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State detection of explosive welding structure by dual-tree complex wavelet transform based permutation entropy

Yue Si [1,2], ZhouSuo Zhang [*1], Wei Cheng [1,2] and FeiChen Yuan [1,2]

[1] *School of Mechanical Engineering, Xi'an Jiaotong University, Xi'an 710049, China*
[2] *State Key Laboratory for Manufacturing Systems Engineering, Xi'an Jiaotong University, Xi'an 710049, China*

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Abstract. Recent years, explosive welding structures have been widely used in many engineering fields. The bonding state detection of explosive welding structures is significant to prevent unscheduled failures and even catastrophic accidents. However, this task still faces challenges due to the complexity of the bonding interface. In this paper, a new method called dual-tree complex wavelet transform based permutation entropy (DTCWT-PE) is proposed to detect bonding state of such structures. Benefiting from the complex analytical wavelet function, the dual-tree complex wavelet transform (DTCWT) has better shift invariance and reduced spectral aliasing compared with the traditional wavelet transform. All those characters are good for characterizing the vibration response signals. Furthermore, as a statistical measure, permutation entropy (PE) quantifies the complexity of non-stationary signals through phase space reconstruction, and thus it can be used as a viable tool to detect the change of bonding state. In order to more accurate identification and detection of bonding state, PE values derived from DTCWT coefficients are proposed to extract the state information from the vibration response signal of explosive welding structure, and then the extracted PE values serve as input vectors of support vector machine (SVM) to identify the bonding state of the structure. The experiments on bonding state detection of explosive welding pipes are presented to illustrate the feasibility and effectiveness of the proposed method.

Keywords: explosive welding structure; bonding state detection; dual-tree complex wavelet transform; permutation entropy; vibration response signals analysis

1. Introduction

Explosive welding is a solid state welding method in which two or more plates are welded together under high temperature and high pressure coming from explosive detonation (Findik 2011, Zareie Rajani and Akbari Mousavi 2012). Explosive welding structures possess some superior properties such as high temperature resistance, high pressure resistance, corrosion resistance, etc. With those superior properties, such structures have been widely applied in a variety of fields including oil and gas, aviation and aerospace, chemical industry and military industry. Like all welding methods, interfacial bonding state dominates the ultimate mechanical and metallurgical characteristic of such structures (Gulenc 2008).The poor interfacial bonding state may cause defects such as wrinkling, bulge, separation and peeling in service, which may leads to the

∗Corresponding author, Professor, E-mail: zzs@mail.xjtu.edu.cn

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degradation of the service performance, failure and even catastrophic accidents. Thus, it is urgent to develop an effective method for the bonding state detection of explosive welding structures.

At present the destructive detecting methods such as the tensile-shear test, charpy impact test and bending test (Akbari Mousavi *et al*. 2008, Kaya and Kahraman 2013) have been used to detect the bonding strength of explosive welding structure. However, those methods have the disadvantages that they are destructive inspection with high cost and low efficiency; they can be only used to detect the local area of the structure, and cannot be used for global and online detection. The existing nondestructive testing methods such as ultrasonic (Chen *et al*. 2012), acoustic emission (Scholey *et al*. 2010), x-ray (Hanke *et al*. 2008) etc. are mainly used to detect the defects of the structures such as lamination, crack, pore, etc. But for detecting the defect of bonding interface of explosive welding structure which is close-grained but without enough bonding strength, those methods don't work well. There are very few nondestructive detecting methods reported in the literatures to detect the bonding state of such structures. Therefore, it is important to develop an effective nondestructive method to detect the bonding state of explosive welding structures.

Structural vibration response signals carry a great deal of information on the state or damage of the structures. The vibration response analysis is a potential way for structure health monitoring and has been often used in structure damage identification (Liu *et al*. 2010, Wang *et al*. 2010a, Hester and González 2012) and machine fault diagnosis (Jayaswal *et al*. 2010, Feng and Zuo 2013). Structure state detection based on vibration response signals analysis method is mainly to extract sensitive feature information from response signals of structure under certain excitation, and then identify and assess the structural state according to the change of the extracted feature information. However, because the explosive welding structure is made of two different materials, the vibration response signal of the structure is complex and non-stationary. Furthermore, the change of vibration response signal induced by the change of local bonding state is very weak. Thus, detection and extraction of the bonding state information from vibration response signals is the key point to bonding state detection of explosive welding structures.

