

## Research Article

# Research on Identification Technology of Explosive Vibration Based on EEMD Energy Entropy and Multiclassification SVM

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In this study, the authors introduced energy entropy as a reference feature into the field of blast vibration recognition classification and achieved good results. On the basis of the previous experimental database, 4 kinds of typical vibration signals were selected to form the sample group (building collapse vibration, surface rock blast vibration, underground tunnel blast vibration, and natural gas pipeline explosion vibration). EEMD (ensemble empirical mode decomposition) algorithm was used to calculate the energy entropy of each signal. Taking eigenvector composed of CEE (components of energy entropy) as input, multiclassification SVM algorithm was used for training and prediction. Prediction accuracy was more than 80%. Compared with BP (backpropagation) neural network algorithm, SVM (support vector machine) algorithm has higher training efficiency. The research results can be used in urban vibration monitoring, identify the nature of vibration source in time, and provide technical support for rapid response of emergency rescue.

## 1. Introduction

The blasting vibration signal is a typical short-time non-stationary random signal. The characteristics of the blasting vibration signal can reflect the blasting type, blasting parameters, and site media information. The feature extraction of blasting vibration signal is the basis of studying blasting vibration prediction, structural response under blasting vibration excitation, and reducing blasting vibration. At present, the characteristics of blasting vibration signals mainly include peak characteristics, spectral features, time-holding characteristics, and energy characteristics. A large number of scholars have carried out in-depth research on the influence of characteristics and blasting parameters on signal characteristics. Min et al. [1] studied the strain law of buried pipeline under collapse vibration load. Through range analysis and variance significance analysis, it was found that the dynamic strain of buried pipeline under impact was more significant than that of collapse height and self-weight. Lu [2] obtained the energy distribution of each frequency band after multiscale lifting wavelet packet decomposition of the measured blasting vibration signal and

summarized the energy distribution characteristics of the frequency band of the blasting vibration signal. Based on the dimension analysis theory, Zhong [3] discussed the influence factors of blasting vibration holding time and deduced the prediction formula of blasting vibration holding time.

With the deepening of research, a new branch of blasting vibration characteristics has appeared: energy entropy. Shannon referred to the concept of thermodynamics and called the average amount of information excluding redundancy “energy entropy” [4]. Energy entropy is an important concept in information theory and a description of the degree of system uncertainty. It can reflect the degree of random change of signals. In recent years, it has been widely used in mechanical fault diagnosis [5–7], speech signal processing [8], mine micro-earthquake signal recognition [9, 10], and other fields [11–13]. In this paper, EEMD algorithm was used to decompose the energy entropy of vibration signal, and the energy characteristics of each IMF are obtained as the input vector of SVM. Through the analysis and training of many kinds of vibration signals, the accurate prediction of vibration types was realized. The research results can provide technical reserves for urban vibration

monitoring system and quick and accurate information of explosion source types for decision-makers of disaster prevention and mitigation command departments.

## 2. EEMD Energy Entropy

The EEMD (ensemble empirical mode decomposition) algorithm is a mature nonstationary random signal decomposition algorithm based on the EMD (empirical mode decomposition) algorithm. The original intention is to decompose any nonstationary random signal into multiple IMFs (intrinsic mode function), so as to provide feasibility for further Hilbert transform. EMD algorithm is different from the traditional wavelet and Fourier transform, its decomposition process has no fixed base, it has adaptive characteristics, and so it is famous for its efficiency and accuracy. But, the frequency aliasing effect of EMD algorithm has been perplexing scholars. The improved idea of EEMD is to add white noise at the beginning of EMD decomposition cycle, so as to solve the problem of frequency aliasing in traditional EMD algorithm.

The signal was decomposed by the EEMD algorithm to obtain a plurality of IMFs, which represent the characteristic distribution of the signal energy. Due to the difference of explosion source, initiation mode, and propagation medium of different types of explosion vibration signals, the energy distribution characteristics of IMFs are different.

Here we introduce the concept of EEMD energy entropy:

$$H_{En} = - \sum_{i=1}^n \frac{E_i}{E} \log \frac{E_i}{E}, \quad (1)$$

where  $E$  is the total energy of the signal and  $E_i$  is the energy of each IMF. In this paper,  $-E_i/\log E_i/E$  is called CEE (components of energy entropy).

Several vibration signals from different sample groups are selected for decomposition, and their respective energy entropies are calculated, as shown in Table 1. The signal acquisition parameters are shown in Table 2. A simple statistical analysis of the energy entropy data of four kinds of vibration shows that their statistical characteristics are significantly different. Therefore, the vibration energy entropy can be studied in depth as a characteristic parameter of vibration signal classification.

