

Article

Detection of Track Bed Defects Based on Fibre Optic Sensor Signals and an Improved Hidden Markov Model

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Abstract: Railway track bed defects affect the normal operation of trains and pose great safety risks. In order to detect such issues early, we developed a railway track bed defect detection method which uses optical fibre sensors and an improved HMM (hidden Markov model) to detect the signals collected by a DAS (distributed acoustic sensing) system. First, by analysing the physical process of train operation and determining the number of hidden states, a waveform segmentation method based on average amplitude was used to solve the problem of unequal signal lengths. Second, an adaptive power spectrum energy ratio calculation method was employed to extract track fault features, a set of which was constructed by combining various quantity features. Then, normal and abnormal models were trained according to the sensor measurement area. Finally, the probability of detecting the signal with each model was compared to determine whether the signal was abnormal. Experiments were conducted to compare the applicability of the waveform segmentation method and the feature extraction method. The results show that the HMM based on both waveform segmentation and track bed defect feature sets had the highest recognition rate, the lowest number of false detection areas, and a greater impact on the signal in the early development stage of track bed defects. The proposed method, therefore, has strong recognition ability, which makes it suitable for track bed defect detection.



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Keywords: signal processing; distributed acoustic sensing; hidden Markov model; track bed defect detection

1. Introduction

Metro rail is arguably the most important form of rail transport. The prerequisite of its punctuality and efficiency, which make it convenient for people's daily journeys [1], is that rail transit lines operate normally. Track defects are among the many factors that affect the normal operation of rail transit. As the service life of rail lines increases, track bed defects gradually appear. Although early track bed defects do not have a major impact on the normal operation of trains, as time goes by, early symptoms gradually appear and develop into problems that significantly threaten the safety of rail transport, such as track bed bulging, subsidence, fractures, track slab and ballast voids, etc. [2–5]; in particular, the separation of the track slab from the substructure significantly affects normal train operation, so it is becoming increasingly important to identify and prevent this problem in time.

In this study, a DAS system was used to collect driving vibration signals [6]. During train operation, the train itself acts as a vibration source, causing vibrations in the track bed. A DAS system collects vibration signals through sensors placed on the track bed. The internal structures of a normal track bed and a damaged track bed are different, and so are the response signals collected with the sensors. This feedback reflects differences in the internal structure of a track bed and allows for the detection of defects that cannot be identified by using existing technology. However, there is currently no complete set of

technological devices and methods for analysing track bed defects based on the vibration signals of rail transit trains.

Driving vibration signals are time-series data. Methods for detecting anomalies in time series are mainly classified in three categories: clustering-based methods [7–10], deep learning-based methods [11–13], and statistical-analysis-based methods [14,15]. For driving vibration signals, there are structural differences in anomaly-containing measurement areas, resulting in large differences compared with normal measurement areas. Therefore, cluster analysis is prone to misjudgement under unsupervised conditions, making this method not suitable for driving vibration signal anomaly detection. Methods based on deep learning have high detection accuracy, but their computational complexity is high, and they cannot meet the real demand of detecting a large amount of data every day. As a dynamic statistical analysis model, the HMM can make full use of the contextual relationships of signals, has strong recognition ability for temporal signals, and displays good accuracy in detection results; thus, it has become a mainstream technology in speech recognition and other fields [16]. In recent years, the HMM has also been applied to the field of time-series anomaly detection [17–20]. As a machine learning method, it has higher detection accuracy and lower computational complexity than deep learning models.

In driving vibration signal anomaly detection, the application of the HMM requires the length of the input sequence to be consistent. In traditional methods, first, the time series is aligned with DTW (dynamic time warping) or resampling technology [21,22]; then, the window is shifted based on fixed window length and frame shifting to divide the signal into equal-length frames to ensure that the signal enters the HMM. The input sequence lengths are thus constant. In case of a large amount of data, the use of DTW or resampling technology is time-consuming and laborious, and the fixed window length and frame shift framing methods produce transition frames between different states when applied, which affects model efficiency. In addition, rail transit lines are complex, and there are large differences among normal signals, which requires a more in-depth feature analysis of abnormal signals. Traditional feature extraction methods have some practical applications, but they cannot be employed to fully describe the characteristics of defects.

In response to the above problems, in this study, we developed a railway track bed defect detection method (DAS-HMM) based on optical fibre sensor signals and an improved HMM. It was verified on real driving vibration signal data that this method can effectively improve accuracy in track bed defect detection.

The principal innovations and contributions of this study are outlined below.

We established a waveform segmentation algorithm based on average amplitude to address the issue of variable-length vibration signals. This algorithm ensures that input sequences are of equal length, thereby avoiding signal alignment problems and improving short-term signal quality.

A new feature quantity suitable for roadway defect detection, the adaptive power spectrum energy ratio, which can adequately describe frequency domain differences among abnormal signals, is proposed.

The HMM method was applied to the driving vibration signals sensed by a DAS system for the first time. The experimental results on real data sets demonstrate that the proposed feature quantity and waveform segmentation method exhibit greater accuracy than traditional methods.

The structure of this article is as follows. In Section 2, theoretical knowledge related to the HMM is presented. In Section 3, we elaborate on the specific methods of applying the HMM based on DAS signals and present preliminary experimental comparisons with real signals. In Section 4, we describe the setup of the experiments performed to verify the effectiveness of the recommendations, and we present and analyse the results. Finally, in the Section 5, we summarise the key findings and explore potential avenues for future research.