With the advantage of multi-resolution analysis, wavelet transform is an effective tool for non-stationary signal processing, and is very useful in structural damage detection (Yan *et al*. 2010, Ren and Sun 2008). However, traditional wavelet transform such as discrete wavelet transform (DWT) and second-generation wavelet transform (SGWT) frequently suffers from the disadvantages that spectral aliasing and shift-variant, which may cause the redundancy and loss of the feature information. Dual-tree complex wavelet transform (DTCWT), has many attractive properties such as reduced spectral aliasing, nearly shift-invariance, perfect reconstruction and limited data redundancy. All those properties can help overcome the problems of traditional wavelet transform. DTCWT was first proposed by Kingsbury (1998) and further investigated by I. Selesnick *et al*. (2005). It has been applied in many fields. Wang *et al*. (2010b) adopted the DTCWT to detect the multiple faults of industrial equipment and successfully extract the multiple features of air compressor. Chen *et al*. (2009) proposed an invariant pattern recognition descriptor based on DTCWT and the Fourier transform, which achieved high recognition rates for different combinations of rotation angles and noise levels. Hu (2011) presented a method based on multiscale DTCWT for face recognition and successfully recognized the face images under large illumination variations. Chen (2014) detected EEG seizure by using dual-tree complex wavelet-Fourier features. DTCWT shows great advantage in characterizing the vibration response signal. It can decompose a complex signal into several simple signals with lower spectral aliasing and information losing. In this paper, DTCWT is used to process vibration response signals of explosive welding structures.

One more important problem is how to describe and evaluate the bonding state of explosive welding structure based on the DTCWT coefficients. Permutation entropy (PE), as a complexity measure for time series analysis, was initially proposed by Bandt and Pompe (2002). According to the permutation entropy theory, the most uncertain distribution possesses the largest permutation entropy value, and the more regular the time series is, the smaller the permutation entropy value. Many scholars have successfully used the PE in engineering applications. Yan (2012) used PE to detect the working status of rolling bearings. Tiwari (2013) adopted multi-scale permutation entropy and adaptive neuro fuzzy classifier to diagnose incipient bearing faults. Nicolaou and Georgiou (2012) detected epileptic seizure by using permutation entropy and support vector machines. The PE was also applied for online chatter detection in turning process (Nair *et al*. 2010), and tool flute breakage detection in end milling (Li *et al*. 2008). Explosive welding structure can be taken as a dynamics system with stiffness, mass and damping. Once the bonding state of the structure is changed, the structural model parameters and the dynamic response signal will change. PE is a viable tool to describe the change of the response signals measured on the structures. In this paper, the PE derived from DTCWT is used to extract the state feature from the vibration response signal of explosive welding structures.

After feature extraction, a classifier is required to achieve automated state detection. Support vector machine (SVM) is an effective classification method due to its high accuracy and good generalization capabilities. SVM is good at solving the machine learning problem of small sample and high dimensional, and has been successfully applied to fault diagnosis (Sugumaran *et al*. 2008, He *et al*. 2010), pattern recognition (Tang *et al*. 2010, Lihong *et al*. 2009), etc.

The aim of this study is to develop an online and nondestructive detecting method for bonding state detection of explosive welding structures. Previous studies (Acarer *et al*. 2004, Kahraman *et al*. 2005, 2007, Durgutlu *et al*. 2005, Mousawi and Sartangi 2009, Wronka 2010) are mainly use destructive detecting methods to test the quality of the the interface of explosive welding structures. These methods have the disadvantages of high cost, big error, low speed and low credibility, and cannot be used to detect the structures in service. Moreover, there is no non-destructive detection method reported in the literatures for the purpose. For these reasons, a nondestructive detecting method called dual-tree complex wavelet transform based permutation entropy (DTCWT-PE) and SVM is proposed in this paper.

This method consists of three steps. Initially, DTCWT is used to decompose the vibration response signal into several sub-band signals. Then, the PE values of the sub-band signals are extracted to describe the bonding state of the structures. Finally, support vector machine (SVM) is served as a classifier to identify the bonding state of the structures automatically. The proposed method is applied to the bonding state detection of explosive welding pipes. Comparison with conventional DB wavelet transform (DB4) method, second generation wavelet transform (SGWT) method, dual-tree complex wavelet transform based approximate entropy (DTCWT-AE) and dual-tree complex wavelet transform based morphological fractal dimension (DTCWT-MFD), the proposed method displays a better performance in terms of accuracy and robustness.

2. Methods and principles

2.1 Dual-tree complex wavelet transform

DTCWT possesses two parallel DWTs with two different sets of filters, as shown in Fig. 1, and each set satisfies the perfect reconstruction condition. Let $\psi_h(t)$ and $\psi_g(t)$ respectively denote the real-valued wavelet in the two trees. Then a complex-valued wavelet $\psi^C(t)$ in DTCWT can be obtained as

$$\psi^C(t) = \psi_h(t) + j\psi_g(t) \tag{1}$$

Note that $\psi^C(t)$ is only supported on the positive of the frequency axis with the characteristic of approximate analytic expression. Furthermore, the DTCWT can reduce frequency aliasing and increase shift invariance.