## 3. Multiclassification SVM

Support vector machine is a binary linear classifier with supervised learning mode [14]. As shown in the Figure 1, for a given input, the sample set  $S$  is linearly separable. Each sample contains multiple features, thus forming a feature space (2-dimensional space shown in the figure). The goal of the algorithm is to find the hyper plane with the largest margin  $\omega X + b = 0$  [15]. The decision boundary satisfying the condition actually constructs two parallel hyperplanes as the interval boundary to distinguish the classification of samples [16]:

$$\begin{aligned} \omega X + b &\geq 1, \Rightarrow y = 1, \\ \omega X + b &\leq 1, \Rightarrow y = -1. \end{aligned} \quad (2)$$

All samples above the upper interval boundary belong to a positive class and those below the lower interval boundary belong to a negative class. The distance  $2/\omega$  between two interval boundaries is defined as the margin [17]. The samples of positive and negative classes on the boundary of interval are support vectors.

Support vector machine uses the hinge loss function to calculate the empirical risk. It adds the regularization module to optimize the structural risk and has good robustness [18]. For the nonlinear classification problem, SVM can learn through kernel function method, and the classification effect is still excellent [19].

As mentioned above, SVM is initially a linear classifier. With the in-depth study of scholars, SVM algorithm has been successfully extended to the field of nonlinear separability [20]. The principle is to map the nonlinear separable problem from the original feature space to a higher dimensional Hilbert space by using nonlinear functions [21]. There are hyperplanes [22] in space that can separate positive classes from negative classes as shown in Figure 2.

The standard SVM computing process was used to construct multiple decision boundaries in order to achieve multiclassification of samples [23]. The commonly used structures are “one-to-all (OAA-SVM)” and “one-to-one (OAO-SVM)”. OAA-SVM establishes  $M$  decision boundaries for  $M$  classifications, and each decision boundary determines the attribution of one classification to all other classifications. OAO-SVM used in this paper is a voting method [24]. The calculation process is to establish decision boundaries for any two of the  $M$  classifications, that is, there are  $M(M - 1)/2$  decision boundaries in total. The final sample category is determined by the score order of decision boundary.

## 4. Application of Experimental Data Analysis

In this paper, vibration data under four typical explosion scenarios are selected.

Scene 1: pipeline explosion vibration: at present, the global natural gas pipeline construction mileage has exceeded 370000 km [25]. The pressure of pipeline operation keeps increasing. Due to various reasons, natural gas pipeline explosion accidents occur frequently, which brings hidden dangers to the production safety of human society. Therefore, the author has carried out many full-scale high-pressure natural gas pipeline explosion tests, as shown in Figure 3, and recorded the pipeline explosion vibration data as a kind of sample for this study.

Scene 2: building collapse vibration: with the expansion of the city scale and the exhaustion of the design life of the building itself, the blasting demolition engineering of the high-rise building in the city is increasing day by day. The high-rise building disintegrates in the process of collapse, which causes violent vibration when hitting the ground, a serious threat to surrounding buildings. The research team collected a number of groups of building collapse vibration data as a kind of sample for this study, as shown in Figure 4.

Scene 3: surface rock blast vibration: rock blasting is a key method for the rapid and high-quality construction of

TABLE 1: Comparison of energy entropy of typical vibration signals.

Signal type	Pipeline explosion vibration	Underground tunnel blast vibration	Demolition collapse vibration	Surface rock blast vibration
Energy entropy	Signal 1	2.1656	1.9290	1.5578
	Signal 2	2.2454	2.3216	1.0854
	Signal 3	2.0622	2.2722	1.6836
	Signal 4	2.4368	2.3813	1.6146
	Expectation	2.2275	2.2260	1.4854
Variance		0.1372	0.1758	0.2352
				0.1745

TABLE 2: Parameters of recorder.

Type of recorder	Type of sensor	Number of channels	Frequency response range/Hz	Sampling rate/SPS
TC-4850	Piezoelectric	3	5~500	8000
Blast-UM	Piezoelectric	3	5~300	10000

