Vibration source classification and propagation distance estimation system based on spectrogram and KELM

Zhiyong Chen1, Jiwen Cao1,2✉, Dongyun Lin3, Jianzhong Wang1,2, Xuegang Huang4
1Institute of Information and Control, Hangzhou Dianzi University, Zhejiang, 310018, People’s Republic of China
2Artificial Intelligence Institute, Hangzhou Dianzi University, Zhejiang, 310018, People’s Republic of China
3School of Electrical and Electronic Engineering, Nanyang Technological University, 639798, Singapore
4Hypervelocity Aerodynamics Institute, China Aerodynamics Research and Development Center, Mianyang 621000, People’s Republic of China
✉E-mail: jwcao@hdu.edu.cn

Abstract: Earth surface vibration signals source classification and propagation distance estimation attract increasing attention in recent years due to the wide applications in many areas. In this study, the authors develop a hybrid classification and propagation distance estimation algorithm for general earth surface vibration sources. The spectrogram (SPEC) feature characterising the energy distribution of vibrations is first developed for signal representation in this study. The kernel-based extreme learning machine (KELM) algorithm is then adopted for the vibration source classification and propagation distance estimation. Comparing with the conventional approaches, the proposed KELM + SPEC algorithm is not only effective in characterising the time and frequency-domain features of vibrations, but also superior in accuracy and efficiency. To test the effectiveness of the proposed KELM + SPEC algorithm, experiments on real collected vibration signals are presented, where simulations on both periodic and aperiodic vibrations are carried out in the study. Comparisons to various existing vibration signal extraction and classification algorithms are provided to show the advantages of the proposed KELM + SPEC algorithm.

1 Introduction

Significant research efforts have been devoted to the surface vibration signals processing due to their wide applications [1–6]. To name a few, Sun et al. [1] investigated an instrumentation system for on-line non-intrusive detection of wood pellets in pneumatic conveying pipelines based on vibration and sound analysis. Qu et al. [2] developed a new vibration detection method for the measurement of optical fibre vibration based on the background homogeneity adaptive constant false alarm rate (BHA- CFAR) method. Arun et al. [3] researched the wave propagation of flexural modes of vibration generated by an impact on a solid surface, and propose a new approach for vibration source localisation based on flexural modes. George et al. [4] pointed out the significance of vibration signal processing in footstep detection and developed a statistical feature-based footstep detection algorithm in a noisy environment. Gabriel and Andhelescu [5] investigated a human activity detection system, which can detect the activities of vibrations generated by walking, digging, and vehicle. Ranta et al. [6] proposed a complete instrumentation and detection algorithm based on a biological signature to detect the presence of a person on the bench of a vehicle. He [7] proposed a novel vibration-based fault diagnosis algorithm for a machine condition monitoring system using the wavelet packet transform (WPT) features. In addition to these studies, fruitful achievements on vibration processing can be found in [8–12].

Recently, surface vibration detection has been found effective in urban underground pipeline network protection [13–21], which suffered high damage rate in many developing countries due to the fast urbanising [19–21]. The frequency band energy distribution feature (FBED) has been presented in [19], which characterises the relationship between the propagation distance and the energy distributions of periodic vibration signals. Furthermore, combining with machine learning algorithms, the FBED feature is adopted in [20, 21] for propagation distance estimation. However, the FBED feature has the drawback of high-computation complexity and cannot reflect the energy distribution completely. Besides, the FBED feature is restricted to periodic vibrations. To establish a classification and distance estimation algorithm for general vibration signals which suits both periodic and aperiodic sources, we develop the spectrogram (SPEC) image feature combining the kernel-based extreme learning machine (KELM) [22, 23] based vibration representation, detection and propagation distance estimation algorithm. The proposed SPEC feature can well reflect the energy distribution property and its association with the propagation distance and transmission media. The recent effective KELM algorithm is then adopted for feature learning. To test the classification performance and distance estimation accuracy, the proposed KELM + SPEC algorithm is tested on real vibrations collected by the sensor AWA14400. Five different vibration sources, two periodic and three aperiodic, are recorded under various propagation distances in the experiment. A SPEC feature dataset with labelled vibration source types and propagation distances extracted from raw signals is constructed. To verify the effectiveness of the proposed KELM + SPEC algorithm, comparisons to the WPT-based vibration representation and the FBED feature-based periodic vibration signal characterisation combining with the extreme learning machine (ELM), the regularised ELM (RELM) and the KELM are provided in the study.

