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Incipient loose detection of hoops for pipeline based on ensemble empirical mode decomposition and multi-scale entropy and extreme learning machine

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Abstract. Hoops are very important fittings in hydraulic pipeline, incipient loose detection of hoops will help to prevent hydraulic piping system from breaking down. Since the vibration signals of fluid pipe are non-stationary and of great complexity, multi-scale entropy(MSE), a method characterized by evaluating complexity and irregularity of time series on multiple scales, is used for extracting feature vectors from the vibration signals. In order to obtain components related to system characteristics, ensemble empirical mode decomposition(EEMD) is applied to reconstruct the original signals before the procedure of MSE. Extreme learning machine(ELM) is a new machine learning algorithm characterized by high accuracy and efficiency. In this paper, ELM is introduced as a classifier to identify the different conditions of hoops according to feature vectors extracted by EEMD and MSE algorithms. Thus a novel loose detection method combining with EEMD-MSE and ELM is put forward. The analysis and experimental results demonstrate that the proposed loose detection and feature extraction method for hydraulic pipeline is effective with high performance.

1. Introduction

Hydraulic system pipeline usually works in complex environment such as high temperature, high pressure, strong vibration and fluid-structure interaction and so on. Once frequencies of exciting signals are approximately equal to intrinsic frequency of pipeline, resonance occurs[1]. Resonance phenomena will lead to vibration damage of pipeline. Therefore, it is of great importance to restrain the vibration of hydraulic piping system effectively. One of the most common and economical way is applying hoops to hydraulic pipeline[2]. However, if hoops get loose due to improper assembly or long-time running of hydraulic piping system, it will seriously affect the stability and service life of the hydraulic pipeline. Thus it is necessary for real-time incipient loose detection of hoops in hydraulic piping system, so as to discover hoop failure in time and prevent accidents from happening. In recent years, however, study of hoop mainly focus on modal analysis[3] and optimization of the hoop layout on pipeline[2], relatively few studies on hoop condition monitoring.

Different piping vibration states caused by conditions of hoop can be detected by a vibration sensor, vibration signals under which condition are usually complex non-stationary signal submerged by strong noise[1-3]. As typical signal in field of fault diagnosis, non-stationary vibration signals have been analyzed in time-domain, frequency-domain, and time-frequency domain respectively for many years. Among which empirical mode decomposition(EMD) is a typical one. Although EMD can decompose nonlinear signals into terms of different mode, it still shows mode mixing and end effects problems. To alleviate those problems, ensemble empirical mode decomposition(EEMD) is proposed by Wu and Huang in 2009[4]. In 2015, EEMD method is applied to diagnostics of gear deterioration by Yang et al[5]. It enhanced the accuracy of gear fault diagnosis.

In recent years, feature extraction method based on the statistical analysis has been increasingly introduced into fault diagnosis and condition monitoring of machinery, of which entropy analysis is an important one. In 2015, a fault diagnosis method combined with LMD, sample entropy(SampEn) and energy ratio for roller bearings was presented by Minghong Han[6]. SampEn was an improvement of approximate entropy(ApEn), since ApEn shows apparent disadvantages like the heavy dependence on data length and lack of relative consistency. SampEn shows good traits such as data length independence and trouble-free implementation compared to ApEn. Although SampEn is better and stable than ApEn, it still reflects only single scale information of the time sequence. On this condition, multi-scale entropy(MSE) was proposed by M.Costa et al[7]. MSE actually calculates SampEn on different time scales, it was introduced as a method to evaluate the complexity of time series under different scales. MSE is earliest used in physiological time series analysis, but in recent years, many researchers applied it to mechanical signal analysis and achieved some pretty good results [8]. Unfortunately, there has been only a few study about application of entropy methods in field of hydraulic piping system fault diagnosis thus far.

Generally, after feature extraction of vibration signals for hoop conditions, an intelligent classifier is applied to complete automatic condition monitoring. Automated condition monitoring can make reliable decision quickly and reduce the risk of operation on the running condition of hydraulic piping system. Traditionally, the most widely used intelligent techniques are backward propagation neural network(BPNN) and support vector machine(SVM) and so on. However, gradient-based learning algorithms such as BPNN may face several issues like local minima, improper learning rate and overfitting, etc[9]. SVM has difficulty in large-scale training set because of its huge amount of calculation, and it is also not easy for SVM to make real-time prediction since it normally generate much number of support vectors(computation units). In order to avoid these issues, extreme learning machine(ELM) is proposed by Huang[10], ELM is a new learning algorithm for single-hidden layer feed forward neural networks (SLFNs) which randomly chooses hidden nodes, it tends to reach solutions straightforward without many trivial issues, it has better generalization performance than BPNN and much faster than SVM. The ELM method has been used in many applications[9], in this paper, ELM algorithm is introduced in loose detection of hoops for hydraulic pipeline.

