Mortar layer void detection of ballastless track using the impact echo method based on support vector machine

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Abstract. High-speed railway is developing rapidly nowadays. However, under the repeated load of the natural environment and the train, the mortar layer in the ballastless track as the elastic adjustment layer of the structure could be void and cause void defects, thereby seriously affecting the performance of the track board and the safety of the high-speed train. With its simple operation and the use of portable equipment, the impact echo method is a useful nondestructive detection method for detecting defects inside the structure. However, in traditional impact echo detection, manpower is required for judging the final test results, which is highly subjective and time consuming. A field test was designed in this paper, for which a track slab measuring $6.55 \times 2.55 \times 0.24 \text{ m}$ was constructed. Complete cavitation, foam board, and Pykrete were used to simulate the void defects. A $62 \times 22$ grid with a $0.1 \text{ m}$ interval was drawn on the board, each grid point was tapped, and two sensors were placed at the standard position to collect data. Fast Fourier transform was used to obtain the amplitude–frequency domain spectrogram, while wavelet transform was used to obtain the time–frequency spectra. The spectra were processed to extract effective features and form $62 \times 22 \times 2 = 2,728$ sample data. The sample data were divided into a training set and a test set. The training set was used to train the support vector machine (SVM) to classify and identify whether a void defect exists, and the test set was used to evaluate the performance of the SVM. Genetic algorithm (GA) was applied to optimize the parameters in the SVM. Results showed that GA-SVM had a good classification effect with an accuracy of 84.26% and can effectively identify the mortar layer void of the ballastless track slab.

Keywords: Ballastless track slab, Nondestructive detection, Support vector machine, Mortar layer void, Impact echo method
1. Introduction
Defects caused by the effects of temperature, train weight, and other factors are directly related to the quality of ballastless track and the operation safety of high-speed railway. With the CRTS-II ballastless track board taken as an example, the most common defects include CA mortar deterioration and track board void (Lingyu Zhou et al., 2019; Yanbing Yang, 2015). Among the commonly used nondestructive detection methods, the impact echo method has the characteristics of gradual change, fast speed, light equipment, flexible methodology, low expense, and repeatable tests (Jaehak Park et al., 2018). A short mechanical load is used to generate low-frequency stress waves. The stress waves propagate into the structure and are reflected back from the defects and the construction surface. These reflected waves are then received and recorded by sensors installed near the impact point. The recorded signal has different amplitudes and frequencies due to the difference of the locations and types of the defects (Ting Luo, 2020; Muhammad Tariq A. Chaudhary, 2013). However, the traditional impact echo method requires manual analysis of the spectrum images through fast Fourier transform (FFT), which is subjective and laborious (Xiushu Tian et al., 2019).

With the rapid development of artificial intelligence, including machine learning and deep learning methods, these methods are widely used in various fields, such as defect detection. The impact echo method can be well combined with artificial intelligence, which can extract the characteristic values of processed signals through the algorithm, form the dataset, train the model, and test the accuracy (Chaobo Zhang et al., 2020; Amoussou-Coffi Adoko et al., 2013; A. Tavares et al., 2021).

A commonly used classification algorithm in machine learning is support vector machine (SVM), which maps samples with multiple characteristic values to a higher-dimensional sample space and finds a hyperplane to make the samples linearly separable (Ofir Barzilay et al., 1999; Christopher J.C. Burges., 1998). Satar Mahdevari et al. (2013) aimed to develop a dynamically model based on SVM algorithm for the prediction of convergence in a tunnel. A set of data concerning geomechanical parameters and monitored displacements in different sections of the tunnel were introduced to SVM for training the model and estimating an unknown nonlinear relationship between the soil parameters and tunnel convergence. Hongbo Zhao et al. (2014) used a least-squares-SVM-based response surface method combined with the first-order reliability method to obtain the limited state function for tunnel reliability analysis, and they described the implementation of the method. Wen-Chieh Cheng et al. (2020) explored the potential for SVM with the most popular parameter optimization algorithms to identify changes in soil type during tunneling to reduce the possibility of jamming and geohazard development. All tunneling data were pre-processed to convert time series data into feature-based subseries.