The remaining paper is organised as follows. Section 2 briefly reviews the general vibration signals processing, the FBED feature and the ELM algorithms. The SPEC feature of vibration signals and the proposed KELM + SPEC algorithm for source classification and propagation distance estimation are introduced in Section 3. Experiments, comparisons, and discussions are presented in Section 4. We conclude the paper in Section 5.

2 Related work

2.1 Review of vibration propagation

Absorption attenuation is the main reason for the energy decay of vibration signals in propagation [19]. A general estimation model on the absorption attenuation of vibration in the solid media is

\[ A_d = A_e e^{-\alpha z/d}, \]  

(1)
where \( A_1 \) and \( A_2 \) are the amplitudes of the original vibration and the signal recorded at the distance \( d \), \( q \) is a transmission coefficient, and \( f \) is the signal frequency [24–26]. Apparently, the energy decay is related to the signal frequency and the propagation distance. Fig. 1 shows an illustration sample on the energy distributions of vibration signal collected under different propagation distances.

2.2 FBED feature

The propagation distance estimation of periodic vibration signal was recently studied in [19–21]. A novel feature named the frequency band energy percentage (FBED), which characterises the energy distribution of periodic vibration around the fundamental frequency and its integral multiples has been developed in [19–21]. For periodic vibration signals, two properties on the energy distribution are found [19]: (i) the energy of periodic vibrations generally concentrates around the fundamental frequency and its integral multiples, (ii) the energy decays along with the propagation distance and the high-frequency bands decay faster than the low-frequency bands. Thus, these properties have been adopted in FBED for the periodic vibration representation and its propagation distance estimation. To extract the FBED feature, the fundamental frequency band energy percentage (FBED), which characterises the frequency band energy percentage (FBED) of the periodic vibration representation and its propagation distance estimation.

\[
p_F = \sum \text{PSD}(k_i),
\]

where \( k_i \) denotes the frequency bins belonging the \( i \)th subband. Finally, the FBED feature \( P_{\text{FBED}} \) in [19, 20] is given as

\[
P_{\text{FBED}} = \frac{P}{\|P\|}.
\]

The propagation distance estimation algorithms based on the FBED feature, the improved \( k \)-nearest neighbour and the artificial neural network for periodic vibrations have been presented in [19, 20], respectively.

2.3 ELM algorithms

2.3.1 ELM: ELM has been developed for a single hidden layer feed-forward neural network [22, 23, 27–31]. ELM employs random hidden node parameters, which are unchanged during the training. Then, only the output weights need to be optimised. The output of ELM with \( L \) hidden nodes is

\[
f_L(x) = \sum_{i=1}^{L} \beta_i h_i(x) = H\beta.
\]

where \( \beta \) is the output weight matrix and \( H \) is the hidden layer output matrix. ELM aims to solve the output weight matrix by minimising the cost error with a least-squares method as

\[
\hat{\beta} = H^T T.
\]

where \( H^T \) is the generalised inverse of \( H \) and \( T \) is the target output matrix. Algorithm 1 briefly summarises the ELM.

Algorithm 1: ELM

1. Randomly generate the hidden node parameters \((w_i, b_i)\), \( i = 1, 2, \ldots, L \).
2. Calculate the hidden layer output matrix \( H \).
3. Calculate the output weight by (5).

2.3.2 RELM: The improved RELM minimises not only the cost error but also the norm of output weights as [32]

\[
\min_{\beta} \frac{1}{2} C \|H\beta - T\|^2_2 + \frac{1}{2} \|\beta\|^2_1,
\]

where \( C \) is the trade-off parameter. According to the ridge regression theory [33], the output weight can be solved as

\[
\hat{\beta} = \left( H^TH + \frac{1}{C} I \right)^{-1} H^T T, \quad \text{if } N < L.
\]

\[
\hat{\beta} = \left( \frac{1}{C} + H^TH \right)^{-1} H^T T, \quad \text{if } N \geq L.
\]

RELM is briefly summarised in Algorithm 2.