According to the hydraulic piping dynamics theory, different hoop conditions show different impacts on dynamic characteristics of pipeline[1-3]. Therefore the complexity of signals under different hoop conditions is different, as well as its entropy value. Thus MSE method is applied to loose detection of hoops for hydraulic piping system and the entropy values are used as feature vector to evaluate different loose conditions.

In this paper, a method based on EEMD, MSE and ELM is proposed for loose detection of hoops installed on hydraulic pipeline. EEMD-MSE algorithm is used for feature extraction and ELM is introduced as an intelligent classifier to identify the different conditions of hoops. In Section 2, the methods of EEMD, MSE and the feature extraction procedures based on EEMD-MSE are presented simply, as well as ELM algorithm. Experimental analysis is expressed in Section 3. In this Section, method based on EEMS-MSE and ELM is conducted for loose detection of hoops. Moreover, ELM model is compared with BPNN and SVM in performance of loose detection of hoop based on experimental data. Finally, the discussion and conclusion are provided in Section 4.

2. Methods

2.1. Ensemble Empirical Mode Decomposition

The Empirical Mode Decomposition (EMD), proposed by Huang[11], is an adaptive time–frequency data analysis method designed for nonlinear and non-stationary signal analysis. In the EMD approach, the data $x(t)$ is decomposed into terms of Intrinsic Mode Functions($IMFs$), c_j , i.e.,

$$x(t) = \sum_{j=1}^{n} c_j + r_n \tag{1}$$

where r_n is the residue of original data $x(t)$ after n number of $IMFs$ are extracted. Among which $IMFs$ should satisfies two conditions[11]:

(1) Throughout the whole length of a single IMF , the number of extremes and the number of zero-crossings must either be equal or differ at most by one.

(2) At any data location, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

However, one shortcoming of the EMD method is the mode mixing problem, which is defined as a single IMF including oscillations of dramatically disparate scales, or a component of a similar scale residing in different $IMFs$ .When mode mixing occurs, physical meaning of individual IMF becomes unclear, what's more, it may even suggest wrong time-frequency distribution.

To solve the problem of mode mixing in EMD, the EEMD method is proposed by Wu and Huang[9]. It based on the fact that the white noise could provide a uniformly distributed scale in the time–frequency space. The intrinsic oscillations in the signal with different scales would automatically associate with the similar scales of reference ridings provided by white noise. The detailed procedures of EEMD are described as follows[4]:

(1) Add a white noise series to the targeted data;

(2) Decompose the data with added white noise into IMFs using EMD method;

(3) Repeat step (1) and step (2) again and again, but with different white noise series each time;

(4) Obtain the ensemble means of corresponding $IMFs$ of the decompositions as the final result.

Through the above steps, problem of mode mixing is solved by the elegant use of noise in EEMD.

2.2. Sample Entropy and Multi-scale Entropy

SampEn[12] is proposed as an unbiased estimator of the conditional probability that two similar sequences of m consecutive data points (m is the embedded dimension) would remain similar when one more consecutive point is included. It represents the complexity and irregularity of time series on single scale. However, acceleration signals of hydraulic pipeline usually own correlation in different time scales. In order to indicate the correlation and complexity of time series under different scales, MSE method is introduced in this paper.

MSE is improvement of SampEn, it actually calculates SampEn on different time scales. Its algorithm process contains two parts, the first part is a "coarse-graining" transform of the time series, while the other part is calculation of SampEn . The specific algorithm procedures is as follows:

Consider the discrete time series $\boldsymbol{x} = \{x_1, x_2, ..., x_L\}$ of length L , conduct "coarse-graining" transform of the time series x and get new series $\boldsymbol{y} = \{y_1^{(\tau)}, y_2^{(\tau)}, ..., y_N^{(\tau)}\}$ under scale τ , each element of y is calculated according to Eq.(2):

$$y_j^{(\tau)} = 1/\tau \sum_{i=(j-1)\tau+1}^{j\tau} x_i \qquad (1 \le j \le L/\tau) \tag{2}$$

where $\tau = 1, 2, ...$ represents the scale factor, $N = L/\tau$, represents length of each "coarse-graining" series y . If scale $\tau = 1$, the new series is original sequence.