According to the wavelet theory, the wavelet coefficients $d_l^{\Re e}(k)$ and scaling coefficients $c_J^{\Re e}(k)$ of the real part transform are obtained via inner products as (Wang *et al*. 2010b).

$$d_l^{\Re e}(k) = 2^{l/2}\int_{-\infty}^{+\infty} x(t)\psi_h(2^l t - k)dt \quad l = 1,\cdots,J \tag{2}$$

$$c_J^{\Re e}(k) = 2^{J/2}\int_{-\infty}^{+\infty} x(t)\varphi_h(2^J t - k)dt \tag{3}$$

In which, l is the scale factor and J is decomposition level. Similarly, the coefficients of the imaginary part transform can be computed as

$$d_l^{\Im m}(k) = 2^{l/2}\int_{-\infty}^{+\infty} x(t)\psi_g(2^l t - k)dt \quad l = 1,\cdots,J \tag{4}$$

$$c_J^{\Im m}(k) = 2^{J/2}\int_{-\infty}^{+\infty} x(t)\varphi_g(2^J t - k)dt \tag{5}$$

Where the wavelet filter bank ψ_h and ψ_g must form an appropriate Hilbert transform pair $\psi_g = H\{\psi_h\}$. There are various approaches to design the filters for DT-CWT (Selesnick *et al*. 2005). In this paper, we use the (13,19)-tap near-orthogonal filters at level 1 and 14-tap Q-shift filters at level beyond 1 (Kingsbury 2001). Thus, the wavelet and scaling coefficients of DTCWT can be obtained as follows (Wang *et al*. 2010b)

$$d_l^C(k) = d_l^{\Re e}(k) + jd_l^{\Im m}(k) \quad l = 1,\cdots,J \tag{6}$$

$$c_J^C(k) = c_l^{\Re e}(k) + jc_J^{\Im m}(k) \tag{7}$$

Then, the scaling or wavelet coefficients can be reconstructed as follows (Wang *et al*. 2010b)

$$d_l(t) = 2^{(l-1)/2}[\sum_n d_l^{\Re e}(k)\psi_h(2^l t - n) + \sum_m d_l^{\Im m}(k)\psi_g(2^l t - m)] \quad l = 1,\cdots,J \tag{8}$$

$$c_J(t) = 2^{(J-1)/2}[\sum_n c_J^{\Re e}(k)\varphi_h(2^J t - n) + \sum_m c_J^{\Im m}(k)\varphi_g(2^J t - m)] \tag{9}$$

The vibration signal $x(t)$ decomposed by DTCWT can be expressed as

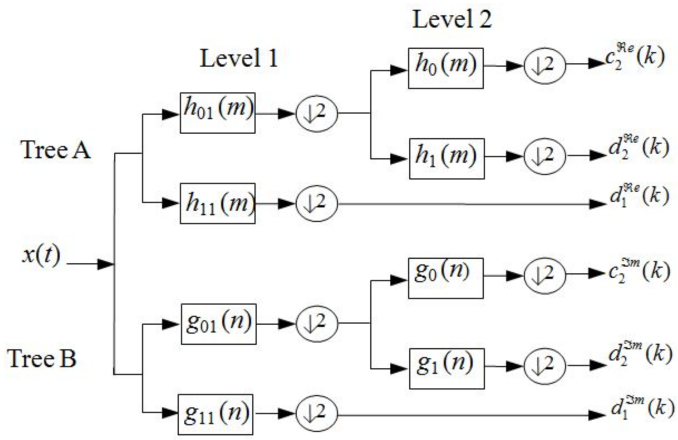


Fig. 1 The flow chart of two-stage DTCWT decomposition

$$x(t) = c_J(t) + \sum_{l=1}^{J} d_l(t) \tag{10}$$

Note that $d_l(t)$ $l = 1, 2, \ldots, J$ and $c_J(t)$ are the sub-band signals, arranging from high frequency to low frequency. For the dynamic response signal of explosive welding structure, a set of simple oscillation modes with lower spectral aliasing and information losing can been obtained after DTCWT.

