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Vibration-based RF-SVM for PC structural defect detection and assessment

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Abstract. Machine learning techniques have great potential in structural health monitoring (SHM) and damage assessment of precast concrete (PC) structures. However, traditional damage assessment methods, such as finite element analysis, structural reliability analysis, and model testing, have limitations in terms of accuracy, efficiency, and applicability to complex real-world scenarios. This article proposes a hybrid machine learning approach combining random forest (RF) and support vector machine (SVM) for damage detection and classification in PC structures. The proposed RF-SVM method utilizes continuous wavelet transform (CWT) to extract damage-sensitive features from vibration response data and employs RF for initial feature selection and damage classification. The RF output is then concatenated with the original features to form an enhanced feature vector, which is fed into the SVM model for precise damage type identification. The RF-SVM model is trained and tested using vibration response data generated from a simplified PC frame structure finite element model built in OpenSEES software. The experimental results demonstrate that the proposed method achieves an overall accuracy of 82.5% in detecting and classifying typical damage types in PC structures, with high precision, recall. However, the model's performance in identifying joint connection damage is relatively lower due to the subtle changes in vibration responses caused by this damage type. Compared to traditional methods that require extensive damage scenario data, the RF-SVM method simplifies the data preparation process and reduces computational complexity by utilizing only baseline data for training. This hybrid approach not only advances the field of SHM for PC structures but also offers a robust tool for infrastructure management, potentially increasing safety and reducing maintenance costs.

1 Introduction

In recent years, precast concrete (PC) structures have gained widespread application in new construction projects due to their rapid construction, hghly standardized production and construction, and significant economic benefits. However, ensuring the quality and safety of such structures during the construction phase and long-term use remains a major challenge. PC structures may develop various defects, from construction errors to damage caused by natural environments and operational loads over time. These defects can not only affect the

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performance of the structure in the short term but also lead to structural failure, safety incidents, and economic losses during long-term use. Therefore, timely and accurate assessment of the impact of defects in PC structures is crucial for ensuring the quality, safety, and sustainability of engineering construction. Currently, methods such as finite element analysis (FEA), structural reliability analysis, and model testing are commonly used to assess the impact of defects in such structures. FEA can provide detailed analysis of the effects of defects (such as cracks, holes, or corrosion) on the stress distribution, deformation, and strength of the structure by constructing a computational model [1]. Structural reliability analysis, based on statistical principles, assesses the probability of structural failure during future use, considering uncertainties in material properties, load effects, and the presence of defects [2]. Model testing involves physical loading of structural models or components under controlled conditions to directly observe their behavior and identify and assess the impact of defects [3]. Although these methods have their unique advantages and application scenarios in the assessment process, they also face some common challenges and limitations. For example, while finite element analysis can provide detailed information, its accuracy is highly dependent on the establishment of the model and the accuracy of input parameters. Structural reliability analysis requires a large amount of data and complex statistical analysis, and it may sometimes be difficult to obtain sufficient accuracy. Model testing, although it can intuitively demonstrate structural behavior, is often time-consuming, costly, and difficult to fully simulate the complex environment under actual use conditions.

Vibration-based structural damage detection (SDD) is currently one of the most commonly used methods for structural health monitoring (SHM) of large civil structures. Nonparametric SDD methods can directly detect structural damage based on measured accelerations using statistical methods [4]. These methods use statistical techniques to extract damage features that may not be easily attributed to physical changes in the structure. By not requiring a priori knowledge of the structure's physical properties, this nonparametric approach can more effectively detect subtle or complex damage patterns that may not be captured by traditional model-based methods [5].

As a rapidly developing research hotspot, machine learning brings new opportunities to construction technology with its powerful capabilities in data processing and pattern recognition. The application of machine learning in construction may lead to opportunities such as automatic detection, quality assessment, and intelligent maintenance, demonstrating its great potential in improving the intelligence level and efficiency of construction engineering [6]. The high standardization of PC structures not only optimizes the construction process and improves production efficiency but also facilitates the application of machine learning technology. This standardization ensures the consistency and comparability of data, laying the foundation for the training and application of machine learning models, thus creating conditions for machine learning to exhibit higher accuracy and efficiency in assessing the impact of defects in PC structures.