For each time series corresponding scale τ , given the embedding dimension m , and threshold r ,calculate the sample entropy $SampEn(\tau, m, r)$ [12] of them.

Multi-scale entropy is defined as a collection of sample entropy in multiple scales. So MSE of the time series is as follows:

$$MSE = \{\tau \mid SampEn(\tau, m, r)\} \tag{3}$$

Multi-scale entropy indicates the complexity of time series under different scales. Generally higher entropy value means higher complexity. Therefore, if the entropy values of a time series are higher than another in most of the scales, the former is considered more complicate than the latter. If the entropy values of a time series progressively decrease as the time scales increase, the sequence is considered to be with simple structure and there is more information on lower scales. Otherwise, if the entropy values of a time series progressively increase as the time scales increase, it indicates that there is more information on higher scales.

2.3. The Procedures of Method Based On EEMD-MSE

In this paper, a method based on EEMD and MSE to extract features of hydraulic pipeline is proposed. The whole processing procedure includes reconstructed procedure use EEMD and feature-obtaining procedure with MSE. The detailed procedure is described as follows:

(1) Set the parameter k, calculate k $IMFs$ of original signal $x(n)$ using EEMD method;

$$x(n) = \sum_{j=1}^{k} c_j(n) + r \tag{4}$$

(2) Calculate the Pearson product-moment correlation coefficient r_j of $x(n)$ with each IMF, $c_j(n)$:

$$r_j = \frac{\sum_{i=1}^{n}(x(i)-\overline{x})(c_j(i)-\overline{c_j})}{\sqrt{\sum_{i=1}^{n}(x(i)-\overline{x})^2}\sqrt{\sum_{i=1}^{n}(c_j(i)-\overline{c_j})^2}} \quad (j = 1, 2, \ldots, k) \tag{5}$$

where $\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x(i)$ and $\overline{c_j} = \frac{1}{n}\sum_{i=1}^{n} c_j(i)$.

(3) Sort $r_1, r_2, \ldots, r_k$ in descending order, choose $IMFs$ whose correlation coefficients with $x(t)$ are greater than threshold λ, add all of them together as the reconstructed signal $y(n)$. Generally $\lambda = 0.4$, when $r_j > 0.4$, it means $c_j(n)$ is significant correlation with $x(n)$.

(4) Calculate MSE of the reconstructed signal $y(n)$, the entropy values of which are treated as feature vector.

2.4. Extreme Learning Machine

Extreme learning machine(ELM) is a new learning algorithm for single-hidden layer feed forward neural networks (SLFNs) which randomly chooses hidden nodes and analytically determines the output weights of SLFNs[10]. In theory, this algorithm tends to provide good generalization performance at extremely fast learning speed.

In ELM model, the input layer is connected to the input feature vector $\mathbf{x}$.The number of input nodes is denoted as N.

At the hidden layer, the number of hidden nodes is denoted as L.The output of a hidden node indexed by i is denoted as $g(\mathbf{x}; \mathbf{w_i}, b_i) = (\mathbf{x} \bullet \mathbf{w_i} + b_i)$, where g is the activation function, $\mathbf{w_i}$ is the input weight vector between the hidden node and all input nodes, b_i is the bias of the node and $i = 1, \ldots, L$.

At the output layer, the number of output nodes is denoted as M, each output node represents a traffic sign class. The output weight between the i th hidden node and j th output node is denoted as $\beta_{i,j}$, where $j = 1, \ldots, M$. The value of a output node indexed by i is denoted as:

$$f_j(\mathbf{x}) = \sum_{i=1}^{L} \beta_{i,j} \times g(\mathbf{x}; \boldsymbol{\omega}_\mathbf{i}, b_i) \tag{6}$$

Thus, the output vector for the input vector $\mathbf{x}$ can be written as:

$$f(\mathbf{x}) = [f_1(\mathbf{x}), ..., f_M(\mathbf{x})] = \mathbf{h}(\mathbf{x})\boldsymbol{\beta} \tag{7}$$

where

$$\boldsymbol{\beta} = \begin{bmatrix} \boldsymbol{\beta}_\mathbf{1} \\ \vdots \\ \boldsymbol{\beta}_\mathbf{L} \end{bmatrix} = \begin{bmatrix} \beta_{1,1} & \cdots & \beta_{1,M} \\ \vdots & \vdots & \vdots \\ \beta_{L,1} & \cdots & \beta_{L,M} \end{bmatrix} \tag{8}$$

Class label of input vector $\mathbf{x}$ is determined as $\max f_j(\mathbf{x})$, where $j = 1, ..., M$.