2. DAS and Theoretical Basis of the HMM

2.1. DAS System

The advantage of DAS systems is that they can perform full-time and full-domain monitoring. The DAS system used in this study to detect the vibration signals of trains is shown in Figure 1. The continuous light emitted by the narrow linewidth laser is modulated into an optical pulse signal of fixed pulse width by an electro-optical modulator. The optical pulse signal is then amplified by an erbium-doped fibre amplifier and transmitted through a circulator to a UWFBG (ultra-weak fibre Bragg grating) array located in the monitored structure. As the fibre monitors the strain change caused by vibration, the grating in the fibre grating array returns a pulsed light signal at different times. Each grating vibration sensor has a reflection spectrum that enters the demodulator. The interferometer calculates the wavelength parameters of the measurement area by demodulating the reflection spectrum between two adjacent UWFBGs and outputs the interference result to three photodetectors. In this way, the vibration signal of a rail transit train can be obtained after photoelectric conversion. The length of the delay fibre in the Michelson interferometer is the same as the interval between adjacent UWFBGs in the optical cable. The distance between adjacent grating vibration sensors is 5 m. Each pair of sensors and the optical fibres between them form a measurement area.

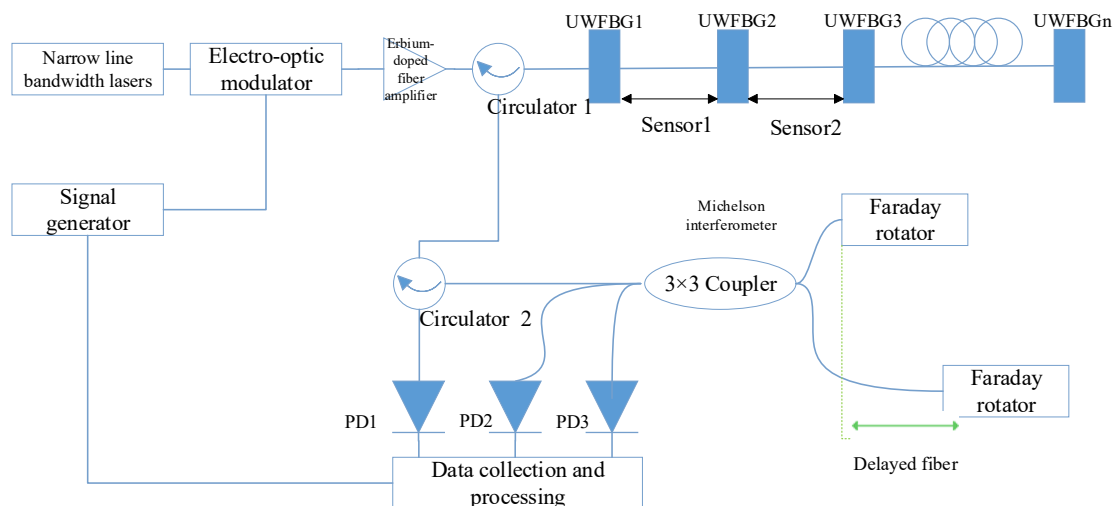


Figure 1. DAS system diagram.

2.2. Theoretical Basis of the HMM

The HMM has a strong ability to identify temporal information. This model is derived from the Markov chain and contains hidden states, but the problem described here is more complex than the Markov model. It essentially describes a dual stochastic process, including the randomness of state transitions and the randomness of the observation events that depend on the states. When processing driving vibration signals, each state of the HMM can correspond to multiple frames of observations, i.e., the feature vector extracted from the short-term signal. The HMM can be divided into the discrete HMM and the continuous HMM according to the calculation method of the occurrence probability of the observation sequence. The distribution of the observation values of the driving vibration signal is continuous, and the differences within the normal measurement range are large; thus, it is not appropriate to use the clustering algorithm to represent the continuous sequence and then use the discrete HMM. In this study, we used HMM-GMM (hidden Markov model–Gaussian mixture model) for modelling.

HMM-GMM mainly includes five parameters; the model can be expressed as $\lambda = (\pi, A, B, \mu, U)$. The initial state matrix is $\pi = \pi_i, 1 \leq i \leq N$, where N is the number of states and π_i represents the probability that the state is S_i at the initial moment, where $S = \{S_1, S_2, \dots, S_N\}$ is the set of all state values. The probability of transition

between states is represented by the state transition matrix. When the observation value is given, the probability density in different states is determined by the emission matrix, B , which includes M (the GMM order), the mean vector, μ , and the covariance matrix, U , representing the probability of occurrence of O_k in a state. The specific derivation of the above algorithm can be found in [16].

3. DAS-HMM Method

The detection of track bed defects based on a DAS system is essentially a time-series anomaly detection problem. The process flow of the DAS-HMM method established in this study is shown in Figure 2. To solve the problem of input sequence inconsistency caused by signal length, we designed a waveform segmentation method that avoids complex signal alignment algorithms and ensures that the input sequence length is the same. Based on the abnormal fluctuations of abnormal signals, a track bed defect feature set was constructed, which solved the problem of the low discrimination of existing features.

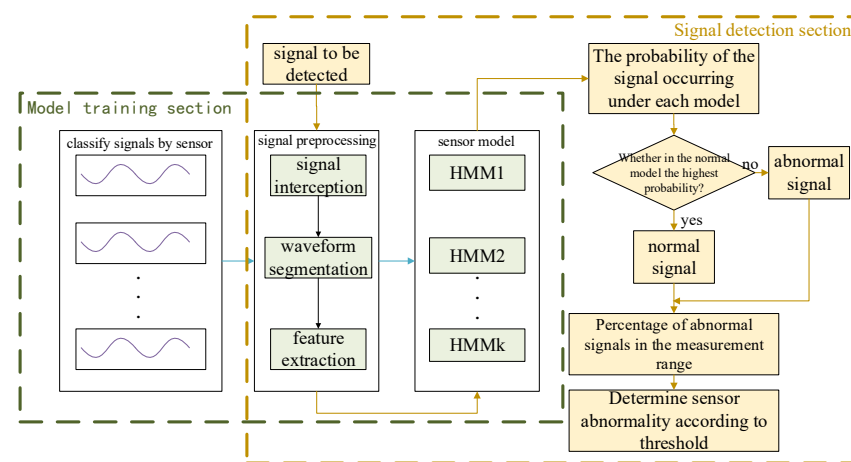


Figure 2. Flow chart for detection of track bed defects based on HMM.