Decision trees (DT) and random forests (RF) are popular for their simplicity and strong interpretability, and they are particularly suitable for handling classification and regression problems. They can provide rapid predictions of defect impact based on historical datasets. Models using DT ensemble methods can predict the location of single-point damage with high accuracy; however, the prediction performance for multi-point damage is somewhat reduced [7]. Therefore, when dealing with more complex data relationships, more complex models may be needed. Support vector machines (SVM) are more adept at handling high-dimensional data and discovering complex nonlinear relationships. By optimizing the marginal error and regularization parameters, SVM can generate models with high generalization ability. When implementing nonlinear principal component analysis (NLPCA) for structural damage detection, it helps avoid overfitting, thereby enhancing the predictive ability of new datasets. By effectively distinguishing between the effects of damage and changes in the operating environment, it improves the robustness of structural health monitoring systems in the face of environmental and operational condition changes [8].

Against this background, this study utilizes RF and SVM algorithms, combining the two methods to fully mine the complex relationships in the data while maintaining the robustness and generalization ability of the model. By adaptively inducing and learning the normal operating conditions of the structure from the accumulated data features, and then using a model combining RF and SVM methods to identify deviations indicating potential damage, the impact of defects in prefabricated PC structures can be assessed more accurately and effectively.

2 Methodology

This section mainly introduces the proposed vibration-based RF-SVM method for PC structure defect detection and assessment. The overall schematic diagram of the method is shown in Fig. 1. First, forced vibration or ambient vibration response data of the PC structure are collected, and the classified structural data are preprocessed by denoising, normalization, and standardization to derive the data feature set of the PC structure. The data feature set of the undamaged PC structure will be used for RF model training. After that, the output of RF will be used as a new feature and input into the SVM model training together with the original features for SVM model training. For a new target PC structure, the same method is used to collect its vibration response data and preprocess it. After extracting its feature matrix and inputting it into the trained RF model, the output of the RF model is obtained. Then, the output of the RF model is concatenated with the original feature vector to form a new feature vector, which is input into the trained SVM model to obtain the final damage detection result.

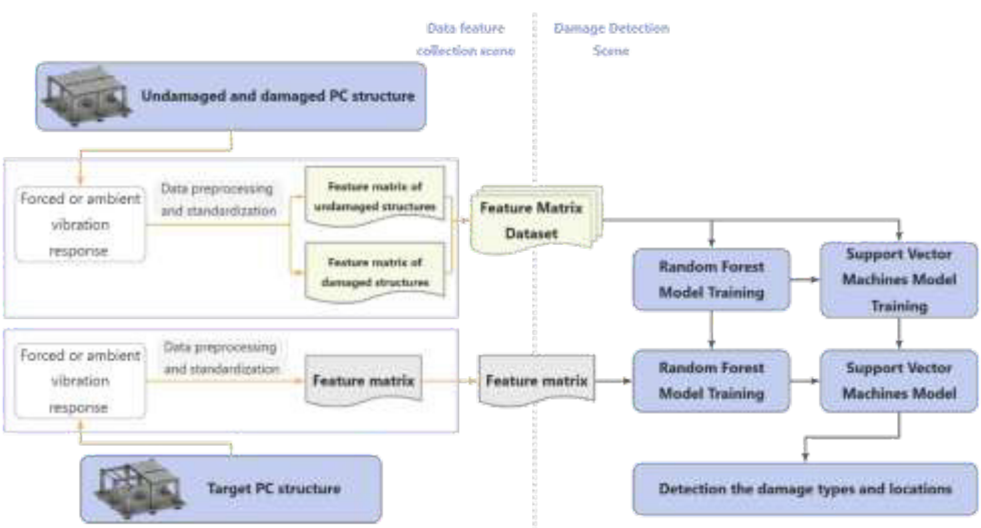

Fig. 1. Schematic illustration of the steps of the described method.

2.1 Data preprocessing and collection of feature matrix sets

Since the actually collected vibration response data may contain noise, it is first necessary to denoise, standardize, and extract feature data. In the field of SHM, one of the most commonly used data preprocessing methods is wavelet transform. Among the extensions of wavelet transform, continuous wavelet transform (CWT), as a time-frequency analysis tool, can steadily and effectively capture local features and dynamic changes in vibration signals and is particularly suitable for the analysis of non-stationary signals. Chen et al. used CWT to convert one-dimensional sensor data into time-frequency images and then extracted features and identified the degree of structural damage through a deep convolutional neural network (DCNN) [9]. The experimental results achieved extremely high accuracy, but due to the complexity of the neural network, the training time was relatively long [9].