For a supervised training with N training sample pairs, each input feature vector corresponds to a ground truth class label vector $\mathbf{t}_k = \left[t_{k,1}, ..., t_{k,M}\right]$ where $k = 1, ..., N$. All labels form a matrix denoted as $\mathbf{T} = \left[\mathbf{t}_\mathbf{1}, ..., \mathbf{t}_\mathbf{N}\right]^T$.

Suppose vector $\mathbf{y}_\mathbf{k}$ represents actual output for the input feature vector $\mathbf{x}_\mathbf{k}$,taking all training samples into equation (12), can form a linear representation:

$$\mathbf{H}\boldsymbol{\beta} = \mathbf{Y} \tag{9}$$

where

$$\mathbf{H} = \begin{bmatrix} \mathbf{h}(\mathbf{x}_\mathbf{1}) \\ \vdots \\ \mathbf{h}(\mathbf{x}_\mathbf{N}) \end{bmatrix} = \begin{bmatrix} g(\mathbf{x}_1; \mathbf{w}_1, b_1) & \cdots & g(\mathbf{x}_1; \mathbf{w}_L, b_L) \\ \vdots & \vdots & \vdots \\ g(\mathbf{x}_N; \mathbf{w}_1, b_1) & \cdots & g(\mathbf{x}_N; \mathbf{w}_L, b_L) \end{bmatrix} \tag{10}$$

And

$$\mathbf{Y} = \begin{bmatrix} \mathbf{y}_\mathbf{1} \\ \vdots \\ \mathbf{y}_\mathbf{n} \end{bmatrix} = \begin{bmatrix} y_{1,1} & \cdots & y_{1,M} \\ \vdots & \vdots & \vdots \\ y_{N,1} & \cdots & y_{N,M} \end{bmatrix} \tag{11}$$

Aim of the training process is to minimize the training error which is defined as $\|\mathbf{T} - \mathbf{H}\boldsymbol{\beta}\|^2$ and obtain the norm of output weight $\boldsymbol{\beta}$.

Giving a set of training feature vectors $\left\{(\mathbf{x}_\mathbf{k}, \mathbf{y}_\mathbf{k})_{k=1,...,N}\right\}$, activation function g and number of hidden node L the training routine for the ELM-based classifier is described as follows[10]:

(1) Randomly generate hidden neuron parameter such as input weight vector $\boldsymbol{\omega}_\mathbf{i}$ and bias b_i, where $i = 1, ..., L$.

(2) Calculate the hidden layer output matrix $\mathbf{H}$ through formula(10);

(3) Calculate the minimum norm least squares solution $\boldsymbol{\beta}$ of $\mathbf{H}\boldsymbol{\beta} = \mathbf{Y}$, therefore, $\boldsymbol{\beta}$ is the estimation of the output weight $\boldsymbol{\beta}$.

Thought procedures described above, a classifier based on ELM with great performance is established.

3. Experiment Analyses

3.1. Experiment Introduction

To confirm the effectiveness of the algorithm, hoop experiments are carried out on fluid flow pipeline. The experimental setup is depicted in Figure 1. It consists of hydraulic station, a straight metal pipe, two hoops, one accelerometer, valves and fittings and so on. Parameters of the pipe in experiment are shown in table 1. Filled with hydraulic oil, the tested pipe is clamped on a fixed support platform and excited by fluid and various external vibrations. The two hoops are installed on the surface of the pipe. Installation positions of the hoops are near the joints on each end of the pipe, as shown in Figure 1.