In the model training step, a set of long-term signals, i.e., all signals returned by the sensors within a certain time period, is selected from each of the k measurement areas. First, a long-term signal is intercepted [23], and the multi-segment driving vibration signal obtained after interception is retained. For each measurement area, several sets of driving vibration signals are used as training sets. The signals are divided into sub-waveforms by the waveform segmentation module; then, feature extraction is performed on these sub-waveforms to obtain the feature vector of each sub-waveform. At this point, each segment of the driving vibration signal is converted into an observation sequence of the same size, which is, in turn, used as input for the Baum–Welch algorithm. After the iterative solution is found, the model parameters of the HMM are obtained, and a total of k models are trained.

In the signal detection step, first, the signal to be detected is preprocessed; then, the probability of its occurrence under all models is calculated, and its vector in all measurement area models is obtained. The model corresponding to the maximum value in the vector element is then found. If the corresponding model is a normal measurement area model, the signal is determined to be normal; otherwise, it is determined to be abnormal. Finally, the classification status of the signals in the measurement area and the proportion of abnormal signals are calculated, and the health status of the measurement area is determined by delimiting the threshold.

3.1. State and Signal

The signal comes mainly from the vibration of the train, which is transmitted through the bogie to the track bed, and finally converted into a digital signal by the sensor. When a train passes through the measurement area, there are four bogie states, which are listed in

Table 1. The actual scenario corresponding to each state is shown in Figure 3. The power of the signal is shown in Figure 4.

Table 1. Physical processes corresponding to four states.

Hidden State	Number of Bogies	Main Signal Source
S_1	0	White noise
S_2	1	Front or rear bogie
S_3	0	Residual waves of front and rear bogies
S_4	2	Front and rear bogies

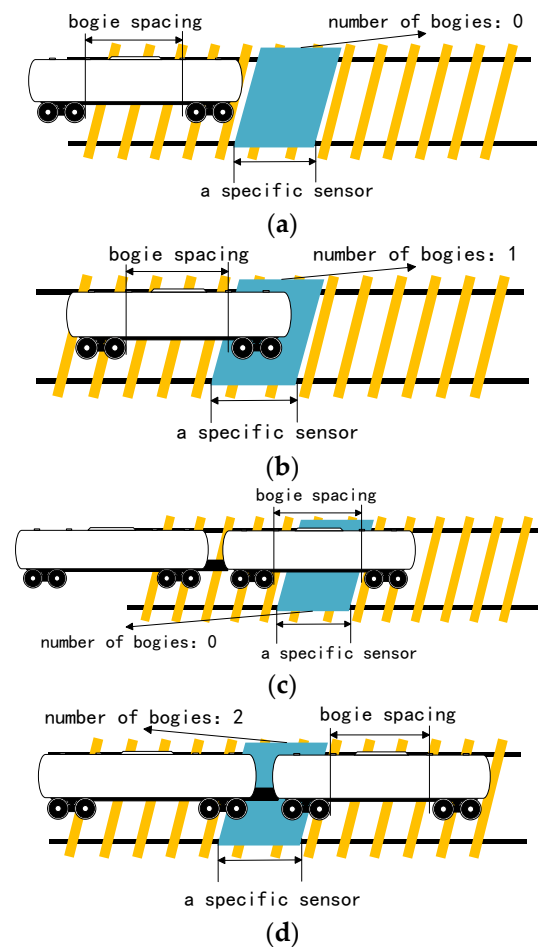


Figure 3. Schematic representation of each state of train operation corresponding to the actual scenario: (a) state S_1 ; (b) state S_2 ; (c) state S_3 ; and (d) state S_4 .

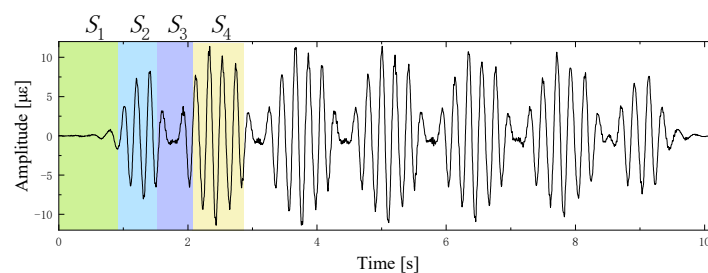


Figure 4. Signal state division diagram.

For example, the actual driving scenario of a train in S_2 corresponds to Figure 3b. In this case, one bogie of the train is located in the measurement area, and the signal comes

mainly from the vibration transmitted from the bogie to the sensor, as shown in the S_2 part of Figure 4.

3.2. Waveform Segmentation Based on Average Amplitude

In the traditional framing method, first, a complex signal alignment algorithm is required to make the time series equal in length; then, the frame is divided by using a fixed sliding window. With this method, the transition between different states of the signal is not taken into account, which makes it suitable for processing high-frequency signals. The fundamental frequency of the driving vibration signal is low, and the state transitions are frequent. With the traditional framing method, there are a large number of transition frames between different states. The framing effect of the traditional method on the driving vibration signal is shown in Figure 5. For example, the red part of the signal in Figure 5 contains almost half of the S_2 state and all of the S_3 state. It is difficult for the model to accurately predict the state at this time.

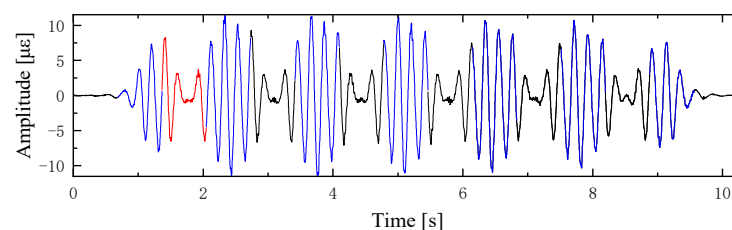


Figure 5. Traditional method of framing rendering.