For the original signal $x = x_1, x_2, \ldots, x_n$, CWT itself has a certain denoising ability and can effectively suppress high-frequency noise, but to further improve signal quality, it is necessary to first use the traditional wavelet threshold denoising method to set a threshold λ for pre-denoising the vibration response data matrix W after wavelet transform.

$$\hat{x} = w^T(sign(W_X) \cdot \max(|W_X| - \lambda, 0)) \tag{1}$$

After initial denoising, CWT can be obtained by integrating the product of the signal function and the complex conjugate function of the wavelet function.

$$W_{\hat{x}}(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} \hat{x}(f)\, \psi^*\left(\frac{t-b}{a}\right) \mathrm{d}t \tag{2}$$

Where, $\psi(t)$ is the mother wavelet function, a is the scale parameter, and b is the time shift parameter. Although theoretically the mother wavelet function here can be arbitrarily selected, in actual engineering practice, considering the accuracy of the final result, the a and b should be selected to be as consistent as possible with the denoised signal function.

Energy features, statistical features, and singular value features are extracted from the obtained CWT as damage-sensitive features. By introducing the concept of energy features, $E(a)$ measures the vibration intensity or activity intensity of the signal at the scale parameter a:

$$E(a_i) = \int_{-\infty}^{\infty} \left|w_{\hat{x}(a_i,b)}\right|^2 \mathrm{d}b \tag{3}$$

By calculating the energy feature values at different scales a_i, for m scales, an energy feature vector E can be obtained, which can be regarded as a compact representation of the energy distribution of the original signal at different time scales:

$$\boldsymbol{Energie} = [E(a_1), E(a_2), \ldots, E(a_m)] \tag{4}$$

A series of statistical features, including mean, variance, skewness, and kurtosis, are extracted from the CWT function to further characterize the video characteristics of the vibration signal. At different scales a, for N time shift parameter b values, the mean, variance, skewness, and kurtosis of the CWT coefficients can be defined respectively as:

$$\mu(a_i) = \frac{1}{N} \sum_b \omega_x(a,b) \tag{5}$$

$$\sigma^2(a_i) = \frac{1}{N-1} \sum_b (\omega_x(a,b) - \mu(a_i))^2 \tag{6}$$

$$\gamma(a_i) = \frac{1}{N} \sum_b \left(\frac{\omega_x(a,b) - \mu(a_i)}{\sigma(a_i)}\right)^3 \tag{7}$$

$$\kappa(a_i) = \frac{1}{N} \sum_b \left(\frac{\omega_x(a,b) - \mu(a_i)}{\sigma(a_i)}\right)^4 - 3 \tag{8}$$

The mean value $\mu(a_i)$ reflects the average amplitude or intensity of the signal at the scale parameter and can be used to measure the basic trend or background value of the signal. The variance value $\sigma^2(a_i)$ measures the degree of energy dispersion or fluctuation at the scale parameter and reflects the degree to which the signal deviates from the average level at that scale. The larger the value, the more intense the signal fluctuates and the more dispersed the energy distribution. The skewness value $\gamma(a_i)$ measures the direction and degree of skewness of the signal distribution at the scale parameter. If the skewness is positive, it means that the tail on the right side of the signal distribution is longer than the tail on the left side, i.e., the distribution is skewed to the right; if the skewness is negative, it means that the distribution is skewed to the left; if the skewness is zero, it means that the distribution is symmetric. The kurtosis $\kappa(a_i)$ characterizes the peakedness or flatness of the signal, and the larger the value, the steeper the signal peak. Similar to the energy feature vector, for m scales, four statistical feature vectors $\boldsymbol{Mean}$, $\boldsymbol{Variance}$, $\boldsymbol{Skewness}$, and $\boldsymbol{Kurtosis}$, representing the compact representation of the mean, variance, skewness, and kurtosis can be obtained.

When structural damage occurs, the main components or energy distribution of the vibration signal will change. In order to effectively reflect the changes in the vibration signal caused by damage, singular values are introduced in CWT to capture this feature. Singular value decomposition (SVD) is used to decompose the CWT coefficient matrix into the product of left singular vectors, singular values, and right singular vectors. For the CWT coefficient matrix $W_{\hat{X}}$ its SVD can be expressed as:

$$W_{\hat{X}} = U\Sigma V^T \tag{9}$$

Where, U and V are orthogonal matrices representing the left and right singular vectors, respectively, and Σ is a diagonal matrix. The diagonal elements are the singular values σ_i, which represent the projection length or energy of the CWT coefficient matrix in the direction of the i-th singular vector. The larger singular values correspond to the main components or features of the signal, while the smaller singular values correspond to the minor components or noise. The top k largest singular values are selected to form the feature vector $\boldsymbol{Singular}$, and the value of k is determined through cross-validation to balance the amount of information and dimensionality of the features. At this point, we can combine the above CWT features into an overall feature matrix $\boldsymbol{F}$.