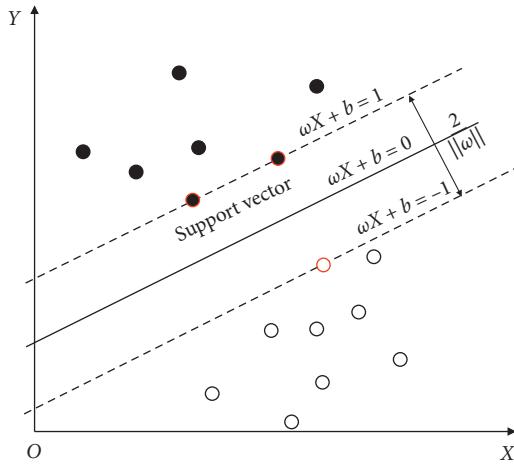
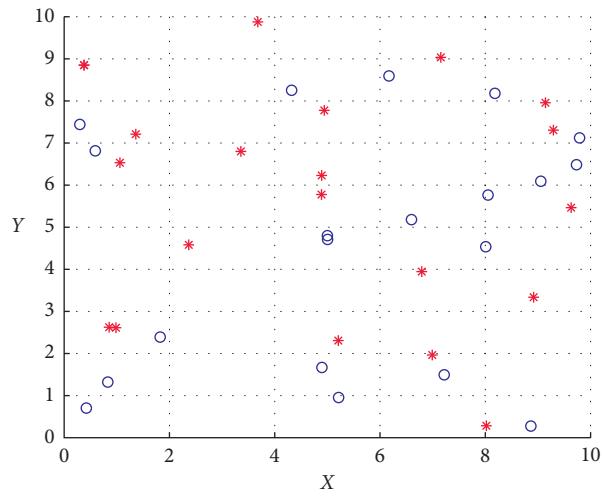
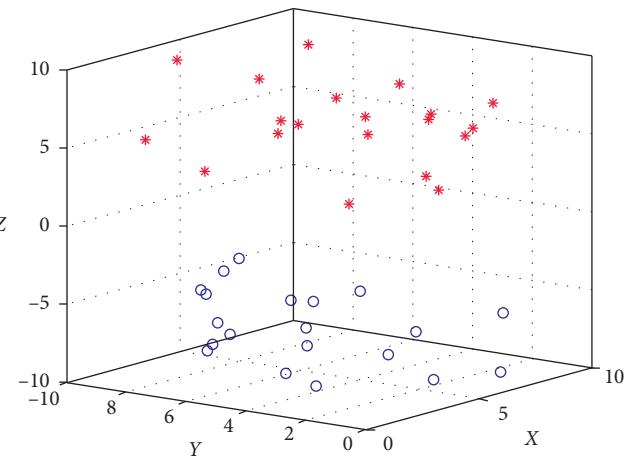


FIGURE 1: Schematic diagram of SVM.



(a)



(b)

FIGURE 2: Nonlinear separable case.

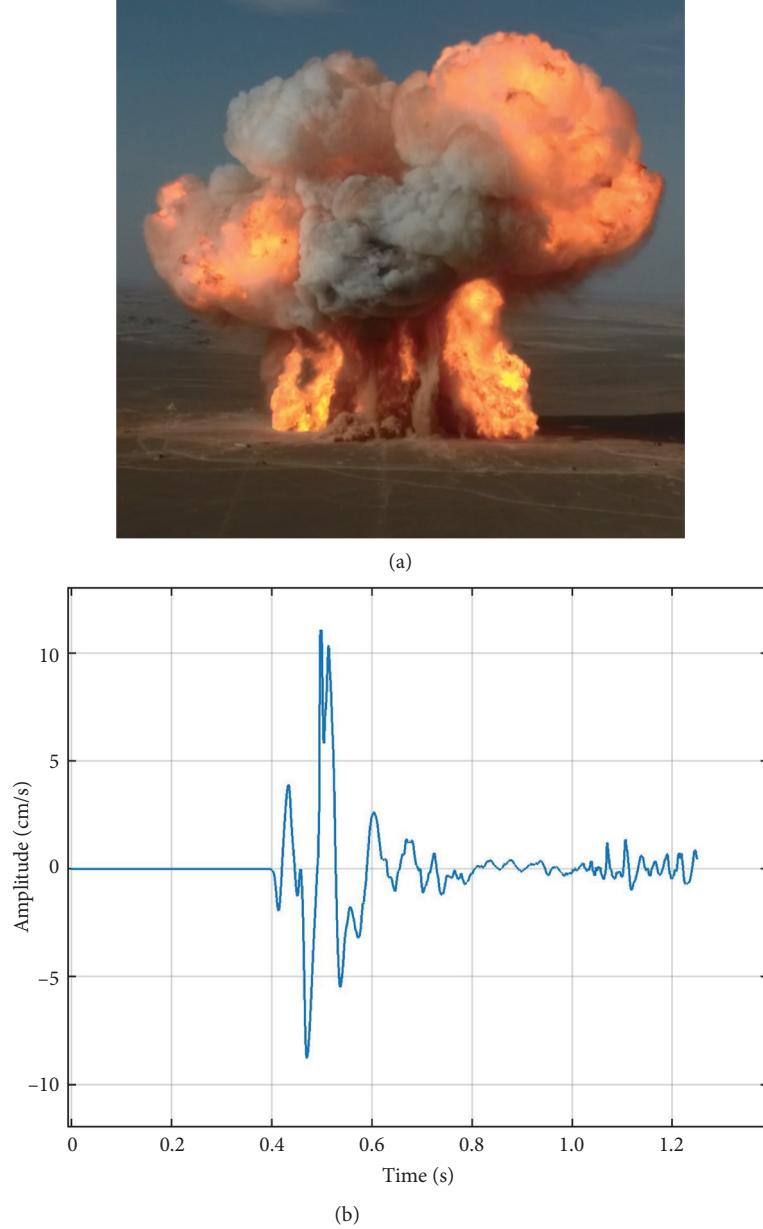


FIGURE 3: Pipeline explosion vibration. (a) OD1422-12Mpa explosion experiment of natural gas pipeline [26]. (b) Vibration signal.