In this paper, a field test is designed, and the impact echo method is used to detect the void defects. FFT and wavelet transform (WT) are used to process the signal, and the eigenvalue of the data is extracted. SVM optimized by particle swarm optimization and genetic algorithm (GA) is used to classify and recognize the data, achieving good effects.

2. Support vector machine
SVM is a class of generalized binary linear classifiers, which classify data according to supervised learning. Its decision boundary is the maximum-margin hyperplane solved for the learning sample.

2.1. Support vector machine algorithm
For a given set of training samples $D = \{(x_1, y_1), (x_2, y_2), \cdots, (x_m, y_m)\}, y_i \in \{-1, +1\}$, as Figure 1 shows, the most basic idea of classification learning is to find a division hyperplane in the sample space on the basis of training set $D$ to separate samples of different categories. One of the advantages of SVM is that the final partition of the hyperplane depends on only a few sample points closest to the hyperplane, which are called support vectors.
The classification hyperplane can be expressed by linear equation $w^T x + b = 0$. The hyperplane where support vectors are located can be expressed by linear equation $w^T x + b = \pm 1$ and the margin represents the sum of distance for two different types of support vectors. To find the optimal hyperplane, the final hyperplane should have the maximum margin to ensure the generalization ability and anti-jamming performance of SVM. In the solving process of SVM, the Lagrange multiplier method is used to address the dual problem shown as Equation (1), where $\alpha$ is a Lagrange multiplier.

$$\max_{\alpha} \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} \alpha_i \alpha_j y_i y_j x_i^T x_j$$
$$s. t. \sum_{i=1}^{m} \alpha_i y_i = 0,$$
$$\alpha_i \geq 0, i = 1, 2, \ldots, m.$$  \hspace{1cm} (1)

In the process of solving hyperplane parameters, the commonly used efficient algorithm is the sequential minimal optimization algorithm proposed by Platt in 1998. However, an often difficult task is to determine a hyperplane that can completely separate the training samples and prevent the problem of overfitting at the same time in real tasks. For this reason, we allow the SVM to fail on a portion of the samples and introduce the soft-margin SVM. To maximize the margin while ensuring that the number of samples that do not satisfy the constraint is as small as possible, penalty coefficient $C$ and the slack variable $\xi$ are introduced to obtain the commonly used soft-margin SVM. $\alpha$ also needs to meet $\alpha \leq C$. The new KKT condition is shown in Equation (2), where $\mu$ is the Lagrange multiplier corresponding to the new variable $\xi$.

$$\begin{align*}
\alpha_i \geq 0, & \mu_i \geq 0, \\
y_if(x_i) - 1 + \xi_i \geq 0, & \\
\alpha_i (y_if(x_i) - 1 + \xi_i) = 0, & \\
\xi_i \geq 0, & \mu_i \xi_i = 0.
\end{align*}$$  \hspace{1cm} (2)

2.2. Kernel function

As shown in Figure 2, in some tasks, the sample cannot be linearly separable in the low-dimensional space, but we can find the linearly separable hyperplane by mapping the sample points to a higher-dimensional sample space through the function.

In the solution of the dual problem, because of the import of the mapping function, a mapping function inner product will be found in the equation. In the case of a complex high-dimensional calculation, we imagine a function $\kappa(x_i, x_j) = \langle \phi(x_i), \phi(x_j) \rangle = \phi(x_i)^T \phi(x_j)$. The function $\kappa(\cdot, \cdot)$ is the kernel function. In this way, we can skip the mapping function and go straight to the appropriate kernel function to simplify the calculation.
The selection of kernel functions is often the key to the effectiveness of SVMs. In general classification problems, the most commonly used kernel functions are linear kernel, polynomial kernel, and radial basis function (RBF) kernel, among others. RBF is used in this paper, as Equation (3) shows, where $\gamma$ is a parameter of RBF, which will also affect the performance of SVM.

$$\kappa(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$$

### 2.3. Parameter optimization

Both $C$ and $\gamma$ are parameters that will affect the performance of SVM, and the best value needs to be found to optimize the performance of SVM.