2.2 Permutation entropy

PE is a complexity measure for time series based on comparison of neighboring values in reconstructed phase space (Cao *et al*. 2004). According to the embedding theorem, the phase space of a time series $x(i) = \{i = 1, 2, \ldots, N\}$ can be reconstructed as

$$X = \begin{pmatrix} X(1) \\ X(2) \\ \vdots \\ X(i) \\ \vdots \\ X(N-(m-1)\tau) \end{pmatrix} = \begin{pmatrix} x(1) & x(1+\tau) & \ldots & x(1+(m-1)\tau) \\ x(2) & x(2+\tau) & \ldots & x(2+(m-1)\tau) \\ \vdots & \vdots & \vdots & \vdots \\ x(i) & x(i+\tau) & \ldots & x(i+(m-1)\tau) \\ \vdots & \vdots & \vdots & \vdots \\ x(N-(m-1)\tau) & x(2+(m-2)\tau) & \ldots & x(N) \end{pmatrix} \tag{11}$$

Where m is the embedding dimension and τ is the time lag. For a given embedding dimension m, there will be $m!$ permutations. The m real values contained in each $X(i)$ can be arranged in an increasing order as $x(i + (j_1 - 1)\,\tau) \le x(i + (j_2 - 1)\,\tau)) \le x(i + (j_m - 1)\,\tau)$. Whenever an equality occurs, e.g., $x(i + (j_1 - 1)\,\tau) = x(i + (j_2 - 1)\,\tau))$ their original positions are sorted such that for $j_1 < j_2$, we write $x(i + (j_1 - 1)\,\tau) < x(i + (j_2 - 1)\,\tau))$, Hence, each vector $X(i)$ is uniquely mapped onto $\pi_j = [j_1, j_2, \ldots, j_m]$, $(1 \le j \le m!)$, where π_j is one of $m!$ permutations. For permutation π_i, we determine the relative frequency by

$$p(\pi_j) = \frac{Number\{t_j \mid t_j \le N-(m-1)\tau, X(i) \ has \ type \ \pi_j\}}{N-(m-1)\tau} \tag{12}$$

Thus, based on the concept of Shannon entropy, the PE of order m for the time series $x(i) = \{i = 1, 2,..., N\}$ can be defined as

$$H_{PE}(m) = -\sum_{j=1}^{m!} p(\pi_j) \ln p(\pi_j) \tag{13}$$

PE can describe the time series quantitatively. When all permutations of the time series have the same probability, i.e., $p(\pi) = 1/m!$, the PE H_{PE} has the maximum value. The smaller the value of H_{PE}, the more regular the time series is. The change of H_{PE} can reflect the subtle change of the time series.

2.2.1 Simulation analysis

In this research, the vibration response signal of explosive welding structure is a kind of unilateral oscillation damping signal. In order to study the validity of PE for detecting the change of this kind of signal, a simulated impact response signal is designated as

$$\mathrm{y}(t) = \exp(-\zeta 2\pi ft)\sin(2\pi ft\sqrt{1-\zeta^2}) + 0.01n(\mathrm{t}) \tag{14}$$

In which f represents the natural frequency, ζ represents the damping ratio and $n(t)$ is the noise signal. Fig. 2 shows the simulation signal at $f = 200$ Hz, $\zeta = 0.005$.The sampling frequency is 1000 Hz and the data points are 1000.

Figs. 3 and 4 respectively show the change of H_{PE} with the change of the signal under different natural frequency and damping ratio, where embedded dimension $m = 6$ and delay time $\tau = 1$. It can be seen from the two figures that the values of H_{PE} increase with the increase of the natural frequency and damping ratio of the signal, and the PE H_{PE} is much more sensitive to the change of damping ratio than natural frequency of the signal. Meanwhile, the damping ratio is just one of the sensitive parameters for the change of the bonding state of explosive welding structure. Thus, PE is a powerful statistical index to detect the change of the bonding state of explosive welding structure.