The accelerometer is installed at the entrances of the fluid flow pipeline to monitor vibration states of the pipe, acquisition of the accelerometer data is conducted by LMS Test.Lab 14A, a high speed multi-channel data acquisition equipment produced by LMS company. The hydraulic station is equipped with various sensors such as pressure sensor, temperature sensor and flow sensor so as to monitor the system status in real time. Control and acquisition platform is depicted in Figure 2. The hydraulic control console is applied to control pressures and flow rate in pipeline, which can be collected through the data acquisition card and can be shown on laptop-A. The LMS equipment is used for acquisition of the accelerometer data, which can be shown on laptop-B in real time.

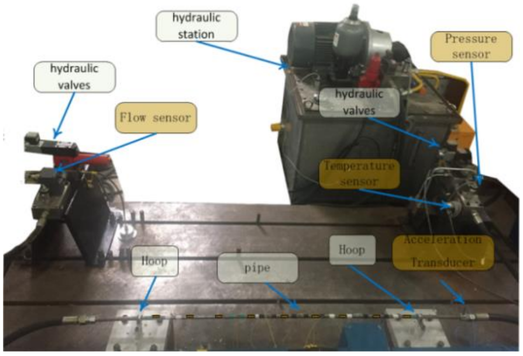

Figure 1. Experimental setup.

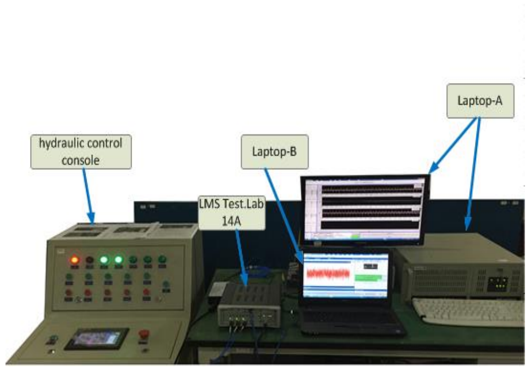

Figure 2. Control and data acquisition platform.

Table 1. Parameters of pipe in experiments.

Length (m)	Outside diameter(mm)	Wall thickness(mm)	Material
1.2	15	1	Steel

Experiments are conducted in fluid flow condition with pump and valve opening. In order to verify the robustness of the algorithm, three experiments are conducted on different days. In each experiment, experimental conditions keep similar. For example, sampling frequency of the accelerometer is 4096Hz, fluid flow rate is controlled at 98mL/s and keep basically stable, pressures in the pipeline varies from 3MPa to 15MPa with interval 3MPa. Both of fluid flow rate and pressure in pipeline can be set through the hydraulic control console and showed in laptop-A. There are two conditions of the hoop, one is normal assembly and the other is loose condition, for loose condition, it is divided into left side loose and right side loose.

Accelerometer data is collected under different pressures and hoop conditions. Sampling frequency is 4096Hz. Experiments are repeated three times, from which 210 samples are collected in total. Duration of each sample is 3 seconds. Number of samples of each hoop state is shown in Table 2.

Table 2. Number of samples of each hoop conditions.

Hoop Condition	Number of Samples
Normal Condition	70
Left Side Loose	70
Right Side Loose	70

3.2. Experimental Results

Three working conditions of hoops for hydraulic pipeline are analyzed through our method. Time domain waveforms and frequency spectrums of the original acceleration signals under normal and loose conditions of hoops are shown in Figure 3. Among which loose conditions consist of left side loose and right side loose respectively. Obviously, it is very difficult to distinguish three hoop conditions just through waveforms of time domain or frequency domain.

To reconstruct the original signals, EEMD is applied to decompose the acceleration signals and then correlation coefficients are used to select fault related. The Pearson product-moment correlation coefficients of each with its original signal under three hoop conditions are shown in Figure 4. In this paper, the threshold of correlation coefficient is 0.4, that is to say, whose correlation coefficients with the original signals exceed 0.4 are chosen to reconstruct the signal while the others are filtered since they show low correlation with system characteristics. The reconstructed signals are shown in Figure 5. Compared to original signals, high frequency components have been filtered and low frequency parts are more pure in reconstructed signals. All of which can be found in frequency spectrums.

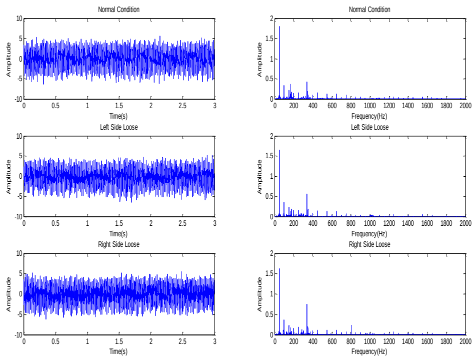

Figure 3. Acceleration signals of three hoop conditions.