Although the lengths of driving vibration signals are different, the same physical process occurs when the train passes a sensor; therefore, these signals behave similarly in waveform and can be seen as different degrees of stretching in the time dimension. Based on this, we established a waveform segmentation method based on average amplitude according to the characteristics of the driving vibration signals, as shown in Figure 6. The idea is to find the waveform in S_3 . The amplitude of this part of the signal is relatively small, and the interval between adjacent waveforms is long, making it easy to distinguish. Except for S_1 , all transitions between different states must pass through S_3 , so finding all S_3 allows for the separation of all the waveforms.

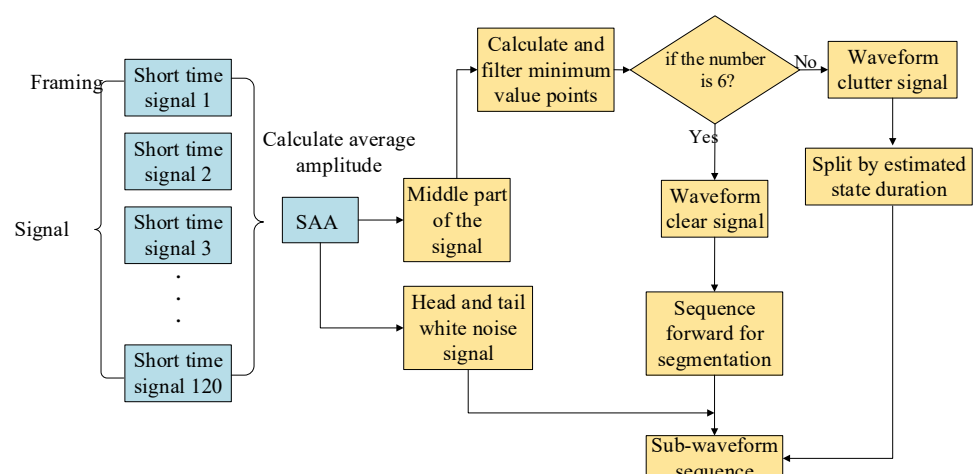


Figure 6. DAS-HMM waveform segmentation method flow chart.

First, the driving vibration signal is processed into frames. When evaluating the signal waveform, it is important to divide it into detailed frames to minimise the interference of the transition frames with the waveform assessment. This is particularly crucial for signals with a short duration, where it is necessary to retain an adequate number of frames.

However, the frames should not be too fine, as this may result in incomplete information about the waveform within each frame and increase the computational load. In general, the state with the shortest duration represents approximately 0.07 of the entire signal. To meet the above requirements, it is sufficient to maintain this state for 8 to 10 frames. Therefore, in our method, the signal is divided into 120 frames for waveform segmentation.

The average amplitude of each frame of the signal is calculated, and the short-term signal average amplitude (SAA) sequence is generated. The long-term signals collected by the DAS system contain a large number of white noise signals when no trains are passing; as these signals are meaningless in detecting track bed defects, we need to remove them to improve the quality of the data set. To do so, it is common practice to discard the first and last six frames. As the amplitude of white noise signals is often less than 0.5, in our method, we divide the long-term signal into frames. Each frame is 1 s long and contains 1000 points of short-term signals. If the average amplitude of the signal in this frame is less than 0.5, it is discarded immediately; otherwise, it is regarded as the beginning of the driving vibration signal; on the other hand, it is regarded as the end of the signal if the average amplitude of the following frames is less than 0.5. It should be noted that when a driving vibration signal is intercepted, the frame length is set to 1000 sample points for high interception efficiency. As a result, there is still a small amount of white noise in the intercepted signal, i.e., state 1, which affects waveform segmentation. Therefore, we need to further remove this white noise. This part of white noise is usually about 0.05 of the total signal length, so it can be effectively separated by removing the first and last six frames of the signal, as mentioned above. Since the key is to find state 3, even if part of the waveform in state 2 is deleted by applying the above method, this does not affect waveform segmentation.

After removing the white noise, we search for the minimum points of the SAA sequence. These extreme points contain not only S_3 but also some noise. Therefore, we need to filter these minimum points and retain the points that are 1.3 times greater than the minimum and less than 2 times greater than the minimum. Finally, the waveform state is determined based on the number of filtered extreme points. If the number of extreme points after filtering is the same as the actual number of S_3 , i.e., six (corresponding to the number of wagons), the signal is determined to be a clear waveform signal. Since the minimum value point corresponds to the mean time of S_3 , it is necessary to shift the sequence of minimum value points forward by approximately half the number of frames, typically three to five frames, to match the state start time, and then segment the signal. If the number of minimum value points after screening is not six, it means that the SAA sequence is unclear and that the signal waveform is poor; the signal is then identified as a chaotic waveform signal.

Signals with complex waveforms are segmented based on the pre-estimated duration ratio of each state. The motion signal is also segmented into 15 segments to match the number of segmented frames. An effect diagram of the waveform segmentation and framing method based on average amplitude is shown in Figure 7. Taking the red part of the signal in Figure 5 as an example, the frame generated by applying waveform segmentation contains only one state, S_3 . The transition parts between different states in Figure 5 are correctly segmented (orange ellipse part).

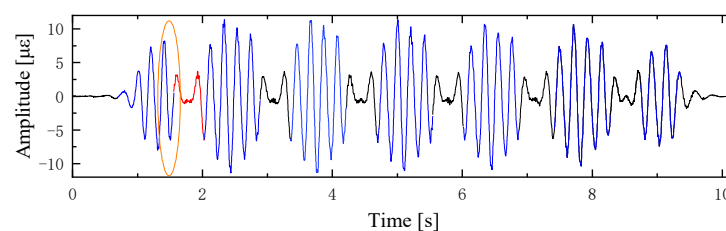


Figure 7. DAS-HMM waveform segmentation rendering.

3.3. Feature Extraction Based on Anomalous Fluctuations and Autoencoders

3.3.1. Existing Feature Extraction Methods and Abnormal Signal Power Analysis

In this study, we aimed to develop a method for extracting track bed defect features from DAS system signals, an area not fully covered by the existing literature. Signal feature extraction focuses on three aspects: the time domain, the frequency domain, and model coefficients. Feature quantities for time domain analyses are very versatile. Commonly used feature quantities include mean, variance, energy, extreme value, zero crossing rate, etc. Frequency domain analysis relies more on signal characteristics, among which features based on power spectral density and spectral entropy are widely used. In terms of parameter models, most are based on the AR (auto regressive) and MA (moving average) models. The former focuses on the influence of past values of the time series itself, while the latter focuses on the influence of past error terms. The abnormal signal manifestations and the track bed defect feature set constructed based on them are presented below.