Algorithm 2: RELM

\[
\begin{align*}
1 & \text{ Randomly generate the hidden node parameters } (w_i, b_i), \\
2 & \text{ Calculate the hidden layer output matrix } H, \\
3 & \text{ Calculate the output weight by (5).}
\end{align*}
\]

Fig. 1 Spectrograms of periodic vibrations recorded in different propagation distances.
Thus, the KELM shows the SPEC of aperiodic vibration generated by a freely dropped iron ball at a height of 1.3 m. The energy decay of vibrations is mainly related to the high-frequency bands decays faster than those in low-frequency bands. As stated in the previous illustrations, we can refer to Fig. 1 for the spectrograms of periodic vibration signals with two periodic and two aperiodic components (19.75 and 45.05 Hz) while Fig. 2 for the spectrograms of different vibrations (including both periodic and aperiodic vibrations collected at different propagation distances and dropped iron ball at a height of 1.3 m. One can readily observe from Fig. 1 that (i) the energy of periodic vibration signal concentrations on the fundamental frequency band and its integral multiples and (ii) the energy of high-frequency bands decays faster than those in low-frequency bands. Figs. 2a and b depict the spectrograms of periodic vibrations with different $f_{sd}$ (19.75 and 45.05 Hz) while Fig. 2c shows the SPEC of aperiodic vibration generated by a freely dropped iron ball at a height of 1.3 m.

### 2.3.3 Kernel-based extreme learning machine (ELM): The kernel learning has been applied in ELM to obtain better generalisation and less user intervention [32]. Defining a kernel matrix $\mathbf{\Omega}$ with the kernel function $K$ as

$$
\mathbf{\Omega} = \mathbf{HH}^T; \mathbf{\Omega}_{ij} = h(x_i)h(x_j) = K(x_i, x_j).
$$

(8)

Thus, the KELM $f_{\text{KELM}}$ can be represented as

$$
f_{\text{KELM}}(x) = h(x)\mathbf{H}\left(\frac{1}{\mathbf{C}} + \mathbf{HH}^T\right)^{-1}\mathbf{H}^T \left(\frac{1}{\mathbf{C}} + \mathbf{\Omega}\right)^{-1}
$$

(9)

The KELM algorithm is briefly summarised in Algorithm 3.

**Algorithm 3: KELM**

1. Calculate the kernel matrix $\mathbf{\Omega}$ by (8).
2. Calculate the transformation matrix $\mathbf{C} = ((1/\mathbf{C}) + \mathbf{\Omega})^{-1}\mathbf{T}$.

### 3 Proposed KELM + SPEC algorithm

#### 3.1 SPEC feature

SPEC is powerful in describing the energy distribution of signals in both the time- and frequency-domain. As stated in the previous section, the energy decay of vibrations is mainly related to the signal frequency, the propagation distance, and the transmission media. Different vibration sources propagating in different distances can be thus well-characterised in terms of the SPEC. For illustrations, we can refer to Fig. 1 for the spectrograms of periodic vibration signal collected at different propagation distances and Fig. 2 for the spectrograms of different vibrations (including both the periodic and aperiodic) collected at the same propagation distance. One can readily observe from Fig. 1 that (i) the energy of periodic vibration signal concentrations on the fundamental frequency band and its integral multiples and (ii) the energy of high-frequency bands decays faster than those in low-frequency bands. Figs. 2a and b depict the spectrograms of periodic vibrations with different $f_{sd}$ (19.75 and 45.05 Hz) while Fig. 2c shows the SPEC of aperiodic vibration generated by a freely dropped iron ball at a height of 1.3 m.

Similar observations to Fig. 1 can be found in Figs. 2a and b. While the impulse-like vibration in Fig. 2 produces a distinct power spectrum distribution to the periodic vibration signals. Hence, the SPEC image feature can be explored for vibration classification and distance estimation.

The SPEC feature is extracted based on the fast Fourier transform (FFT) algorithm. Given a vibration signal $x(n)$ with the length $N$ and the sampling frequency $f_s$, a dataset $A$ is obtained by dividing the vibration $x(n)$ into short frames with the frame length $L_f$ and the frame shift $f_{inc}$ denoted as

$$
A = \{x^q(n)\} | n = 1, \ldots, L_f, k = 1, \ldots, f_{inc}\},
$$

where $x^q(n)$ is the $q$th frame and $f_{inc}$ is the number. Here, $f_{inc}$ can be calculated as

$$
f_{inc} = (N - L_f)/f_{inc} + 1.
$$

(10)

To preserve the dynamic characteristics of the vibration signal, the consecutive frames in the time domain are adopted to construct the SPEC for the SPEC feature. Assuming that $M$ consecutive frames are used in the SPEC, for each frame $x^q(n)$ the frequency spectrum $X^q(\omega)$ is derived as

$$
X^q(\omega) = \text{FFT}(x^q(n)) = \sum_{n=1}^{L_f} x^q(n)e^{-j\pi\omega nL_f},
$$