large-scale infrastructure projects such as nuclear power plants, airports, tunnels, and ports. The high standard, high difficulty, and high strength of large-scale engineering construction put forward new challenges to the application of blasting technology. The impact of blasting vibration of subsequent projects on the projects that have been put into operation cannot be ignored. The research team obtained a large number of surface rock blast vibration data from the foundation pit excavation project of Fujian Fuqing Nuclear Power Plant for this study, as shown in Figure 5. The blast parameters are shown in Table 3.

Scene 4: blasting vibration in tunneling: because of its strong adaptability to geological conditions and low excavation cost, DBM (drilling and blasting method) is especially suitable for the construction of hard rock tunnel,

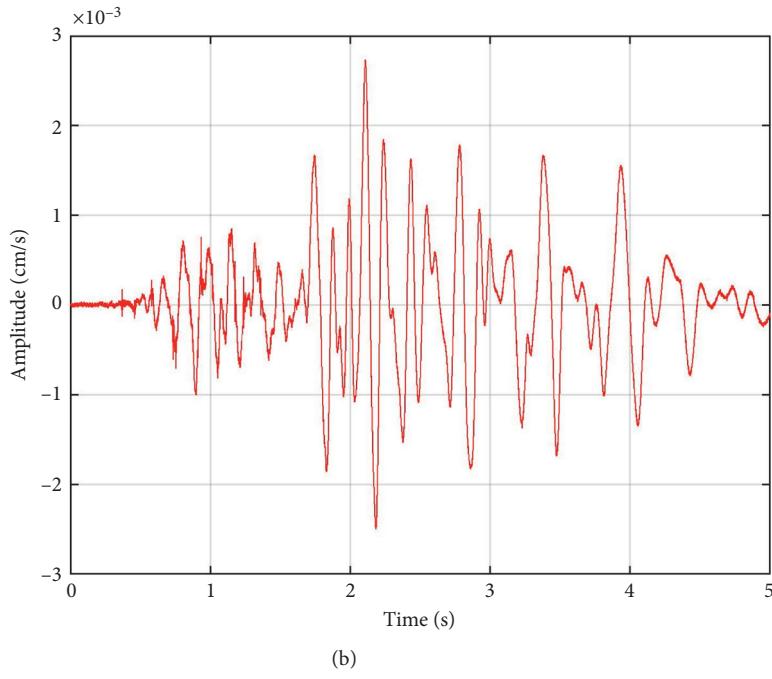
broken rock tunnel, and a large number of short tunnels [27]. The vibration effect of DBM on the surrounding buildings, especially the subway lines which have been built and in operation, cannot be ignored. The research team had been stationed at the construction site of Nanjing Metro Tunnel for a long time, as shown in Figure 6, and collected the blasting vibration data of metro tunnel as a kind of sample for this study. The blast parameters are shown in Table 4.

The above data are collected by TC-4850 and Blast-UM vibration recorders, and the specific sampling parameters are shown in the table.

As mentioned above, the data samples in this study were divided into four categories, each of which takes 10 groups of data, 40 samples in total. In each training-prediction cycle,



(a)



(b)

FIGURE 4: Demolition collapse vibration. (a) Blasting project of investment Plaza building in Jingzhou, Hubei Province. (b) Vibration signal.

30 groups of data were randomly selected as training sets, and the remaining 10 groups were detection sets. EEMD decomposition was carried out for each data. According to statistics, the number of IMF of 40 sample data was between 10 and 13. Considering that the main energy components were concentrated in the first several IMF layers, the CEE of the first nine IMF layers was taken and normalized to obtain the input matrix as shown in Table 5.

The feature matrix of  $40 \times 9$  was input into OAO-SVM to train and test. The results are shown in Figure 7.