2.2 Random forest decision tree

RF as a integrated machine Learning Method, are actually combinations of tree predictors in which each tree depends on the value of a random vector that is sampled independently and has the same distribution for all trees in the forest [10]. In its application to civil structures, RF is first trained on a dataset containing undamaged and damaged PC structural vibration response features. This training helps extract and classify features related to structural integrity. The model learns patterns associated with undamaged structures and uses these patterns to identify potential anomalies in new data. Because each tree in the random forest is grown using a random subset of the training data (bootstrap sampling) and a random subset of features at each split point, this randomization helps reduce overfitting and improve the generalization ability of the model [11-13]. Compared to a single decision tree, the aggregation of multiple trees helps eliminate individual errors and biases [11-13]. The standardized characteristics of PC structures further ensure the consistency and comparability of vibration data, enabling the RF model to perform training and classification more accurately and thus better identify potential defects in the structure.

Using the bootstrapping method, N samples (with replacement) and m features are randomly drawn from the feature matrix $\boldsymbol{F}$ to construct a decision tree. As shown in Fig. 2, k ($k \ll m$) features are randomly selected from the m features, and samples are assigned to left and right child nodes based on the values of the k features. This process is recursively maintained until all samples are assigned to leaf nodes or a preset stopping condition (such as the maximum depth of the tree) is reached. The above steps are repeated T times to obtain T decision trees, which constitute the random forest.

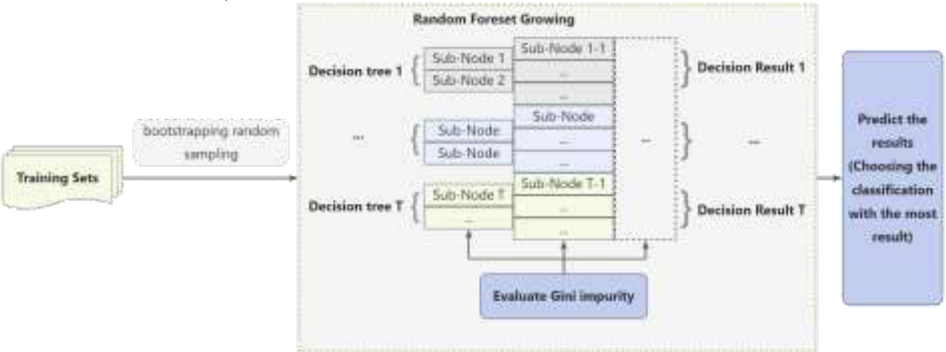

Fig. 2. Random Forest Training Node Schematic.

In the growth process of the decision tree, we need to select the optimal feature and threshold to split the nodes so that the classes or values of the child nodes after splitting are as pure as possible. Different nodes need to use Gini Impurity to evaluate the quality of splitting. For a certain node, the Gini impurity is defined as:

$$G_{ini}(n) = 1 - \sum_{i=1}^{C} p_i^2 \tag{10}$$

Where C is the number of classes (including the undamaged class), and p_i is the proportion of samples belonging to the i-th class.

In the trained RF model, each decision tree will give a prediction of the damage category. The prediction results of all trees are voted on to obtain the final damage state and type. If the majority of trees predict no damage to the structure (class 0), it is judged that the structure is undamaged; otherwise, the damage type predicted by the majority of trees is taken as the final damage type.

To further improve the performance of damage assessment, we concatenate the output $\boldsymbol{D}$ of the RF model with the original feature vector $\boldsymbol{F}$ to obtain an enhanced feature vector $\boldsymbol{F}' = [\boldsymbol{F}, \boldsymbol{D}]$, which will be used as input to the SVM model for prediction to obtain more accurate damage assessment results.

2.3 Support vector machine

SVM is a supervised learning model based on statistical learning theory, which has unique advantages in dealing with small samples, nonlinear, and high-dimensional data. SVM finds an optimal hyperplane in the feature space to separate data samples of different classes and maximize the classification margin [14]. For the enhanced small feature sample $\boldsymbol{F}'$, inputting it into the SVM model can fully utilize the advantages of both models and improve the accuracy of damage assessment while extracting complex nonlinear relationships in the data.