(11)

where $\omega = 1, \ldots, L_f, q = 1, \ldots, M$. The frequency components contained in the SPEC range within $[0, f_s/2]$. Thus, the amplitude spectrum $X^q_\omega(\omega)$ can be calculated with the front half points of $X^q(\omega)$ as

$$
X^q_\omega(\omega) = |X^q(\omega)|, \quad \omega = 1, \ldots, (1 + L_f/2), \quad q = 1, \ldots, M.
$$

(12)

Each element in $X_\omega(\omega)$ corresponds to a frequency component and the element value represents the energy of the frequency component. The energy distribution vector $P^q = [X^q_\omega(1), X^q_\omega(2), \ldots, X^q_\omega(1 + L_f/2)]$ of the frame $x^q(n)$ can be obtained and the SPEC feature $P_{\text{SPEC}}$ constructed with a combination of the $M$ energy distribution vectors can be expressed as $P_{\text{SPEC}} = [P^1, P^2, \ldots, P^M]^T$, where the dimension of $P_{\text{SPEC}}$ is $(1 + L_f/2) \cdot M$. For a better understanding the extraction of SPEC feature, a brief summary is given in Algorithm 4.

As an illustration, we draw the SPEC features of four different vibration signals with two periodic and two aperiodic in Fig. 3, respectively. These vibration signals are recorded in the 4 m propagation distance and denoted as VIB1–VIB4 correspondingly.
For each vibration, 40 SPEC feature vectors $P_{\text{SPEC}}$ are plotted, the frame length $L_t$ and the frame number $M$ are set to be 256 and 3, respectively. As clearly shown in the figure, the energy of periodic vibrations concentrates on the fundamental frequency sub-bands while for aperiodic vibrations, the energy is distributed evenly on each frequency bin.

Algorithm 4: SPEC feature

**Given:**
- A vibration signal $x(n)$ with the length of $N$.
- The frame length $L_t$.
- The frame shift $f_{\text{shift}}$.
- The parameter $M$.

1. Divide the vibration $x(n)$ into short frames as
   $$ A = \{x^i(n) \mid n = 1, \ldots, L_t; k = 1, \ldots, f_{\text{shift}}\}, $$
   $$ f_{\text{shift}} = (N - L_t)/f_{\text{shift}} + 1. $$
2. Compute the frequency spectrum $X^i(\omega)$ of $x^i(n)$ using FFT as
   $$ X^i(\omega) = \text{FFT}(x^i(n)) = \frac{L_t}{\sqrt{2\pi}} \sum_{n=1}^{L_t} x^i(n)e^{-j\omega n L_t}. $$
   where $\omega = 1, \ldots, L_t, q = 1, \ldots, M$.
3. Compute the amplitude spectrum $X^i_\omega(\omega)$ as
   $$ X^i_\omega(\omega) = \left| X^i(\omega) \right|, \quad \omega = 1, \ldots, L_t / 2, q = 1, \ldots, M. $$
4. Compute the energy distribution vector $P^i$ for $x^i(n)$
   $$ P^i = \left[ X^i_1(1), X^i_2(2), \ldots, X^i_q(1 + L_t / 2) \right]. $$
5. Obtained the SPEC feature vector $P_{\text{SPEC}}$ with $M$ frames as
   $$ P_{\text{SPEC}} = \left[ P^1, P^2, \ldots, P^M \right]^T. $$

3.2 KELM + SPEC algorithm

With the extracted SPEC feature, a novel vibration signal classification and propagation distance estimation algorithm is developed in this subsection. The KELM algorithm is adopted for both the vibration classification and propagation distance estimation. The proposed KELM + SPEC algorithm mainly consists of three stages: (i) The SPEC feature extraction, for the classifier and the propagation distance estimation model learning, a training dataset $\{\{P_{\text{SPEC}}, c_i, d_i\}\}_{i=1, \ldots, N}$ including the SPEC feature vector $P_{\text{SPEC}}$ with its associated vibration class label $c_i$ and the propagation distance $d_i$ is constructed. (ii) The KELM algorithm training, a classifier built on the dataset $\{\{P_{\text{SPEC}}, c_i\}\}_{i=1, \ldots, N}$ is first trained using the KELM algorithm. Then, a distance regression model based on the dataset $\{\{P_{\text{SPEC}}, d_i\}\}_{i=1, \ldots, N}$ is constructed with KELM. (iii) The testing stage, given a segment of testing vibration signal, its SPEC feature vector $P_{\text{SPEC}}$ is extracted with Algorithm 4 and feed to the trained classifier and regression model for the vibration classification and the propagation distance estimation.