It can be seen from the figure that the prediction accuracy can be maintained above 80% in multiple training

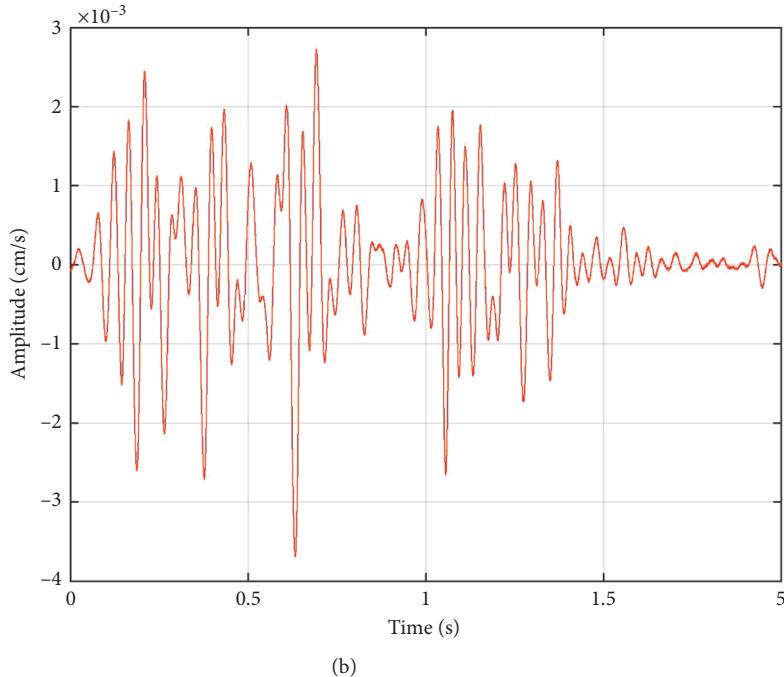
and tests. The prediction accuracy statistics of the four types of signals is shown in Table 6.

It can be seen from the statistical results that this method has high prediction accuracy for underground tunnel blast vibration and surface rock blast vibration. On the other hand, this algorithm often misjudges the pipeline explosion vibration. The cause of this phenomenon may be that the sample size was too small.

The EEMD-SVM algorithm provides us with a new means for vibration classification. Compared with commonly used BP neural network algorithms, the new method has the characteristics of high accuracy and short training



(a)



(b)

FIGURE 5: Surface rock blast vibration. (a) “Hualong No.1” foundation pit blasting project. (b) Vibration signal.

TABLE 3: Parameters of rock blasting.

Hole spacing (m)	Row spacing (m)	Hole diameter (mm)	Hole depth (m)	Explosive mass (kg)	Resistance line (m)	Explosive type	Delay time (ms)
5.5	3.2	115	13	85	2.2	Emulsion explosive $\varphi 90$	50

time. The comparison between the two methods is shown in Table 7.

It can be seen from the table that SVM algorithm has certain advantages in prediction accuracy compared with neural network algorithm, while in training efficiency, it was much better than neural network algorithm.

Furthermore, the approximate entropy and permutation entropy are calculated on the basis of the inherent modal components as input eigenvectors, which are compared with the results of the algorithm in this paper, as shown in Table 8. It can be seen that, in terms of prediction accuracy and learning efficiency, the three algorithms are