GA is a searching algorithm that aims to simulate the genetic mechanism and the natural survival law of population and pursue adaptive thought. A typical GA starts with an initial set of random solutions called a population. Each member of the population is called a chromosome. New chromosomes are produced either by merging two chromosomes (from the current generation) through crossover operations or by modifying chromosomes through mutation operations. Parents and generation are chosen on the basis of their objective values and are a key component of the new generation.

### 3. Field test and data processing

#### 3.1. Impact echo method

Commonly used nondestructive detecting methods for concrete structures include rebound method, ultrasonic method, and radar method. Each method has its own scope of application and limitations. To detect the thickness and internal defects of a concrete structure with only a single detection surface, a new nondestructive detecting method called impact echo method was proposed in the mid-1980s.

The impact echo method uses a short mechanical load (with a small steel ball or small hammer tapping concrete surface) to produce a low-frequency stress wave and the stress wave will spread to the internal structure, reflected by defects and structure bottom. The reflected wave is received by the sensors installed near the impact point and sent to a built-in high-speed data acquisition and signal processor of portable instruments. The amplitude spectrum analysis of the recorded signal shows that the obvious peak in the spectrum is precisely caused by the transient resonance of the multiple reflections between the impact surface, defects, and other outer surfaces, which can be identified and used to determine the thickness of concrete structures and the location of defects.

#### 3.2. Field test

A field test of a ballastless track board is designed in this paper. The model test site is located in the first phase of Hangzhou–Ningbo Expressway double-track project in Ningbo City, Zhejiang Province. The height of the ground of the test site is similar to that of the concrete base and the material.
requirements are the same. Thus, the pouring of the concrete base is eliminated in the experiment. The top layer of the model is the ballastless track board. Considering the convenience of construction and the authenticity of the test, the size of the track board model is set to $6.55 \times 2.55 \times 0.2\,\text{m}$, and the ballastless track board model adopts C50 concrete. The water–binder ratio is 0.33, the sand rate is 41%, and the density is $2380\,\text{kg/m}^3$. HRB335 grade steel bar is used in the concrete track board, the thickness of the protective layer around the steel bar is 75 mm, and the thickness of the upper and lower protective layers is 50 mm. A mortar layer with a thickness of 40 mm is poured between the track board and the ground, and the mortar layer is made of M10 cement mortar.

In the model test, a total of 14 void defects are set in the mortar layer, including two defects at the corner of the board with a size of $50 \times 50\,\text{mm}$, four defects at the edge of the board with a size of $300 \times 600$ and $300 \times 300\,\text{mm}$, and eight defects in the board with a distance of 225 and 368 mm from the edge, respectively. The layout location of voids and of the detection networks are shown in Figure 3.

The void defect of ballastless track board has three different manifestations: (a) The mortar layer in the edge position of the track board is broken, cracking, or falling off; (b) the bond force between the mortar layer and the track board is lost, resulting in cracks at the edge of the board; and (c) the exhaust of mortar is not sufficient during the pouring process, which leads to the appearance of a large area of bubbles in the board and finally the development of void defect. To ensure that the defects can be distinguished conveniently, the above three kinds of void defects with different manifestations are respectively named fragmentation void defect, loss-of-cohesiveness void defect, and bubble-type void defect. The void severity of these three defects decreased in turn. The fragmentation void type indicates that the track structure has been damaged and the upper track board is in a completely suspended state. Even though the loss-of-cohesiveness void indicates that the mortar layer loses its bonding ability and its lateral limiting ability is weakened, the layer still has some supporting function in the vertical direction. The bubble-type void indicates that although the mortar layer has a void inside, it still forms a relatively complete overall structure with the track board. These three types all cause damage to the structure. As shown in Figure 4, to research these three types of defects, this model test adopted three different methods, namely, complete cavitation, foam board support, and Pykrete, to simulate different types of void defects.