A brief description of the proposed KELM + SPEC vibration classification and propagation distance estimation method is given in Algorithm 5. Note that in Algorithm 5, the function $\arg \max \cdot$ returns the index of the largest entry in the vector. It is due to the fact that the classification problem is transformed to a multi-output regression in ELM algorithms by using the “one-against-all” rule.

Algorithm 5: KELM + SPEC algorithm

**Given:**
- A SPEC feature dataset $\{\{P_{\text{SPEC}}, c_i, d_i\}\}_{i=1, \ldots, N}$.
- The number of hidden nodes $L$ for KELM.
- The parameter $M$.

1. Train a classification model $f_X(\cdot)$ using KELM of Algorithm 3 based on the dataset $\{\{P_{\text{SPEC}}, c_i\}\}_{i=1, \ldots, N}$.
2. Train a distance regression model $f_d(\cdot)$ using KELM of Algorithm 3 based on the dataset $\{\{P_{\text{SPEC}}, d_i\}\}_{i=1, \ldots, N}$.
3. Compute the SPEC feature vector for the testing signal with Algorithm 4 as $P_{\text{SPEC}}$.
4. Derive the class label of the testing signal with the trained classification model as $c' = \arg \max f_X(P_{\text{SPEC}})$.
5. Calculate the propagation distance of the testing signal with the trained regression model as
   $$ d' = f_d(P_{\text{SPEC}}). $$

4 Experiments and discussions

4.1 Experimental setups

To test the classification performance and the distance estimation accuracy of the proposed KELM + SPEC algorithm, experiments on real recorded vibrations by the sensor AWA14400 are conducted in this section. Five different vibration sources (denoted as VIB1–VIB5), two periodic (VIB1 and VIB2) and three aperiodic (VIB3, VIB4, and VIB5), are recorded under various propagation distances $(2, 4, 6, 8, 10, 12)$ m in the experiments. VIB1 and VIB2 are generated by two electric hammers with different fundamental frequencies $f_{\text{hammer}}$ 44.05 and 19.75 Hz, respectively. VIB3–VIB5 are generated by freely dropping iron balls with different weights at the same height of 1.3 m. All vibration signals are collected on the concrete road surface. Fig. 4 draws the samples of the five vibration signals. For each vibration, the number of frames at each propagation distance $(2, 4, 6, 8, 10, 12)$ m are listed as follows: VIB1 (148, 140, 206, 322, 201, 142), VIB2 (1146, 1770, 1943, 2415, 1554, 910), VIB3 (1993, 1972, 1949, 1912, 1912, 2011), VIB4 (2058, 1813, 1872, 1998, 1805, 1977) and VIB5 (654, 924, 540, 458, 450, 686). The frame length is set to be $L_t = 256$.

A SPEC feature dataset with labelled vibration source categories and the associated propagation distances is constructed. To verify the effectiveness of the proposed KELM + SPEC, comparisons to various feature extractions and classification algorithms are given, including the WPT, the raw vibration signal, the FBED [19, 20] for periodic vibrations combining with the ELM, the RELM, and the KELM classifiers. The activation function used in ELM and RELM is Sigmoid, and the kernel function used in KELM is the radial basis function. Three different kinds of WPTs have been tested in the experiment, which are the Daubechies (the db5 and db7 wavelet decomposition in Matlab are used) and the Fejer–Korovkin wavelet functions, respectively. The decomposition levels of the three wavelet functions are set to be 5, 6, and 7, and the coefficients of the last node are adopted for vibration signal representation. For the SPEC feature, we set the parameter $M = 3$ for the subsequent source classification and propagation distance estimation experiments. The number of features for each vibration signal recorded on the five propagation distances is as follows: VIB1 (49, 46, 68, 107, 67, 47), VIB2 (382, 590, 647, 805, 303), VIB3 (664, 657, 649, 637, 670), VIB4 (686, 604, 624, 666, 601, 659) and VIB5 (218, 308, 180, 182, 150, 228). Three experiments are carried out in this section, where the first one focuses on the vibration classification, the second one shows the performance on the propagation distance estimation and the last one analyses the affection of the number of consecutive frames used in the SPEC on the classification performance.