Track bed defects [24] mainly manifest in three aspects. Firstly, the original rigid structure of the track bed appears to have changed. When external forces are applied, the displacement in a defective track bed is larger than that in a normal track bed, the amplitude of the corresponding signal is larger, and the instantaneous impact is stronger [16]. Secondly, when the track bed structure is damaged, the interaction within the track bed is enhanced when a train passes, exacerbating damage to the track bed structure [17]. This interaction is different from the excitation of the track bed by a train and produces abnormal fluctuations that are not found in normal signals. In addition, due to the changes in the vibration transmission process caused by the damage to the internal structure, the signal waveform of a defective track bed is different from that of a normal signal, and there are certain differences in its model coefficients. A typical abnormal signal is shown in Figure 8. The above physical analysis of track bed defects is reflected in these signals. The peak value of the signal waveform exceeds 50, which is larger and has more ridges than the normal signal shown in Figure 4. The waveform of the normal signal is more regular.

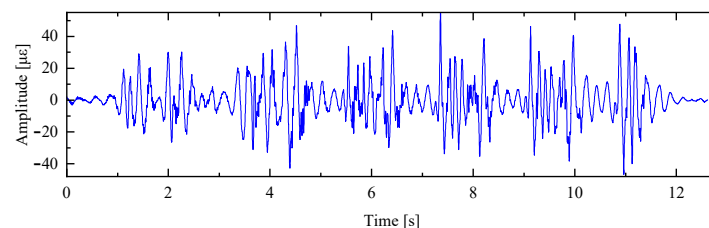


Figure 8. Typical abnormal signal.

Conditions in railway measurement areas are complex. For example, the track bed near the expansion joints has a large vibration amplitude, and so does the signal; furthermore, some sensing fibres conflict with existing lines, resulting in chaotic waveforms and high spectrum complexity. These cases require comprehensive feature extraction. Existing feature extraction methods are inadequate in distinguishing the frequency domain features and model parameters of driving signals. In this study, we developed an adaptive power spectrum energy ratio calculation method in the frequency domain; in terms of model parameter features, an AR+ autoencoder is selected based on the changes before and after defect development. The final feature set of the track bed defect includes the following feature quantities: average amplitude, energy, spectral entropy, power spectrum energy ratio, and AR+ autoencoder.

3.3.2. Adaptive Power Spectrum Energy Ratio for Abnormal Fluctuations

To accurately describe the difference in abnormal fluctuations, we propose a new feature quantity in the frequency domain: the adaptive power spectrum energy ratio. A driving signal has a main-frequency component that is related to speed and has high energy. However, a train accelerates and decelerates during its journey, so the main frequency fluctuates to some extent. A power spectrum energy comparison diagram of normal and

abnormal signals is shown in Figure 9. The range of such fluctuations in the main frequency is small, generally within 2 Hz, but abnormal fluctuations are evident from 0 to 6 Hz above the main frequency. On the basis of the above differences, the adaptive power spectrum energy ratio feature quantity is proposed.

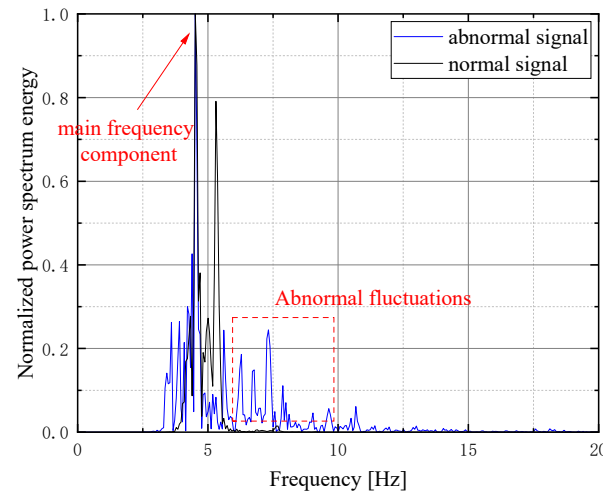


Figure 9. Signal power spectrum energy ratio comparison chart.

The method for calculating the adaptive power spectrum energy ratio is as follows. First, the Fourier transform of signal $x(n)$ is calculated with Equation (1):

$$X(k) = \sum_{n=0}^{N-1} e^{-j\frac{2\pi}{N}nk} x(n) \quad (1)$$

Above, $k = 0, 1, \dots, N - 1$, where N is the number of Fourier transform points, which is the smallest power of 2 greater than the number (L) of data points in the signal; e is the natural logarithm; and j is the imaginary unit. Then, we calculate the power spectrum energy of the signal with Equation (2):

$$P(k) = \frac{1}{N} |X(k)|^2 \quad (2)$$

The main frequency (F) is given by Equation (3):

$$F = \max[P(k)] \quad (3)$$

The energy of abnormal fluctuations is mainly distributed in the frequency range 2.5 Hz to 5.5 Hz above the main frequency of the signal, and this frequency band is recorded as the abnormal fluctuation frequency band. We calculate the energy ratio (R) of the abnormal fluctuation frequency band with Equation (4):

$$R = \frac{P_2}{P_1} \quad (4)$$

Above, R is the energy ratio of the adaptive power spectrum, P_2 is the energy portion of the range 2.5 Hz to 5.5 Hz above the main-frequency component of the signal, and P_1 is the energy portion of the signal range 0 Hz to 50 Hz.