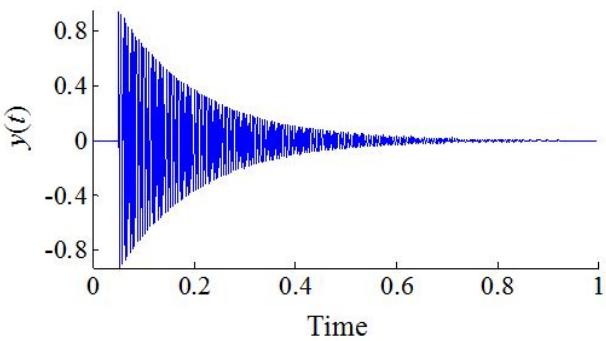


Fig. 2 The simulation signal

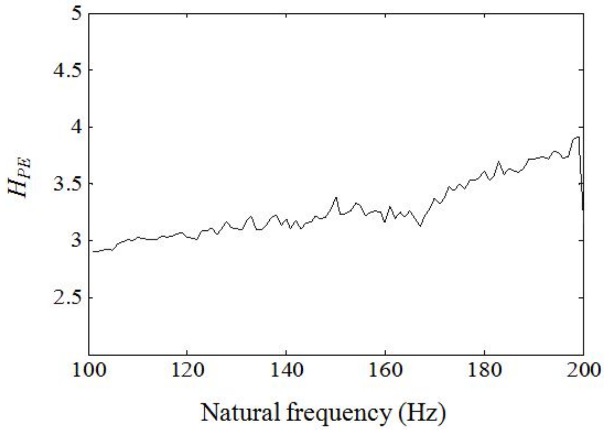


Fig. 3 Effect of natural frequency on PE value

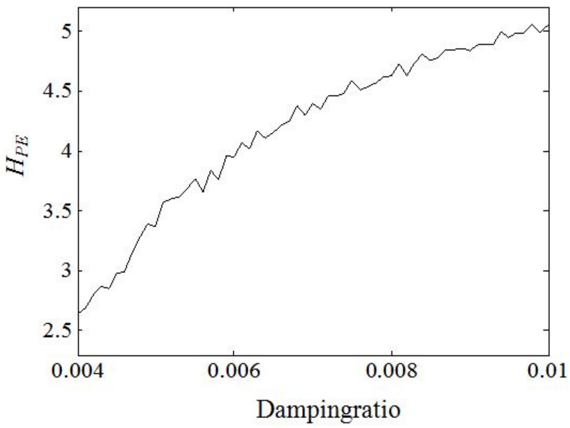


Fig. 4 Effect of damping ratio on PE value

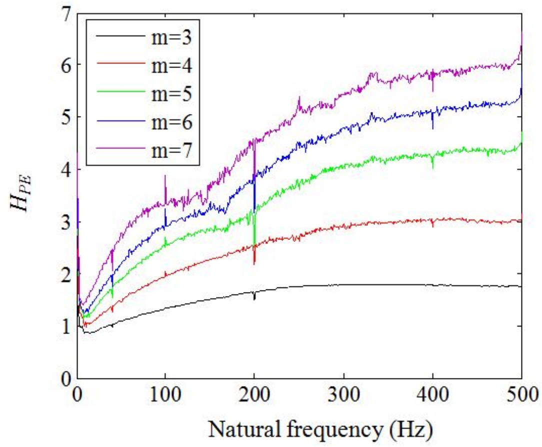


Fig. 5 Effect of embedded dimension *m* on PE entropy value

2.2.2 Selection of parameters

The parameters embedded dimension m and time delay τ also affect the calculation of PE. Selecting suitable m and τ are important for PE to detect the change of the vibration response signals. In the literature (2002), Bandt and Pompe recommended to select $m = 3 - 7$. In this research, the simulation signal in Section 2.2.1 is used to investigate the effect of m and τ on the PE H_{PE}.

The relationship between the PE H_{PE} of the signal and embedded dimension m is illustrated in Fig. 5, where the H_{PE} is calculated by selecting $m = 3-7$, under time delay $\tau = 1$. From Fig. 5, it can be seen that the larger the embedded dimension is, the more sensitive the PE to the change of the signal. However, the larger embedded dimension is, the more expensive the computation of PE. Thus, we select $m = 6$ in this research. The relationship between the PE H_{PE} of the signal and time delay τ is illustrated in Fig. 6, where the H_{PE} is calculated by selecting $\tau = 1-4$, under embedded dimension $m = 6$. It can be found in Fig. 6 that the change of H_{PE} with respect to different time delay τ is much small. Therefore, we select $\tau = 1$ and $m = 6$ to calculate the H_{PE} of the vibration response signals in this paper.

3. The proposed detection method based on DTCWT-PE

Explosive welding structure can be taken as a dynamics system with stiffness, mass and damping. Once the bonding state of the structure is changed, the structural model parameters are change. The dynamic response signal, which contains a wealth of information about modal parameters such as natural frequency, damping ratio etc., are also change. Thus, extraction of state feature information from vibration response signal is a reliable way for bonding state detection of explosive welding structure. The key issue in bonding state detection is how to extract state feature information from vibration response signal and identify the bonding state. In this paper, a DTCWT-PE and SVM method is proposed for this task. The flow chart of the proposed detection method is shown in Fig. 7. The main steps of the method are given as follows.