![Figure 3. Void defects and detecting network layout.](image)
As shown in Figure 5, the complete set of equipment required by the impact echo method mainly includes vibration acquisition instrument, vibration exciter, sensors, acquisition system, and connecting wire. According to the size of track plate, disease type, and signal characteristics, the instrument models are selected as follows: (a) DH5923 vibration acquisition instrument; (b) SACL60KE vibration exciter; (c) CT1000L sensor; and (d) DHDAS acquisition system.

During the test, each detection point was knocked along the detection network, and two sensors were arranged at about 100 mm on both sides of the detection point to collect data. The validity of the data was checked by real-time FFT, and invalid points were retested until the detection of all point positions was completed.

3.3. Data processing
A total of $2 \times 62 \times 22 = 2,728$ pieces of data were collected. The original data can only be extracted by signal analysis. Commonly used signal analysis methods include FFT, which is used to obtain the amplitude–frequency domain spectrogram, and WT, which is used to obtain the time–frequency spectrums. The two spectra were analyzed and the characteristics of each detection point were extracted successively.

FFT is a fast algorithm for discrete Fourier transform (DFT) and is improved according to the odd, even, virtual, and real properties of DFT. The use of this algorithm can greatly reduce the number of multiplications required by a computer to calculate the DFT, especially because with more sample points N being transformed, the savings of the FFT algorithm becomes more significant.

WT is a local transform of space (time) and frequency, so it can extract information from the signal effectively. The functions of stretching and shifting can be used to refine the function or signal at multiple scales, which solve many difficult problems that FFT cannot solve.

A comparison of the original signals with the spectra processed from FFT and WT at points 15.B, 15.U, 53.H, and 15.L in four different situations is shown in Figure 6.
As shown in Figure 7, the maximum amplitude and five dominant frequencies were extracted from the data processed by FFT as eigenvalues. The maximum energy, the response time, and the maximum frequency and minimum frequency corresponding to 0.6 times the maximum energy extracted by WT are extracted as eigenvalues. The eigenvalues were used to construct the datasets.

4. Results and discussion

4.1. SVM classification results
The dataset was used to train the GA-optimized SVM. The population size is set as 20, the maximum evolutionary algebra is set as 30, and the evolutionary stasis judgment threshold is 1e-6. The performance of SVM is evaluated by 10-fold cross-validation. As shown in Figure 8, the datasets formed by FFT and WT can realize effective defect recognition, with the accuracy rate reaching
84.26% and 83.75%, respectively, and the running time being within 10 seconds. The optimal $C$ and $\gamma$ obtained by FFT dataset optimization are 32.10 and 3.91e-3, respectively, and the optimal $C$ and $\gamma$ obtained by WT dataset optimization are 141.92 and 3.91e-3, respectively.

![Figure 8. GA parameter optimization.](a) FFT dataset (b) WT dataset]

### 4.2. Discussion
- Although the GA-SVM used in this paper can effectively identify the void defects of ballastless track board, the accuracy can still be improved possibly because of errors in data collection, such as uneven percussion, and partly because of flaws in SVM.
- Classification errors often appear near the edge of voids. Further analysis of these points could obtain the effective range of void defect detection by the impact echo method and then the void area can be determined, which will be a great breakthrough in void defect detection.
- In this paper, only the void defects are considered. The emergence of other internal defects in the ballastless track board could make an impact on the results. Whether the current method can meet requirements when multiple defect combinations appear remains to be considered.
- Data from only a few sample points for the three kinds of void defects could be collected because of the limitations of field tests. Thus, forming an effective dataset for classification is impossible. More data could be obtained through numerical simulation such as COMSOL.

### 5. Conclusion
Field model tests were performed for three types of void defects of track slab. With the use of FFT and WT, the impact echo data were transformed to build the learning sample set for the GA-SVM model. The main conclusions are as follows:
- The existence of different types of void defects in track slab can be detected by the impact echo method, which has the advantages of clear principle, convenient operation, and high detection accuracy.
- SVM optimized by GA can effectively classify the signal of the impact echo method. The trained GA-SVM model can realize real-time detection with high accuracy (84.26%).

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