3.3.3. Model Coefficient Feature Extraction

The AR model shows excellent performance on time series with relatively simple spectra and has lower computational complexity than the MA model. Moreover, there is no requirement for the length of the input data, which is suitable for the feature extraction

of short-term signal units. To use the coefficients of the AR model as features, it is also necessary to determine the weight of each order coefficient. The autoencoder can solve the weight problem of the AR coefficient and can also mine the nonlinear information in the AR coefficient and reduce its dimension. Therefore, in this study, we innovatively used AR coefficients and autoencoders. The autoencoder model is trained according to the signal state. The analysis of the signal state is presented in Section 3. Figure 10 is a schematic diagram of the autoencoder training model.

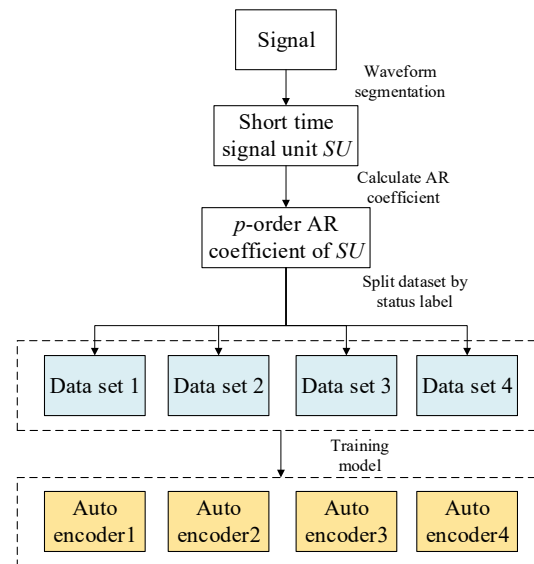


Figure 10. Autoencoder model training diagram.

After the signal has been framed by using the waveform segmentation method introduced in Section 3, each short-term signal unit SU is obtained; then, the 13th-order AR coefficient of each SU , i.e., the short-term signal AR coefficient (SC), is calculated. Each SC vector is assigned its corresponding state label, and these SCs are divided into four data sets according to the state label. For example, the first frame in Figure 6 is S_1 and is divided into data set 1. Finally, the autoencoder model is trained on each data set. After the test set samples have been processed by the trained autoencoder model, the hidden layer representation, which is the model parameter feature of the signal, is obtained.

4. Experimental Analysis

4.1. Experimental Data Description and Software Environment

In the experiment, we used data collected from a specific section of Wuhan Rail Transit Line 8 from 2022 to 2023, with a total of 114 measurement areas. They were collected using a DAS system with a sampling rate of 1000 Hz. The effects of track bed defect development change gradually over time, and we divided it into early and late stages according to the time periods. Early-stage defect development is a gradual transformation process from normal to abnormal and can be further divided into pre-early-stage and post-early-stage development. There were two track bed defects in the interval considered. In order to be close to the actual application scenario, we used the abnormal data in the early and late stages of the first track defect as the training set, and the corresponding data of the second track defect as the test set. Each measurement area used 60 sets of passing traffic signals to train the HMM; as the normal measurement area encompassed various types of track beds, including shock-absorbing track beds [25,26], vibration-absorbing fasteners, and overlapping optical cable lines, the signals in the abnormal measurement area exhibited similar behaviour. To cover all scenarios, a model had to be constructed for each measurement area. Therefore, a total of 112 normal models and 2 abnormal models were trained.

The operating system used was Windows 10 (Professional Edition), and the MATLAB version used was R2023a; the computer configuration is shown in Table 2.

Table 2. Computer configuration.

Project	Configuration	Experimental Use
CPU	Xeon 4216 (32C64P)	Data calculation
Computer memory	256 GB (DDR4 2400 MHZ)	Data exchange
GPU	NVIDIA RTX 3080	Graphics rendering output
Computer disc	50 TB (HDD)	Data storage

4.2. Comparative Experimental Design

To verify the effectiveness of waveform segmentation and feature extraction in this study, three methods were used for experimental comparison. The specific methods are listed in Table 3. For the experimental group, we used the feature set and waveform segmentation proposed in this study to improve the HMM method for track bed defects. For control group 1, we used the HMM method on the traditional feature set, with reference to the time–frequency features used in [18]. For control group 2, we used the time–frequency features proposed in this study. The feature set of control group 2 was similarly based on the traditional feature set, but we did not use the waveform segmentation method. Changes in the feature set may affect the accuracy of the model in classifying events, while the use of waveform segmentation may improve the efficiency and accuracy of the model in processing signals. By comparing three sets of experimental results, the effects of the feature set and waveform segmentation method on track bed defect detection were evaluated.

Table 3. Table of differences in three experimental methods.

Experimental Group	Method
Control group 1	Traditional framing + traditional feature set
Control group 2	Traditional framing + track bed defect feature set
Experimental group	Waveform segmentation + track bed defect feature set

The test set included two data sets, i.e., the early and late development stages of the second track bed defect. The data included 112 normal measurement areas and 2 defect measurement areas. Based on the data balance and actual application scenarios, we conducted two tests with statistical indicators. In the first test, we selected 500 sets of normal samples and 240 sets of abnormal samples from the two test data sets and calculated three indicators: accuracy, recall, and precision. In practical applications, the health status of each measurement area is not known before detection, so the same number of signals was selected for each measurement area for the second test. We selected all measurement areas of the two data sets, each containing 60 sets of passing vehicle data, and calculated the proportion of abnormal signals in these data. The number of false detection areas, NF (number of false sensors), where the proportion of abnormal signals was greater than the threshold, was used as the evaluation index, for a total of four evaluation indices.

4.3. HMM Modelling Test

The HMM requires a number of iterations for training convergence. As shown in Figure 11, we plotted the iteration curves of the HMM in normal and abnormal measurement areas. As can be seen from the figure, all models could converge after two iterations, indicating that the training speed of the HMM is faster. The stopping condition we adopted was that the number of iterations reached 10 or the iteration error was less than 10^{-6} . This stopping condition can effectively avoid the problems of overfitting and underfitting. When calculating the probability of the emission matrix using the HMM-GMM method, the probability of a single point cannot be calculated, so the probability density function values

of the distribution are used instead [16], and these values are allowed to be greater than 1. To avoid data overflow, the logarithm of the probability is considered in the calculation.