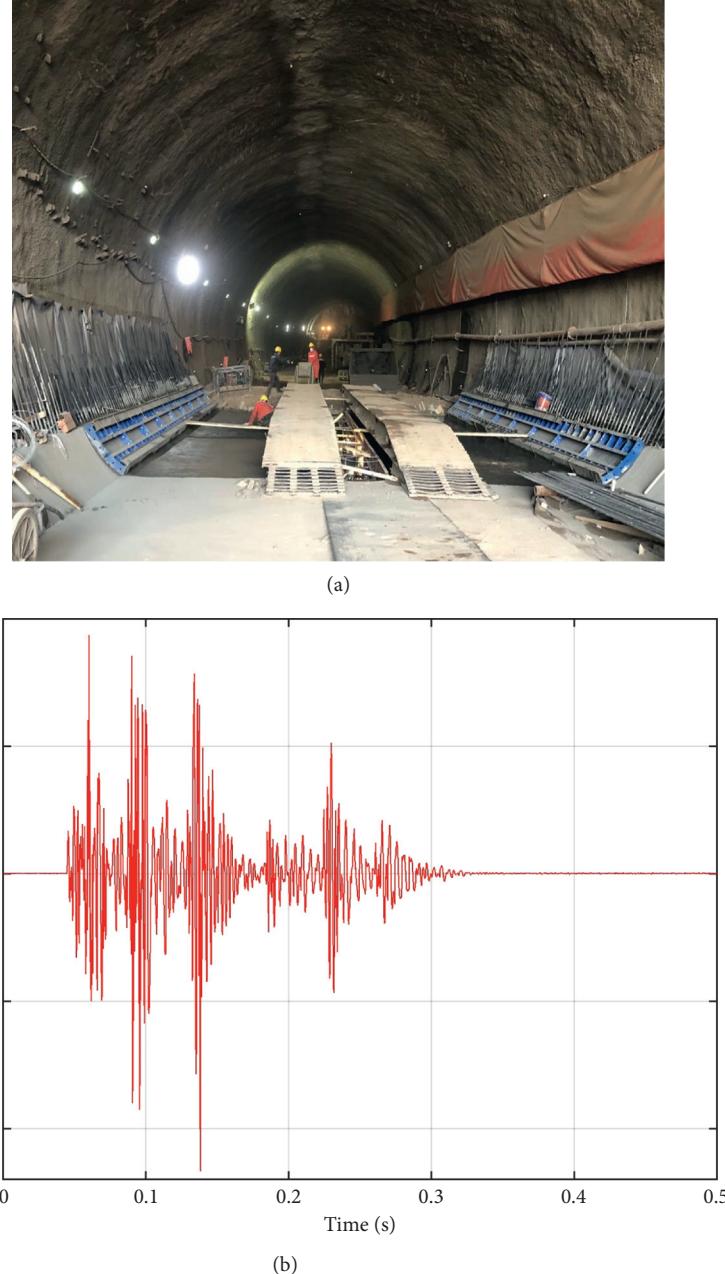


FIGURE 6: Underground tunnel blast vibration. (a) Blasting site of Nanjing metro line 3 tunnel. (b) Vibration signal.

TABLE 4: Parameters of tunnel blasting.

Blasting method	Hole spacing (cm)	Hole diameter (mm)	Hole depth (m)	Specific consumption ( $\text{kg}\cdot\text{m}^{-3}$ )	Explosive type	Delay time (ms)
Cut blasting	50	40	1.2	0.6~1	Emulsion explosive φ32	50

basically the same. However, due to the increase of approximate entropy and permutation entropy in the process of entropy calculation, the CPU time used in the construction of input eigenvectors is significantly increased,

and it is highly related to the embedding dimension (permutation entropy) and reconstruction dimension (approximate entropy) parameters, so the comprehensive efficiency is at a disadvantage.

TABLE 5: Input matrix.

Signal	Serial number	Eigenvectors								
		CEE <sub>1</sub>	CEE <sub>2</sub>	CEE <sub>3</sub>	CEE <sub>4</sub>	CEE <sub>5</sub>	CEE <sub>6</sub>	CEE <sub>7</sub>	CEE <sub>8</sub>	CEE <sub>9</sub>
Pipeline explosion vibration	1	0.0279	0.0075	0.0819	0.2489	0.0217	0.2653	0.4851	0.5305	0.4968
	2	0.0303	0.0163	0.0059	0.0062	0.0125	0.0290	0.0262	0.5166	0.4858
	3	0.0828	0.0027	0.0420	0.0961	0.4683	0.3196	0.5111	0.4434	0.0963
	4	0.0013	0.0282	0.2993	0.5303	0.4825	0.3942	0.3509	0.2898	0.0603
	5	0.0011	0.0162	0.0989	0.4106	0.5162	0.5019	0.3201	0.1050	0.0597
	6	0.0022	0.0221	0.0175	0.4069	0.5110	0.4941	0.3428	0.0698	0.1088
	7	0.0006	0.0047	0.0493	0.0700	0.2878	0.3746	0.4724	0.5305	0.4554
	8	0.0239	0.0036	0.0242	0.0733	0.4083	0.4934	0.4662	0.5040	0.3915
	9	0.0236	0.0907	0.0412	0.0705	0.4006	0.5306	0.4053	0.4942	0.2492
	10	0.0049	0.0172	0.1697	0.3350	0.3698	0.4949	0.4725	0.0911	0.0287
Underground tunnel blast vibration	11	0.5307	0.5300	0.3088	0.3942	0.0873	0.0439	0.0170	0.0097	0.0076
	12	0.3478	0.3438	0.5261	0.5194	0.3942	0.1373	0.0281	0.0133	0.0115
	13	0.3844	0.2399	0.4719	0.5265	0.5042	0.0853	0.0337	0.0118	0.0143
	14	0.3990	0.4214	0.5307	0.4871	0.2307	0.1177	0.1023	0.0685	0.0239
	15	0.2209	0.2740	0.5307	0.5300	0.3747	0.1071	0.0561	0.0226	0.0148
	16	0.4189	0.4115	0.5188	0.5222	0.2383	0.0962	0.0981	0.0332	0.0099
	17	0.5304	0.5026	0.2967	0.3365	0.3651	0.2369	0.1103	0.0315	0.0452
	18	0.3332	0.3404	0.5173	0.4970	0.4597	0.2048	0.0867	0.0247	0.0322
	19	0.3610	0.5030	0.4422	0.5287	0.2982	0.1074	0.0377	0.0463	0.0178
	20	0.4228	0.5306	0.4153	0.3757	0.3952	0.1826	0.0860	0.0401	0.0257
Demolition collapse vibration	21	0.0031	0.0040	0.0016	0.0004	0.0016	0.1478	0.4680	0.4896	0.4417
	22	0.0006	0.0001	0.0012	0.0024	0.1070	0.4057	0.2847	0.2110	0.0726
	23	0.0016	0.0004	0.0001	0.0003	0.4343	0.3062	0.4134	0.1687	0.3587
	24	0.0010	0.0003	0.0002	0.0001	0.0014	0.4967	0.2037	0.5247	0.3866
	25	0.0001	0.0001	0.0000	0.0058	0.3794	0.4942	0.4950	0.3346	0.0972
	26	0.0007	0.0003	0.0001	0.0001	0.0002	0.3554	0.4591	0.4919	0.4404
	27	0.0006	0.0002	0.0001	0.0001	0.4003	0.3324	0.3792	0.2881	0.1832
	28	0.0004	0.0003	0.0034	0.0204	0.0582	0.0786	0.4714	0.5305	0.2545
	29	0.0006	0.0002	0.0001	0.0001	0.0069	0.5259	0.5142	0.2997	0.1634
	30	0.0010	0.0002	0.0001	0.0003	0.1572	0.5283	0.5307	0.4387	0.3204
Surface rock blast vibration	31	0.0008	0.0003	0.0002	0.1390	0.4707	0.5269	0.2577	0.1172	0.0453
	32	0.0010	0.0003	0.0002	0.5307	0.5108	0.5145	0.2442	0.0731	0.0359
	33	0.0003	0.0001	0.0835	0.4339	0.5137	0.5259	0.1329	0.0407	0.0230
	34	0.0003	0.0001	0.0125	0.1499	0.5250	0.5054	0.4730	0.1849	0.1713
	35	0.0009	0.0004	0.0002	0.1870	0.5188	0.5298	0.3780	0.1559	0.0485
	36	0.0006	0.0002	0.0085	0.1743	0.2947	0.3846	0.2294	0.0591	0.0183
	37	0.0007	0.0005	0.0002	0.4827	0.5277	0.5270	0.1483	0.0348	0.0167
	38	0.0026	0.0018	0.0008	0.0878	0.5184	0.5011	0.5090	0.0774	0.0280
	39	0.0021	0.0011	0.0004	0.1693	0.4668	0.5307	0.1530	0.0472	0.0094
	40	0.0054	0.0018	0.0011	0.0007	0.5202	0.5290	0.4917	0.2858	0.2168