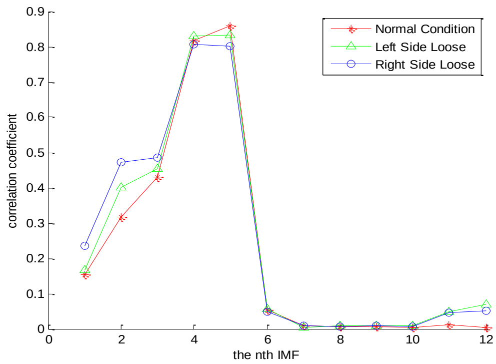

Figure 4. Correlation coefficients of each *IMF* with its original signal.

After reconstruct of the detected signals, the three different conditions of hoops for hydraulic pipeline, such as normal condition, left side loose and right side loose are described by MSE method quantitatively. Figure 6 gives the MSE over 20 scales of the reconstructed signals under different pressures and hoop conditions. It is apparent that different hoop conditions show different entropy values under each pressure. Therefore, hoop conditions can be distinguished by entropy values of MSE over 20 scales regardless of different pressures.

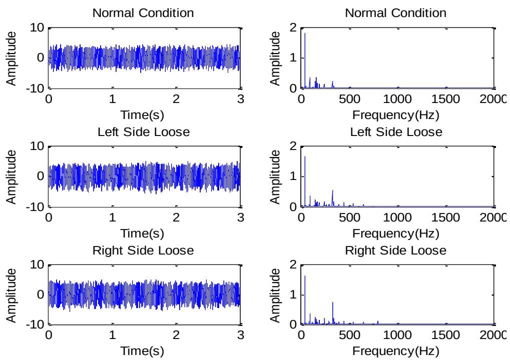

Figure 5. Reconstructed signals of three hoop conditions.

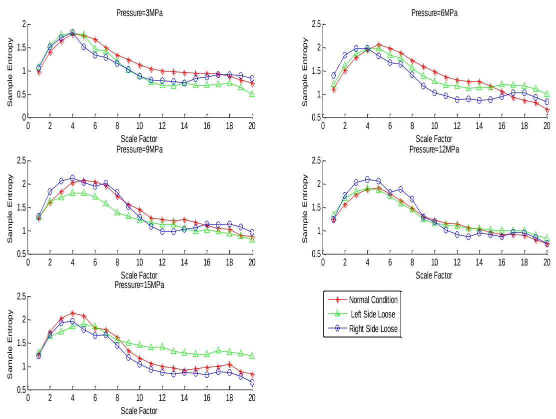

Figure 6. MSE over 20 scales of the reconstructed signals under different pressures and hoop conditions.

However, it may not enough just through the curves of MSE over different scales to identify the different three hoop conditions. In this paper, 20 entropy values of MSE are considered as a feature vector and ELM is used for intelligent condition monitoring. According to experiment introduction, each hoop conditions obtain 70 sets of feature vectors, as is shown in Table 2. In order to simplify the problem and improve the recognition accuracy, firstly detect whether the hoop is loose or not. On this

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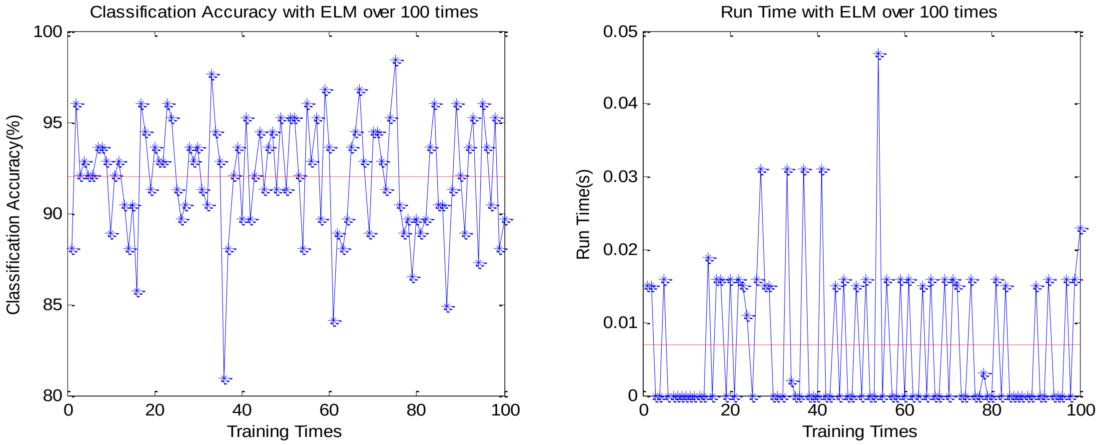
condition, left side loose and right side loose belong to the same class. And then on the premise of loose condition, to detect loosening position. namely left side loose or right side loose.