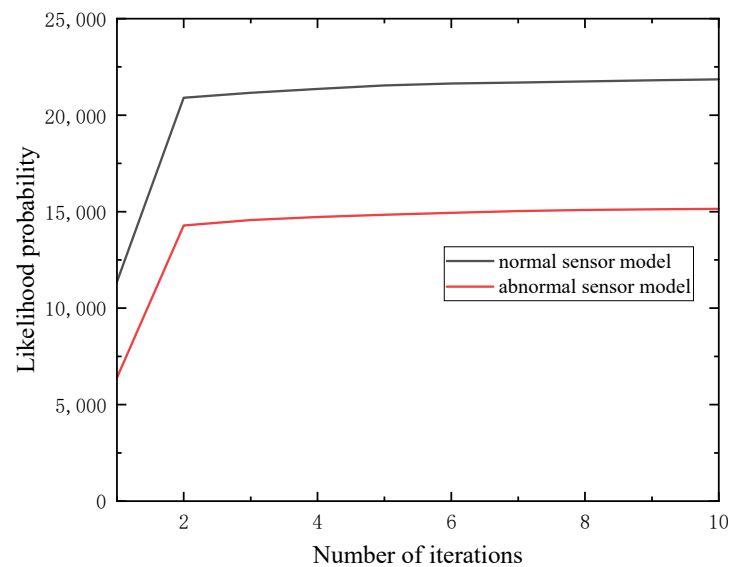


Figure 11. HMM training iteration curve chart.

The development of track bed defects is a gradual process, and the proportion of abnormal signals in the measurement area also increases as defects develop. In the experiment, the assessment threshold of NF was set to 0.4, which is conducive to the early detection of track bed defects. This is an empirical threshold. The test results of the control and experimental groups on the two data sets are shown in Table 4, according to which the detection results in the early development stage of the defect are worse than those in its late development stage. This is because, as time passes, defects gradually intensify, and the abnormal data become more obvious, which is consistent with the actual scenarios.

Table 4. The HMM detection results for the three methods.

Data Set	Method	Precision	Recall	Accuracy	NF
Pre-defect stage	Control group 1	0.5514	0.9833	0.8676	2
	Control group 2	0.7692	1.0000	0.9514	1
	Experimental group	0.8676	0.9833	0.9730	0
Post-defect stage	Control group 1	0.7643	1.0000	0.9500	1
	Control group 2	0.9916	0.9833	0.9959	0
	Experimental group	0.9752	0.9833	0.9932	0

First, if we compare the experimental results of control groups 1 and 2 based on different feature sets, we can see that control group 2 had significantly higher precision and accuracy on the two data sets than control group 1, as well as a smaller NF value. By optimising the feature set, we increased accuracy from 0.5514 to 0.7692, indicating that our proposed feature set for bed defect hazards has better results in real scenarios. Then, by comparing control group 2 and the experimental group based on different framing methods, we can see that there was not much difference in the various indicators in the early and late development stages of the defect and that abnormalities were accurately detected. In the early stage of defect development, the accuracy and precision of the experimental group were higher than those of control group 2, while the experimental group achieved zero misjudgements of the health status of the test area. This shows that the method proposed in this study can be used in situations where the defect is not yet evident. Under this condition, abnormalities can be keenly and accurately detected, and the health status of the measurement area be accurately determined. This function helps to reduce the workload of

public works railway departments in detecting false alarms in the field, and is therefore of great value in practical applications. In general, there was no significant difference in the recall rate between the methods, but the method we propose displayed significant advantages in the detection of early-stage defects, especially in terms of precision and NF.

The track bed defect detection method proposed in this study has a high detection rate for signals in the defect detection area, and it also has accurate results when calculating the optimal hidden state sequence by using the Viterbi algorithm. The hidden state path diagram of a typical normal signal is shown in Figure 12. The experimental results show that the calculated optimal path is highly consistent with the state transition sequence observed in the actual physical process and that the state of each waveform can be accurately determined.

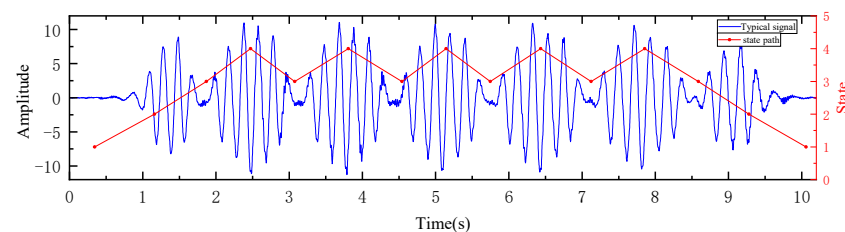


Figure 12. Optimal hidden state path diagram of a typical normal signal.

5. Conclusions

By addressing the problem of different lengths of driving vibration signals, in this study, we developed a waveform segmentation algorithm based on average amplitude to ensure the consistency of input sequence lengths, avoid computationally complex signal alignment algorithms, and improve short-term signal quality. Given the gaps in research on the extraction of track bed defect features from DAS signals, we analysed the performance of our method in detecting track bed defects and improved it with the adaptive power spectrum energy ratio; finally, an AR+ autoencoder feature was developed for model coefficient analysis. Moreover, combined with existing feature extraction methods, a track bed defect feature set was constructed. It was shown that the DAS-HMM method can be used to achieve the accurate and efficient detection of track bed defect signals.

In the future, we will extend our work by considering data dimensionality reduction, i.e., reducing the dimensionality of multiple passing signals from the same measurement area and using a simple algorithm to select a representative sample to achieve more efficient track bed anomaly detection.

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References

1. Cao, C.; Li, X.; Gao, Q. Independent Safety Assessment Strategy for Urban Rail Transit Vehicles. *Urban Rail Transit Res.* **2024**, *27*, 196–201.
2. Li, P. Research on Interlayer Damage and Its Effects of CRTS Type II Plate Track. Ph.D. Thesis, Southwest Jiaotong University, Chengdu, China, 2017.
3. Chen, Z.; Xiao, J.; Zhang, W.; Li, W.; Liu, X. Research on the influence of initial arch deformation on CRTS II track slab camber. *Railw. Stand. Des.* **2018**, *62*, 46–52.