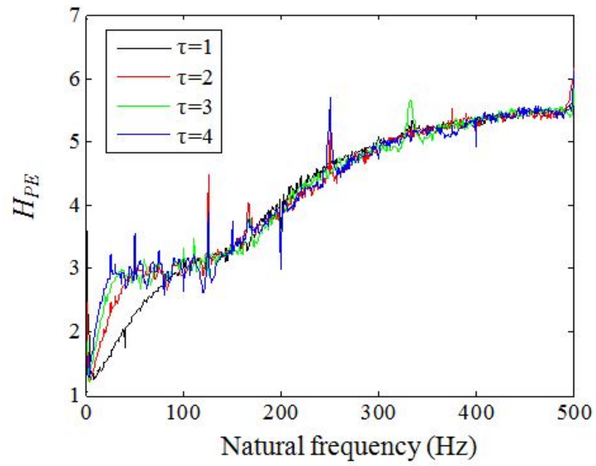


Fig. 6 Effect of time delay τ on PE entropy value

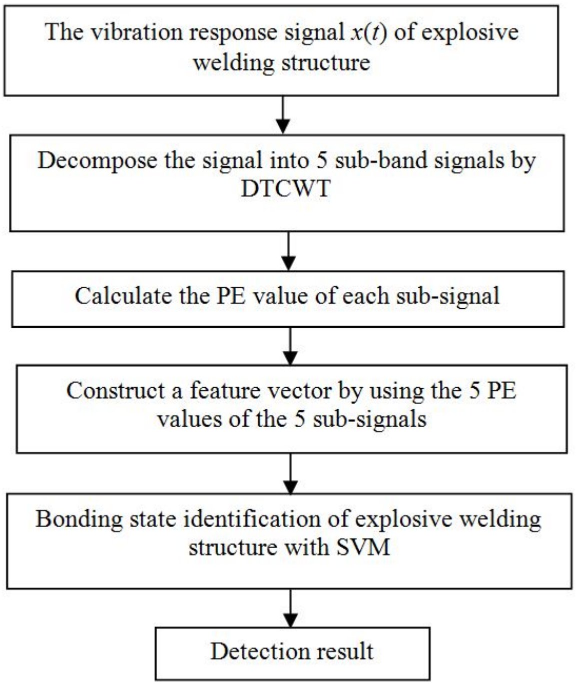


Fig. 7 The flow chart of the proposed method

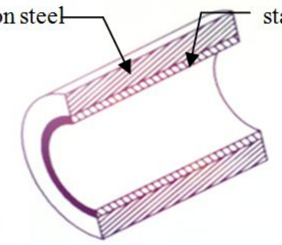
(1) Response signals are collected as samples from the explosive welding structures with different bonding state.
(2) The original response signals are decomposed by DTCWT for 4 levels, and then we get the corresponding DTCWT coefficients $d_1(t)$, $d_2(t)$, $d_3(t)$, $d_4(t)$ and $c_1(t)$.
(3) PE H_{PE} of the DTCWT coefficients are calculated to form a feature vector $[H_{PE}^{d_1} \quad H_{PE}^{d_2} \quad H_{PE}^{d_3} \quad H_{PE}^{d_4} \quad H_{PE}^{c_4}]$.
(4) The feature vectors are input into SVM to classify the bonding state of explosive welding structures, in which the Gaussian RBF is used as the kernel function of SVM.

4. Experimental validations

Explosive welding pipes of stainless steel and carbon steel have been widely used in oil and gas, chemical power and other long-distance pipeline fields. It is important to detect the bonding state of the pipes for avoiding failures. The structure of the pipe is shown in Fig. 8. In this section, three types of explosive welding pipes for bonding state detection are presented to validate the effectiveness of the proposed method.

In order to verify the superiority of the proposed method, the DB wavelet transform (DB4) and second generation wavelet transform (SGWT) are adopted to process the same vibration signals. Similarly, the signals are decomposed by DB4 wavelet and SGWT for 4 levels respectively, and the PE value of each sub-signal is calculated to form a feature vector. The feature vectors DB-PE and SGWT-PE are used as input vectors to SVM to identify the bonding state of the pipes.

(a) The pipe welded by explosive welding



(b) Local structure of the pipe

Fig. 8 Explosive welding pipe

Table 1 Major dimensions and parameters of explosive welding pipes

Types	Number	Size of the pipes				Explosive loads (g)
		Length (mm)	Pipe O.D. (mm)	Thickness of stainless steel (mm)	Thickness of carbon steel (mm)	
Short pipes	1	1000	90	2	5	5
	2	1000	90	2	5	10
	3	1000	90	2	5	15
Medium-length pipes	I	2000	114	3	8	8
	II	2000	114	3	8	13
	III	2000	114	3	8	15
Long pipes	a	9600	114	3	8	8
	b	9600	114	3	8	13
	c	9600	114	3	8	15

Meanwhile, the proposed method is also compared with DTCWT-AE and DTCWT-MFD methods to further validate its advantage.

It is well known that explosive load is one of the most important parameters affecting the quality (state) of the bonds in explosive welding. With the increase of explosive load, the bonding quality is improved (Gulenc 2008, Zareie Rajani and Akbari Mousavi 2012). In order to obtain the explosive welding pipes with different bonding state, the explosive loads is changed for different pipes in the welding when other welding parameters remain constant. The major dimensions and parameters of the three types of pipes are given in Table 1, in which explosive loads represent the weight of explosive in unit length.