Firstly detect whether the hoop is loose or not, at this point there are only two output states: normal condition and loose condition. Feature vectors with a total of 210 sets, of which normal condition 70 sets and loose condition 140sets (As shown in Table 2). Randomly select 60% of feature vectors namely 126 sets as the training dataset, the remaining 40% namely 84 sets feature vectors as testing dataset. ELM algorithm is used as classifier. The process is repeated 100 times, each time the classification accuracy and run time are shown in Figure 7. Among which average accuracy is $92.02\% \pm 3.11\%$ and average run time is $0.0127s \pm 0.0047s$.

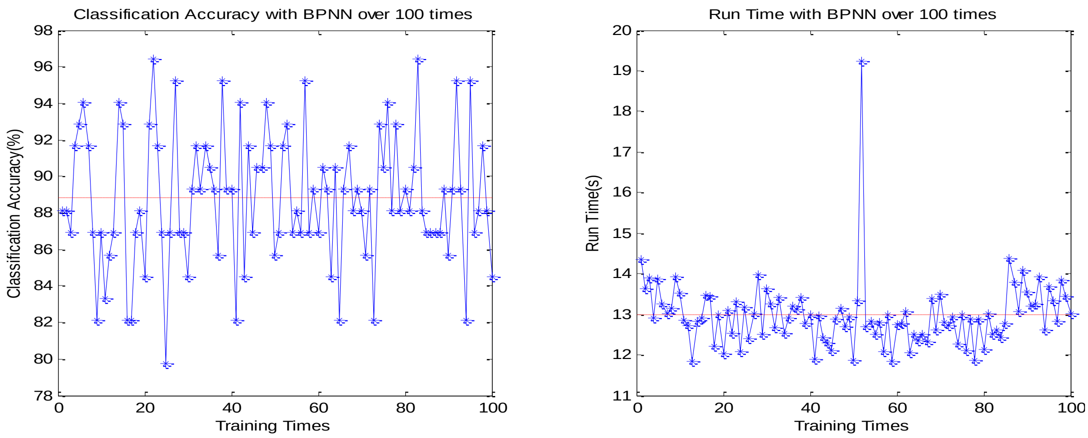
As contrast, results of classification method based on BPNN and SVM in detecting whether hoop is loose or not are shown in Figure 8 and Figure 9, respectively.

Three parameters are selected to evaluate performance of the algorithms, accuracy, efficiency and stability. Accuracy is reflected by average classification accuracy over 100 times training and testing, efficiency is measured by average run time over 100 times training and testing, and stability is measured by standard deviation of classification accuracy and run time. Performance contrast of three classifier method in detecting whether hoop is loose or not is shown in Table 3.



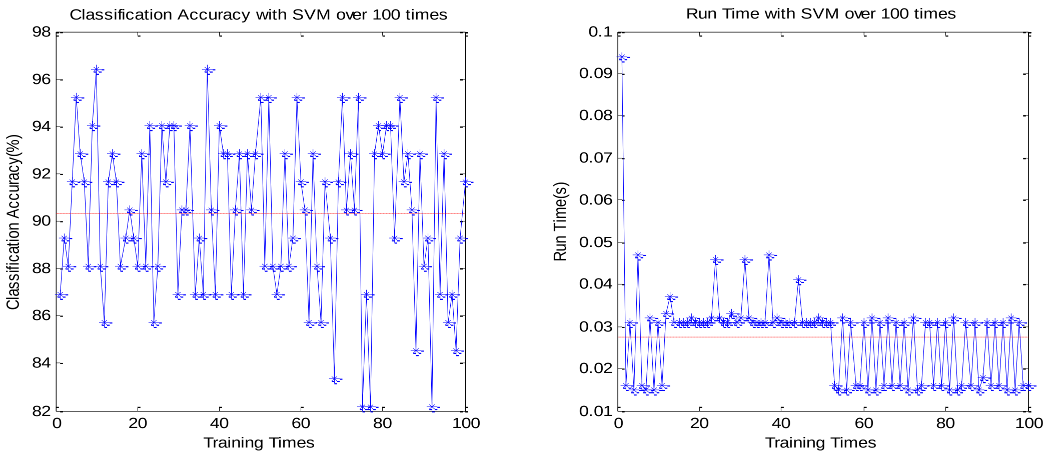
(a) classification accuracy. **(b)** run time.