4. Hu, Z. Research on high-temperature deformation and damage mechanism of high-speed railway CRTS II plate ballastless track. *Railw. Stand. Des.* **2017**, *61*, 46–50.
5. Zhao, L.; Liu, X.; Bi, L.; Li, J. Research on the arch deformation characteristics of CRTS II type slab track under high temperature load. *Trans. Railw. Sci. Eng.* **2019**, *16*, 277–286.
6. Zhang, X.; Ding, Z.; Hong, R.; Chen, X.; Liang, L.; Zhang, C.; Wang, F.; Zou, N.; Zhang, Y. Phase-sensitive optical time-domain reflection distributed optical fiber sensing technology. *Acta Opt. Sin.* **2021**, *41*, 100–114.
7. Jain, A.K.; Dubes, R.C. *Algorithms for Clustering Data*; Prentice-Hall, Inc.: Upper Saddle River, NJ, USA, 1988.
8. Yang, H.; Mao, H.; Huo, W. Research on the application of clustering HMM model in QAR data analysis. *Comput. Appl. Softw.* **2018**, *35*, 85–91.
9. Chen, L.; Chen, C. A multiple-kernel fuzzy c-means algorithm for image segmentation. *IEEE Trans. Syst. Man Cybern. Part B* **2011**, *41*, 1263–1274. [[CrossRef](#)]
10. Pal, N.R.; Bezdek, J.C. On cluster validity for the fuzzy c-means model. *IEEE Trans. Fuzzy Syst.* **1995**, *3*, 370–379. [[CrossRef](#)]
11. Pang, G.; Shen, C.; Cao, L.; Hengel, A.V.D. Deep learning for anomaly detection: A review. *ACM Comput. Surv. (CSUR)* **2021**, *54*, 1–38. [[CrossRef](#)]
12. Munir, M.; Siddiqui, S.A.; Dengel, A.; Ahmed, S. DeepAnT: A deep learning approach for unsupervised anomaly detection in time series. *IEEE Access* **2018**, *7*, 1991–2005. [[CrossRef](#)]
13. Ma, X.; Wu, J.; Xue, S.; Yang, J.; Zhou, C.; Sheng, Q.Z.; Xiong, H.; Akoglu, L. A comprehensive survey on graph anomaly detection with deep learning. *IEEE Trans. Knowl. Data Eng.* **2021**, *35*, 12012–12038. [[CrossRef](#)]
14. Lin, Z.; Houyu, Z.; Siyan, X. A review of anomaly detection methods and their applications. *Comput. Appl. Res.* **2020**, *37*, 9–15.
15. Soule, A.; Salamatian, K.; Taft, N. Combining filtering and statistical methods for anomaly detection. In Proceedings of the 5th ACM SIGCOMM Conference on Internet Measurement, Berkeley, CA, USA, 19–21 October 2005; p. 31.
16. Rabiner, L.R. A tutorial on hidden Markov models and selected applications in speech recognition. *Proc. IEEE* **1989**, *77*, 257–286. [[CrossRef](#)]
17. Zhang, H.; Zhou, J.; Yu, W.; Liu, H.; Zhong, G. UAV anomaly detection method based on HMM and DT. *China Saf. Prod. Sci. Technol.* **2022**, *18*, 193–198.
18. Li, L.; Hansman, R.J.; Palacios, R.; Welsch, R. Anomaly detection via a Gaussian Mixture Model for flight operation and safety monitoring. *Transp. Res. Part C Emerg. Technol.* **2016**, *64*, 45–57. [[CrossRef](#)]
19. Zhang, C.; Chen, Y.; Yin, A.; Wang, X. Anomaly detection in ECG based on trend symbolic aggregate approximation. *Math. Biosci. Eng.* **2019**, *16*, 2154–2167. [[CrossRef](#)] [[PubMed](#)]
20. Ackley, D.H.; Hinton, G.E.; Sejnowski, T.J. A learning algorithm for Boltzmann machines. *Cogn. Sci.* **1985**, *9*, 147–169.
21. Al-Haddad, S.A.R.; Samad, S.A.; Hussain, A.; Ishak, K.A.; Mirvaziri, H. Decision fusion for isolated Malay digit recognition using dynamic time warping (DTW) and hidden Markov model (HMM). In Proceedings of the 2007 5th Student Conference on Research and Development, Selangor, Malaysia, 11–12 December 2007; pp. 1–6.
22. Juang, B.H. On the hidden Markov model and dynamic time warping for speech recognition—A unified view. *ATT Bell Lab. Tech. J.* **1984**, *63*, 1213–1243. [[CrossRef](#)]
23. Young, S. A review of large-vocabulary continuous-speech. *IEEE Signal Process. Mag.* **1996**, *13*, 45. [[CrossRef](#)]
24. Sheng, X.W.; Zheng, W.Q.; Zhu, Z.H.; Qin, Y.P.; Guo, J.G. Full-scale fatigue test of unit-plate ballastless track laid on long-span cable-stayed bridge. *Constr. Build. Mater.* **2020**, *247*, 118601. [[CrossRef](#)]
25. Zbiciak, A.; Kraśkiewicz, C.; Dudziak, S.; Al-Sabouni-Zawadzka, A.; Pełczyński, J. An accurate method for fast assessment of under slab mats (USM) performance in ballastless track structures. *Constr. Build. Mater.* **2021**, *300*, 123953. [[CrossRef](#)]
26. Kraśkiewicz, C.; Zbiciak, A.; Pełczyński, J.; Al Sabouni-Zawadzka, A. Experimental and numerical testing of prototypical under ballast mats (UBMs) produced from deconstructed tires—The effect of mat thickness. *Constr. Build. Mater.* **2023**, *369*, 130559. [[CrossRef](#)]

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