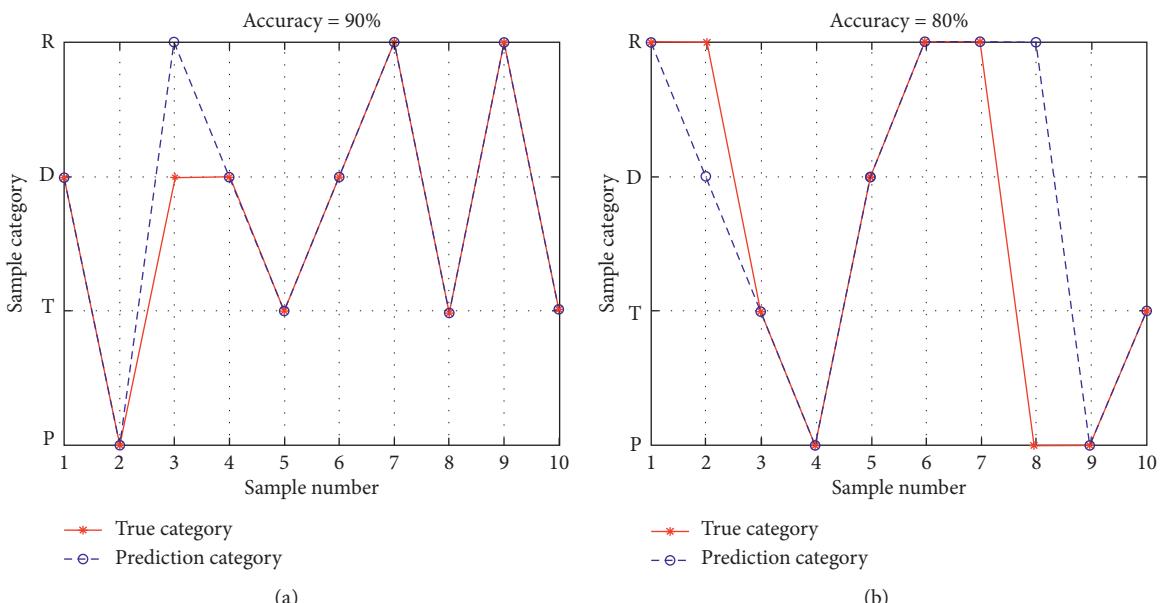


FIGURE 7: Continued.