4.2 Performance on classification

The number of hidden nodes $L$ in ELM is optimised through searching within $\{1000, 2000, \ldots, 20000\}$. The number of hidden nodes $L$ and the regularisation parameter $C$ in RELM are selected by searching for the optimal result on the grids $\{1000, 2000, \ldots, 20000\} \times \{10^{-3}, 10^{-4}, \ldots, 10^{0}, 10^{5}\}$. The regularisation parameter $C$
and the kernel parameter in KELM are optimised within the grids \(\{10^{-5}, 10^{-4}, ..., 10^4, 10^5\} \times \{10^{-5}, 10^{-4}, ..., 10^4, 10^5\}\).

In this experiment, the classifiers training by using the raw vibration signal (denoted as RAW), the three WPT coefficients (denotes as WPT1, WPT2, and WPT3), and the proposed SPEC features are tested for comparisons. To have a fair comparison with the SPEC feature, the datasets on the three WPT coefficients are constructed where each has the same amount of feature samples to SPEC, i.e. for WPT1, WPT2, and WPT3, three datasets are generated and each contains \{1159, 9738, 11,749, 11,523, 3802\} samples for VIB1–VIB5, respectively. For all classifiers, 80% samples are randomly selected from the dataset for training and the rest are used for testing. The average classification accuracies on multiple trials are reported for comparisons.

Table 1 shows the classification accuracy and the training time for each algorithm in detail. It is seen that the raw signal and the three WPT features show poor classification performance. On the contrary, the SPEC-based classifiers provide a higher classification rate than using the raw signal and the WPTs. As emphasised with boldface in the table, the proposed KELM + SPEC algorithm achieves a classification rate of 99.17%, which offers more than 24% increments over the best algorithm obtained by the raw signal and the three WPT features.

To analyse the classification performance of the WPT-based methods, the confusion matrices of ELM + WPT2 and the proposed KELM + SPEC are, respectively, depicted in Figs. 5 and 6 for comparison. As seen in Fig. 5, the ELM + WPT2 is able to classify the two periodic vibration signals with reasonable accuracies but suffers a high misclassification rate on the rest aperiodic vibrations. For VIB5, more than 74 and 20% have been wrongly classified as VIB4 and VIB3. Similarly, for VIB3, there are more than 41% wrongly classified as VIB4. On the contrary, the SPEC-based KELM algorithm achieves high classification accuracy on all five vibration signals. The WPT features are drawn in Fig. 7 for further analysis. It is found in the figure that the three aperiodic vibration signals have a similar distribution of the WPT features.
In this section, the regression model of each vibration source is built, respectively, for propagation distance estimation. The distance estimation experiments are divided into two separate groups, the first group is experimenting for periodic vibrations (VIB1 and VIB2), and the second for aperiodic vibrations (VIB3–VIB5). Besides SPEC datasets and WPT datasets, FBED datasets labelled with propagation distances for each vibration source are constructed [19–21], in the first group experiments. For the FBED feature datasets, the fundamental frequency \( f_d \) is estimated by the EMVF method used in [20] and the bandwidth coefficient is set to be \( \alpha = 0.5 \). The root mean square error (RMSE) between the estimated propagation distance and the true one is computed for performance evaluation.

Table 2 lists the average RMSEs for all algorithms. As highlighted in boldface, the SPEC feature-based algorithms obtain the lowest RMSE on the propagation distance. Particularly, the KELM + SPEC algorithm reaches the lowest RMSEs for four vibration signals and the RELM + SPEC wins the rest one. It is worthy pointing out that for both KELM + SPEC and RELM + SPEC algorithms, the RMSEs are lower than 1 m for all vibration signals. For periodic vibration signals, one can find that the FBED feature developed in [19] is effective in the propagation distance estimation. As emphasised with the italic font, the RMSEs on the two periodic vibration signals obtained by the KELM + FBED algorithm are lower than 0.43 and 0.46, respectively.

### 4.4 Performance analysis on the SPEC dimension M

The number of consecutive frames used to construct the SPEC feature may affect the performance of vibration source classification and propagation distance estimation. Different values of \( M \) may show different capabilities in signal representation. In this section, the influence of the parameter \( M \) in SPEC is analysed in terms of using the classification accuracy and distance estimation error with the ELM + SPEC, RELM + SPEC and KELM + SPEC algorithms. Four different SPEC feature datasets with different \( M \) chosen from \{1, 2, 3, 5\} are constructed for performance evaluation.

Table 3 shows the average classification accuracies obtained by ELM + SPEC, RELM + SPEC and KELM + SPEC, and Figs. 8 and 9 draw the RMSEs by RELM + SPEC and KELM + SPEC with respect to different \( M \), respectively. From the table and figures, it can be seen that the best classification accuracies, as well as the RMSEs for all algorithms, are achieved when \( M = 1 \). The performance degrades slightly when \( M \) is increasing.