4.1 Experimental setup and data acquisition

The experimental setup of explosive welding pipes is shown in Fig. 9, which consists of various explosive welding pipes, hammer, accelerometer and data acquisition instrument. The pipes are freely supported on both ends. The accelerometer is mounted on the middle of the pipes. The pipes are excited by the hammer at the point away from the middle of the pipe 300 mm. The vibration response signal is measured by accelerometer, and the signal is sampled by the data acquisition instrument. Three sets of data are obtained from the short pipes, the medium-length pipes and the long pipes, respectively. The detailed information of the data sets is given in Table 2. The date samples of the nine subsets are shown in Fig. 10.

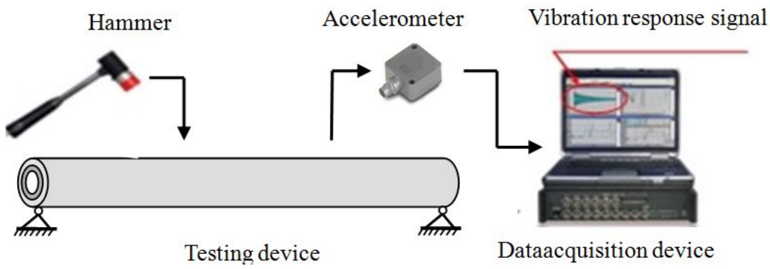


Fig. 9 Experimental setup of explosive welding pipe detection

Table 2 The detailed information of the data sets

Data sets	Subset numbers	Sample numbers of each subset	Training samples of each subset	Testing samples of each subset	Data points of each sample	Sampling frequency
Short pipes	3	30	15	15	5000	10240
Medium-length pipes	3	12	6	6	5000	10000
Long pipes	3	12	6	6	5000	1000

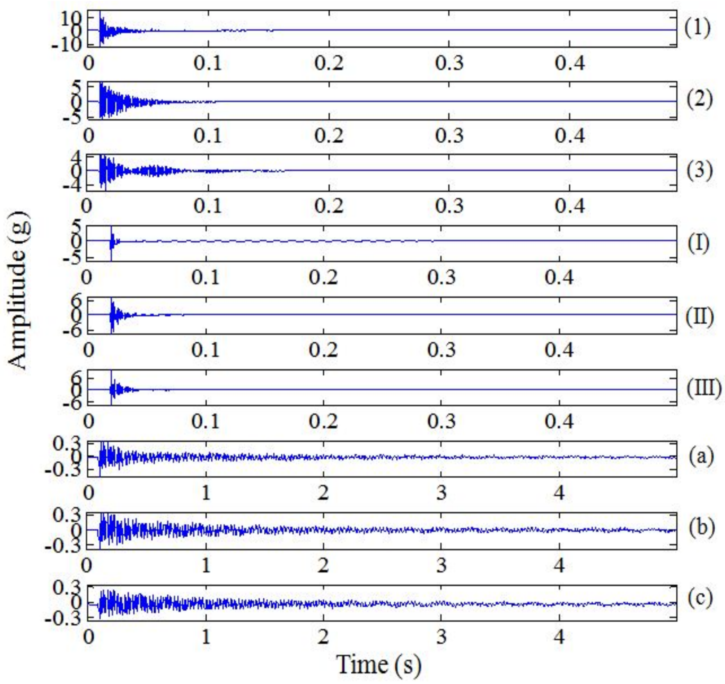


Fig. 10 Data samples of the three type pipes

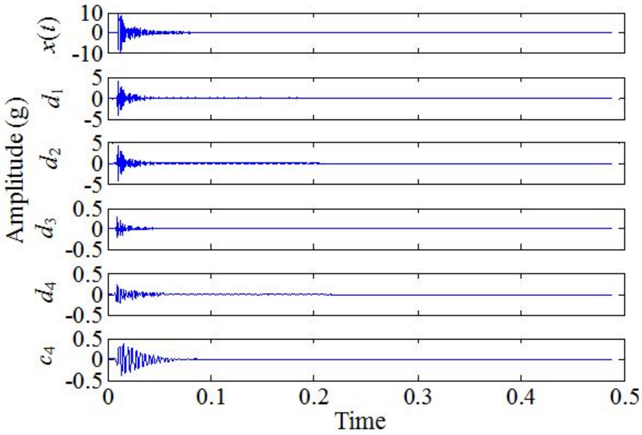


Fig. 11 Decomposition result of the pipe 1 sample $x(t)$

Table 3 Testing accuracies of DTCWT-PE, SGWT-PE, DB4-PE, DTCWT-AE and DTCWT-MFD in the three types of pipes

Type	SVM with DTCWT-PE	SVM with SGWT-PE	SVM with DB4-PE	SVM with DTCWT-AE	SVM with DTCWT-MFD
1	100	97.78	93.33	91.11	93.33
2	100	88.89	83.33	94.44	88.89
3	94.44	83.33	66.67	88.89	88.89