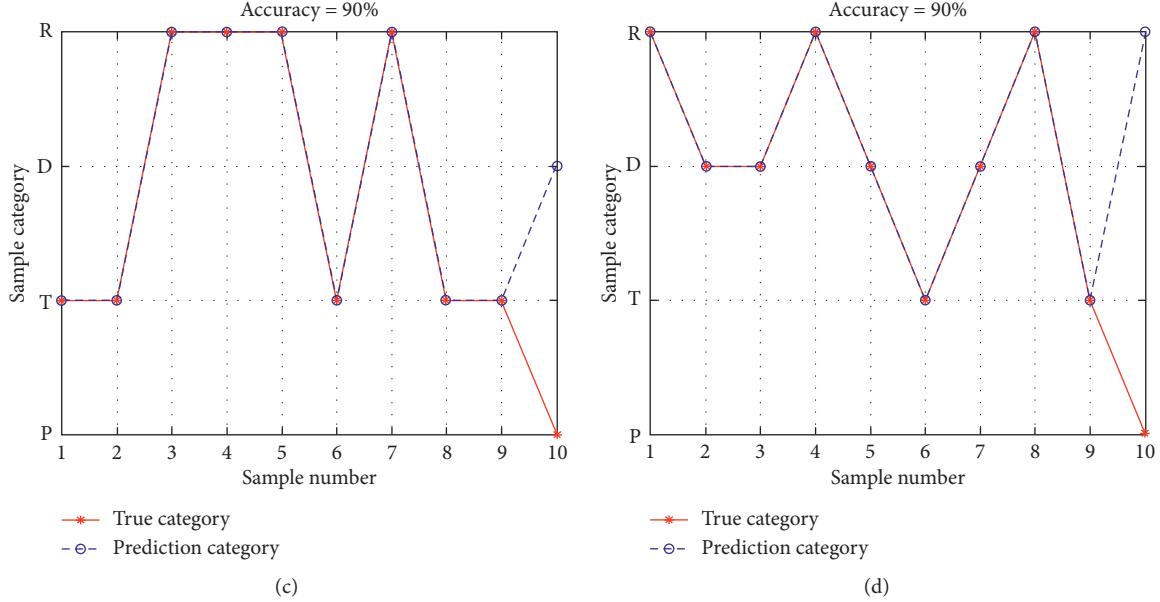


FIGURE 7: Comparison between the prediction results of SVM and the real situation. (a) First operation. (b) Second operation. (c) Third operation. (d) Fourth operation.

TABLE 6: Prediction result statistics.

Signal type	Pipeline explosion vibration (%)	Underground tunnel blast vibration (%)	Demolition collapse vibration (%)	Surface rock blast vibration (%)
Prediction accuracy	50	100	88.9	92.3

TABLE 7: Algorithm effect comparison.

	SVM algorithm		BP neural network algorithm	
	Prediction accuracy	Training time (s)	Prediction accuracy	Training time (s)
Example 1	80	131	70	502
Example 2	90	127	60	478
Example 3	90	152	70	615

TABLE 8: Algorithm effect comparison.

	EEMD energy entropy		Approximate entropy		Permutation entropy	
	Prediction accuracy	Training time (s)	Prediction accuracy	Training time (s)	Prediction accuracy (%)	Training time (s)
Example 1	80	135	80	142	90	129
Example 2	90	124	80	136	90	131
Example 3	90	156	70	161	90	167
Example 4	100	119	80	121	80	118

## 5. Discussion and Conclusion

In this study, through the cross-research of EEMD algorithm and SVM algorithm, combined with the training and prediction of 4 types of typical explosion vibration signals, the relevant conclusions are obtained as follows:

- (1) EEMD energy entropy can be used as a significant feature for explosion vibration signal recognition
- (2) Compared with the traditional BP neural network algorithm, the method in this paper has greater advantages in training efficiency and prediction accuracy

- (3) Compared with permutation entropy and approximate entropy, the method in this paper has no obvious advantages in training efficiency and prediction accuracy, but the comprehensive efficiency of the algorithm has been improved.

The new algorithm can provide reference for urban vibration monitoring and help managers to know the type of accidents in a short time to make timely decisions.

Considering that the prediction accuracy of pipeline explosion vibration signal is insufficient, the author will further collect and sort out the data and expand the sample capacity, in order to achieve higher prediction accuracy.

## Data Availability

The data used in this paper can be obtained in the following link: hyperlink <https://figshare.com/s/185b350ad6803157536c>.

## Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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