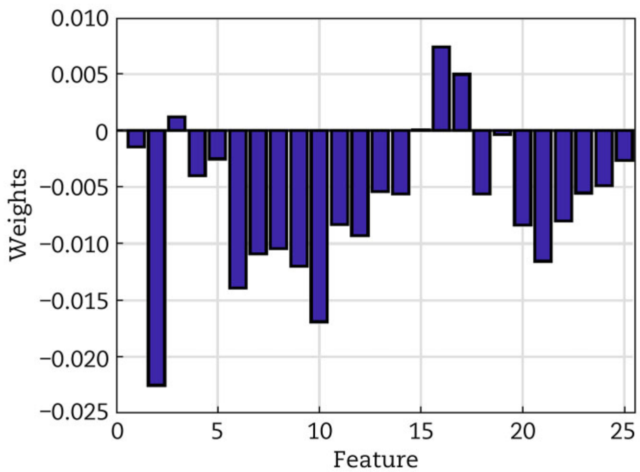

Fig. 6. Weights of the 25 features (EMD energy entropy and statistical features).

4.3 Comparison

To validate the advantages of the presented fault detection and identification strategy based on the integrated feature extraction method (combining VMD energy entropy and statistical features) and ReliefF, some fault diagnosis methods are given as comparisons. There are method1: fault detection strategy using VMD energy entropy and statistical features; method2: fault detection strategy using EMD energy entropy and statistical features and ReliefF; method3: fault detection strategy using VMD energy entropy and ReliefF; and method4: fault detection strategy using statistical features and ReliefF. The fault diagnosis results are given in Table 4 and Fig. 7.

The conclusion can be drawn that the diagnosis effect of conditions f – h is good using all these methods because the distinction characteristics among them are obvious, which can be intuitively reflected from their time-domain waveforms (see Fig. 2). The diagnosis effect of the first five conditions using method1 to method4 is not very satisfying because the first five conditions are similar. Especially, method2 and method4 perform the worst, indicating that EMD energy entropy is not effective for diagnosing faults of railway point machines. The single statistical feature is also not very effective for fault diagnosis using vibration signals. If all extracted features are used (method1), the diagnosis accuracy is 96.57%, which is not very satisfying due to redundant information among these features. Method3 performs much better, demonstrating the effectiveness of VMD energy entropy features. By combining statistical features, the diagnosis accuracy can be further improved (proposed method). Overall, the proposed method has the best effect in the fault detection and identification of railway point machines via vibration signals.

4.4 Discussion

This paper presents a vibration signal-based fault diagnosis strategy for railway point machines via integrated features, ReliefF and SVM. Different from the existing motor current signal-based methods, this approach is based on vibration signal analysis, which is learnt from the studies and works of other fault detection research fields. To improve diagnosis accuracy, the integrated feature distilling approach combining VMD energy entropy and time- and frequency-domain statistical features is developed, which is verified as a more powerful tool for distinguishing similar conditions by combining with ReliefF and SVM. The proposed approach may provide new ideas and ways for fault detection and identification of railway point machines, which can also provide reference to other fault diagnosis fields.

Besides, the presented method in this paper is based on vibration signals of a complete switching process. Vibration signals of a complete switching process are necessary for fault detection and diagnosis using the proposed method. In the future, we will aim

Table 4. Diagnosis results using different fault diagnosis methods.

Condition	Test sample	Correctly detected sample				
		method1	method2	method3	method4	Proposed method
a	24	24	16	24	8	24
b	23	22	7	23	13	23
c	24	24	19	24	19	24
d	16	16	8	16	11	16
e	16	11	11	15	10	16
f	24	24	24	24	24	24
g	24	24	24	24	24	24
h	24	24	24	24	24	24
Accuracy		96.57%	76%	99.43%	76%	**100%**

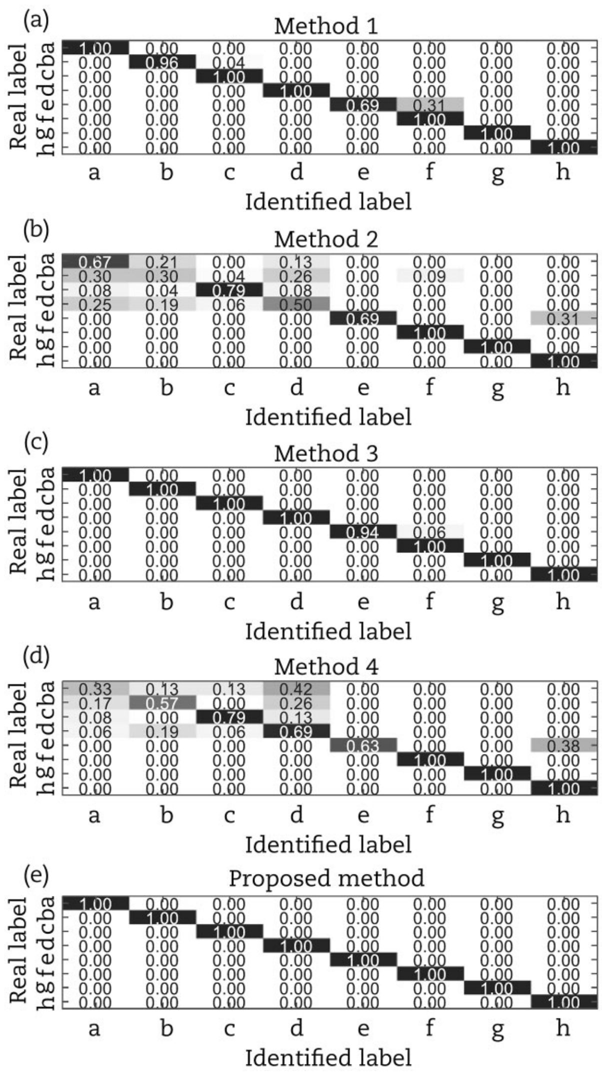

Fig. 7. Confusion matrix of different methods: (a) method 1; (b) method 2; (c) method 3; (d) method 4; (e) proposed method.

to research the fault diagnosis method for railway point machines using dynamic data, which can detect faults in a more timely manner. Besides, the vibration signals may be affected by the adjacent train passing. In the future, we will collect more field vibration signals to do further studies, making the proposed method more suitable for field maintenance.

5. Conclusions

A novel vibration signals-based fault detection and identification strategy of railway point machines is presented. The integrated feature distilling approach using VMD energy entropy and time- and frequency-domain features is developed. The efficient feature selection method ReliefF is introduced and adopted to cut down the dimension of features. SVM is used to realize fault identification. The fault diagnosis accuracy via the presented fault detection strategy reaches 100%. The fault diagnosis effect and advantages of the presented fault detection strategy are also validated through comparisons. This paper creatively uses vibration signals as fault detection means, which can offer assistance for field maintenance staff.

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Author contributions statement

Yongkui Sun and Weifeng Yang designed the methodology. Yongkui Sun and Yuan Cao carried out data analysis and wrote the first draft of the manuscript. Haitao Liu helped organize the manuscript. Shuai Su revised and edited the final version.

Conflict of interest statement

No conflict of interest exits in the submission of this manuscript, and the manuscript is approved by all authors for publication.

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