4.2 Detection results

4.2.1 The short pipes detection result

The three data subsets of short pipes acquired respectively from pipes 1, 2, 3 are applied to validate the effectiveness of the proposed method in detecting the bonding state of explosive welding structures. The signal is decomposed by DTCWT for 4 levels. Fig. 11 shows the decomposition result of the pipe 1 sample $x(t)$. It can be seen from the Fig.11 that the vibration response signal is decomposed into several simple oscillation signals. Then, the PE H_{PE} of each simple oscillation signal is calculated to form a feature vector. Finally, SVM is trained by the training samples, and then the trained SVM is used to identify the testing samples. The number of training samples and testing samples are given in Table 3. The testing results of short pipes are shown in Table 3 and Fig. 12, in which all testing samples of the short pipes are classified correctly. The testing results based on SGWT-PE, DB4-PE, DTCWT-AE and DTCWT-MFD methods are also given in Table 3 and Fig. 12. It can be seen that the DTCWT-PE method shows 100% accuracy while SGWT-PE, DB4-PE, DTCWT-AE and DTCWT-MFD methods show classification accuracies of 97.78%, 93.33%, 91.11% and 93.33% respectively. The proposed method based on DTCWT-PE and SVM gets the best identification result.

4.2.2 The medium-length pipes and long pipes detection results

In order to validate the reliability and robustnessof the proposed method, the bonding state of the medium-length pipes and long pipes are also detected by the proposed method. Table 3 and

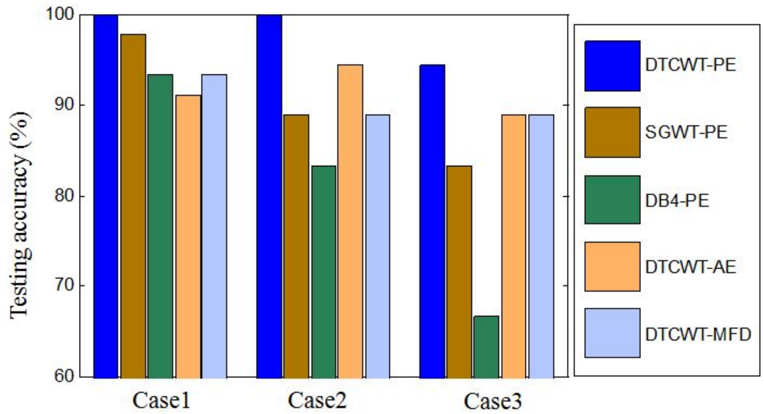


Fig. 12 Testing accuracies of the five methods in the three types of pipes

Fig. 12 present the testing results of the five methods on identifying the different bonding state of medium-length pipes and the long pipes. For the medium-length pipes, the testing accuracies of the five methods are respectively 100%, 88.89%, 83.33%, 94.44% and 88.89%. The proposed DTCWT-PE method can more accurately identify the different bonding state of medium-length pipes than SGWT-PE, DB4-PE, DTCWT-AE and DTCWT-MFD methods. For the long pipes, the testing accuracy of the proposed method is 94.44%, which is higher than the testing accuracies of 83.33%, 66.67%, 88.89% and 88.89% corresponding to the other four methods.

All the results of the three experiments imply that the proposed method based on DCTWT-PE and SVM has higher identification accuracy and better robustness in detecting the bonding state of explosive welding structures, and obviously outperforms DB4-PE, SGWT-PE, DTCWT-AE and DTCWT-MFD methods in this task.

5. Conclusions

order to realize the bonding state online detection of explosive welding structures, a new method based on DTCWT-PE and SVM is proposed in this paper. Benefiting from the complex analytical wavelet function, the dual-tree complex wavelet transform (DTCWT) enjoys better shift invariance and reduced spectral aliasing, which is good for characterizing the vibration response signal. In the proposed method, we use the DTCWT to decompose the vibration response signal of explosive welding structures. PE is a powerful index to detect the change of the signal. The PE values of DTCWT coefficients are calculated to describe the state of explosive welding structure. The SVM is used to classify the structures with different bonding state.

In the experiments, three types of explosive welding pipes such as short pipes, medium-length pipes and long pipes are detected by using the proposed method. The testing accuracies of the proposed method to short pipes, medium-length pipes and long pipes are 100%, 100% and 94.44%, respectively, which demonstrate that the proposed method can detect the bonding state of the pipes efficiently. Compared with SGWT-PE, DB4-PE, DTCWT-AE and DTCWT-MFD methods, the testing results indicate that the proposed method improve the identification accuracy by 11.11%, 27.77%, 5.55% and 5.55% for long pipes. Thus, the proposed method is a much more effective way to detect the bonding state of explosive welding structures online and globally.

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