Figure 7. Classification accuracy and run time in detecting whether the hoop is loose or not based on ELM.



(a) classification accuracy. **(b)** run time.

Figure 8. Classification accuracy and run time in detecting whether the hoop is loose or not based on BPNN.



(a) classification accuracy **(b)** run time

Figure 9. Classification accuracy and run time in detecting whether the hoop is loose or not BASED ON SVM.

Table 3. Performance contrast of three classifiers in detecting whether hoop is loose or not.

Classifier	Features	Average Accuracy(%) Mean ± Std	Average Run Time(s) Mean ± Std
ELM	EEMD-MSE	92.02±3.11	0.0127±0.0047
BPNN	EEMD-MSE	88.81±3.63	12.9931±0.8541
SVM	EEMD-MSE	90.34±3.41	0.0275±0.0109

Note: mean represents average value, and std represents standard deviation.

In Table 3, it is obviously that the maximum of average accuracy is 92.02% in ELM and the minimum of average run time is 0.0127s in ELM. Moreover, the minimum standard deviation of classification accuracy is 3.11% in ELM and the minimum standard deviation of run time is 0.0047s in ELM. It indicates that ELM classifier behaves better than BPNN and SVM both in accuracy, efficiency and stability in detecting whether the hoop is loose or not.

When it comes to detecting loosening position, in this case the output two states are left side loose and right side loose, feature vectors with a total of 140 sets, of which left side loose 70 sets and right side loose 70 sets(As shown in Table 2). Randomly select 60% of feature vectors namely 84 sets as the training dataset, the remaining 40% namely 56 sets as testing dataset. ELM algorithm is used as classifier. It is also repeated 100 times and among which average accuracy is $98.49\% \pm 1.26\%$ and average run time is $0.0051s \pm 0.0008s$.

As mentioned before, accuracy, efficiency and stability are selected to evaluate performance of three algorithms, accuracy is reflected by average classification accuracy, efficiency is measured by average run time and stability is measured by standard deviation of classification accuracy and run time. Performance contrast of three classifier method in detecting which side loose is shown in Table 4.

Table 4. Performance contrast of three classifier methods in detecting which side loose.

Classifier	Features	Average Accuracy(%) Mean ± Std	Average Run Time(s) Mean ± Std
ELM	EEMD-MSE	98.49+1.26	0.0051+0.0008
BPNN	EEMD-MSE	96.12+2.71	12.5961+0.6232
SVM	EEMD-MSE	95.98+3.64	0.0143+0.0084

Note: mean represents average value, and std represents standard deviation.

In Table 4, it is obviously that the maximum of average accuracy is 98.49% in ELM and the minimum of average run time is 0.0051s in ELM. Moreover, the minimum standard deviation of classification accuracy is 1.26% in ELM and the minimum standard deviation of run time is 0.0008s in ELM. It also indicates that ELM classifier behaves better than BPNN and SVM both in accuracy, efficiency and stability in detecting which side loose.

4. Conclusion

In this paper, a method based on EEMD-MSE and ELM is proposed for loose detection of hoops installed on hydraulic pipeline. EEMD is applied to reconstruct the original vibration signals and MSE is used for extracting feature vectors from the reconstructed signals. ELM algorithm is introduced as classifier. In order to simplify the problem and improve the detection accuracy, firstly detect whether the hoop is loose and then detect loosening position. The experimental results indicate that, feature extraction method based on EEMD and MSE is effective in loose detection of hoop, and classification method based on ELM behaves better than BPNN and SVM both in accuracy, efficiency and stability. Therefore, method based on EEMD-MSE and ELM for loose detection of hoops is available with high performance, especially in real-time condition monitoring.

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