## 5 Conclusion

In this study, the SPEC feature, which reflects the energy distribution property, has been first developed for vibration source classification and propagation distance estimation. The proposed KELM + SPEC algorithm has been compared to various existing vibration signal representation algorithms. Experiments on real recorded vibration signals, including two periodic vibrations and three aperiodic vibrations, have been presented for performance evaluation and effectiveness validation. Comparisons to various existing vibration signal representation algorithms have also been provided to show the superiority of the proposed KELM + SPEC algorithm. Experimental results have shown that the proposed algorithm is effective in the classification and propagation distance estimation for both periodic and aperiodic vibrations, and outperforms several existing state-of-the-art algorithms.

## 6 Acknowledgments

This work was supported by the National Natural Science Foundation of China (61503104, U1509205) and the Open Foundation of Hypervelocity Impact Research Center of CARDC (grant no. 20183101).
Table 2  RMSEs (m) of the distance estimation with different algorithms

| Algorithm       | RMSE | RMSE | RMSE | RMSE |
|-----------------|------|------|------|------|
| ELM + FBED/RAW  | 0.90 | 0.76 | 2.71 | 2.39 | 2.22 |
| RELM + FBED/RAW | 0.61 | 0.65 | 2.72 | 2.36 | 2.10 |
| KELM + FBED/RAW | 0.43 | 0.46 | 1.92 | 1.70 | 2.20 |
| ELM + WPT1      | 1.02 | 1.17 | 2.61 | 2.60 | 3.18 |
| RELM + WPT1     | 0.82 | 0.76 | 2.34 | 2.53 | 3.01 |
| KELM + WPT1     | 0.66 | 0.96 | 1.84 | 2.29 | 2.66 |
| ELM + WPT2      | 0.89 | 1.18 | 2.60 | 2.59 | 3.18 |
| RELM + WPT2     | 0.70 | 1.11 | 2.42 | 2.50 | 3.02 |
| KELM + WPT2     | 0.85 | 0.95 | 1.84 | 2.31 | 2.64 |
| ELM + WPT3      | 1.19 | 1.19 | 2.51 | 2.64 | 3.22 |
| RELM + WPT3     | 1.11 | 1.09 | 2.33 | 2.52 | 3.21 |
| KELM + WPT3     | 1.01 | 0.98 | 1.89 | 2.31 | 2.77 |
| ELM + SPEC      | 0.49 | 0.53 | 1.24 | 1.69 | 2.64 |
| RELM + SPEC     | 0.45 | 0.45 | 0.39 | 0.94 | 0.90 |
| KELM + SPEC     | 0.41 | 0.44 | 0.42 | 0.92 | 0.80 |

Table 3  Classification accuracy (%) on different M

| M   | ELM + SPEC | RELM + SPEC | KELM + SPEC |
|-----|------------|-------------|-------------|
| 1   | 89.76      | 89.42       | 99.37       |
| 2   | 89.63      | 88.65       | 97.96       |
| 3   | 89.60      | 87.96       | 99.17       |
| 4   | 86.17      | 86.70       | 81.22       |

Fig. 8  RMSE by RELM + SPEC

Fig. 9  RMSE by KELM + SPEC

7 References

[1] Sun, D., Yan, Y., Carter, R., et al.: ‘On-line noninvasive detection of wood pellets in pneumatic conveying pipelines using vibration and acoustic sensor’, IEEE Trans. Instrum. Meas., 2014, 63, (5), pp. 993–1001
[2] Qu, H., Zheng, T., Bi, F., et al.: ‘Intelligent recognition of acoustic and vibration threats for security breach detection close proximity danger identification and perimeter protection’, IEEE International Conference on Technologies for Homeland Security (HST), Waltham, MA, 2010, pp. 351–356
[3] Faghfouri, A., Frish, M.: ‘Robust discrimination of human footsteps using seismic signals’, Proc. SPIE, 2011, 8046, pp. 357–366
[4] Succi, R., Clapp, D., Prado, G.: ‘Footstep detection and tracking’, Proc. SPIE, 2003, 5090, pp. 155–161
[5] Sun, J., Li, H., Wang, W., et al.: ‘A preprocessing algorithm for the vibration signal of hydraulic pump based upon WMUWD’, J. Vib. Shock, 2015, 34, pp. 93–99
[6] Jiang, B., Wang, Z.: ‘Railway vibration monitoring system based on ARM and acceleration’, 2014 9th IEEE Conf. on Industrial Electronics and Applications, Hangzhou, 2014, pp. 998–1004
[7] Cao, J., Wang, W., Wang, J., et al.: ‘Excavation equipment recognition based on novel acoustic statistical features’, IEEE Trans. Cybernet., 2017, 47, (12), pp. 4392–4404
[8] Cao, J., Huang, W., Zhao, T., et al.: ‘An enhance excavation equipments classification algorithm based on acoustic spectrum dynamic feature’, Multidimens. Syst. Signal Process., 2017, 28, (3), pp. 1–23
[9] Cao, J., Zhao, T., Wang, J., et al.: ‘Excavation equipments classification based on improved MFCC features and ELM’, Neurocomputing, 2017, 261, pp. 231–241
[10] Rezazadeh, E., McCabe, B.: ‘Part based model and spatial–temporal reasoning to recognize hydraulic excavators in construction images and videos’, Autom. Constr., 2012, 24, (7), pp. 194–202
[11] Golparvar-Fard, M., Heydarian, A., Niebles, J., et al.: ‘Vision-based action recognition of earthmoving equipment using spatio-temporal features and support vector machine classifiers’, Adv. Eng. Inf., 2013, 27, (4), pp. 652–663
[12] Valdastighi, F., Hammad, A., Siddiqui, H.: ‘Optimization-based excavator pose estimation using real-time location systems’, Autom. Constr., 2015, 56, pp. 76–92
[13] Sha, S., Cao, J., Wang, J., et al.: ‘Fundamental frequency energy distribution of periodic vibrations and their relation to distance’, IEEE Int. Conf. on Signal Processing, Chengdu, 2017, vol. 261, pp. 96–101
[14] Cao, J., Wang, T., Shang, L., et al.: ‘An intelligent propagation distance estimation algorithm based on fundamental frequency energy distribution for periodic vibration localization’, J. Franklin Inst., 2018, 355, (4), pp. 1539–1558
[15] Cao, J., Wang, T., Shang, L., et al.: ‘A novel distance estimation algorithm for periodic surface vibrations based on frequency band energy percentage feature’, Mech. Syst. Signal Process., 2018, 113, pp. 222–236
[16] Huang, G., Zuo, Q., Siew, C.: ‘Extreme learning machine: theory and applications’, Neurocomputing, 2006, 70, (1), pp. 489–501
[17] Huang, G.: ‘What are extreme learning machines? Filling the gap between Frank Rosenblatts dream and John V on Neumanns puzzle’, Cogn. Comput., 2015, 7, (3), pp. 263–278
[18] Chen, W., Holm, S.: ‘Modified Szabo's wave equation models for lossy media obeying frequency power law’, J. Acoust. Soc. Am., 2003, 114, (5), pp. 2570–2574
[19] Schab, T., Wu, J.: ‘A model for longitudinal and shear wave propagation in viscoelastic media’, J. Acoust. Soc. Am., 2000, 107, (5), pp. 2437–2446
[20] Pritz, T.: ‘Frequency power law of material damping’, Appl. Acoust., 2004, 65, pp. 1027–1036
[21] Cao, J., Zhang, K., Luo, M., et al.: ‘Extreme learning machine and adaptive sparse representation for image classification’, Neural Netw., 2016, 81, pp. 91–102
[22] Wang, T., Cao, J., Lai, X., et al.: ‘Deep weighted extreme learning machine’, Cogn. Comput., 2018, 10, (6), pp. 890–907
[29] Cao, J., Zhang, K., Yong, H., et al.: ‘Extreme learning machine with affine transformation inputs in an activation function’, IEEE Trans. Neural Netw. Learn. Syst., 2018, doi: 10.1109/TNNLS.2018.2877468

[30] Wan, Y., Song, S., Huang, G., et al.: ‘Twin extreme learning machines for pattern classification’, Neurocomputing, 2017, 260, pp. 235–244

[31] Zhu, H., Tsang, E., Wang, X., et al.: ‘Monotonic classification extreme learning machine’, Neurocomputing, 2017, 225, pp. 205–213

[32] Huang, G., Zhou, H., Ding, X., et al.: ‘Extreme learning machine for regression and multiclass classification’, IEEE Trans. Syst. Man Cybern. B, Cybern., 2012, 42, (2), pp. 513–529

[33] Hoerl, A., Kennard, R.: ‘Ridge regression: biased estimation for nonorthogonal problems’, Technometrics, 1970, 42, (1), pp. 80–86