The multi-class problem is transformed into multiple binary problems. For each damage type, a binary SVM model is trained, with samples of that type as positive examples and samples of other types as negative examples. For the i-th damage type, the optimization objective of the corresponding binary SVM model is:

$$\min(w_i, b_i, \xi) \frac{1}{2} \|w_i\|^2 + C \sum (j = 1)^n \xi_j \tag{11}$$

$$\text{s.t.}\, y_j\left(w_i^T \varphi\left(F_j'\right) + b_i\right) \geq 1 - \xi_j \tag{12}$$

Where w_i and b_i are the weight vector and bias term of the i-th SVM model, respectively, $\varphi(\cdot)$ is the function that maps the input features to a high-dimensional space, C is the penalty factor, ξ_j is the slack variable of the j-th sample, $y_j \in \{-1,+1\}$ is the class label of the j-th sample (+1 indicates belonging to the i-th damage type, -1 indicates not belonging to the i-th damage type), and n is the total number of training samples. $\varphi(\cdot)$ is the function that maps the input features to a high-dimensional space. In this study, we choose the radial basis kernel function (RBF) as the mapping function. The RBF kernel function maps the input features to an infinite-dimensional Gaussian feature space, which is defined as:

$$\mathrm{K}\left(F_j', F_k'\right) = \exp(-\gamma\left\|F_j' - F_k'\right\|^2) \tag{13}$$

where γ is the parameter of the RBF kernel function, which controls the width of the kernel function. By introducing the kernel function, we can transform the original nonlinear classification problem into a linear classification problem in high-dimensional feature space, thereby improving the performance of the SVM model. The decision function of the i-th SVM model is:

$$f_i(F) = \mathrm{sign}(\sum(j=1)^n a_j\, y_j K\left(F_j', F_j' est\right) + b_i) \tag{14}$$

If the result of $f_i(F)$ is +1， F is predicted to be the i-th damage type; otherwise, it is predicted not to belong to it. After training all C binary SVM models, for a new test sample F, it is input into each SVM model to obtain C decision function values. The final damage type prediction result is the damage type corresponding to the SVM model with the largest decision function value:

$$y_p red = \mathrm{argmax}(\mathrm{i} = 1,2,\dots,\mathrm{C}) f_i(F_j' est) \tag{15}$$

To further improve the performance of the SVM model, we need to tune two key parameters: the penalty factor C and the RBF kernel parameter γ. We use the grid search method to select the optimal parameter combination through k-fold cross-validation within a preset parameter value range. Specifically, the training set is randomly divided into k subsets of similar size, and each time one subset is selected as the validation set and the remaining $k-1$ subsets as the training set to train the SVM model and test its performance on the validation set. This is repeated k times, with each subset having one opportunity to serve as the validation set. Finally, the average of the performance metrics over the k times is taken as the performance evaluation of the SVM model under that parameter combination. The parameter combination with the best cross-validation performance is selected and used to retrain the SVM model to obtain the final damage type recognition model.

2.4 Support vector machine

To validate the effectiveness of the proposed RF-SVM hybrid model, we used OpenSEES to establish a three-story, two-span PC frame structure model.

Three typical types of damage in PC structures were considered: beam/column component cracking, joint connection damage, and slab cracking. For each damage type, different damage severities (light, moderate, and severe) and damage locations were set, generating a total of 100 damage cases. Time history curves were obtained by extracting acceleration response data from key locations of beams, columns, and slabs, with a sampling frequency of 100 Hz and a sampling duration of 10 s for each measurement point.

Table 1. Performance evaluation of the RF-SVM model on the test set.

Damage type	Precision	Recall	F1-score
No damage	0.90	0.90	0.90
Beam/column cracking	0.846	0.917	0.80
Joint connection damage	0.7	0.636	0.667
Slab cracking	0.857	1.00	0.93

To further analyze the performance of the RF-SVM model, we plotted the confusion matrix of the model on the test set, as shown in Fig. 3. The diagonal elements of the confusion matrix represent the number of correctly classified samples, while the off-diagonal elements represent misclassification cases. It can be seen from the figure that the model has high discriminative accuracy for no damage, beam/column cracking, and slab cracking, while the discriminative accuracy for joint connection damage is relatively lower, mainly because the changes in vibration response caused by joint connection damage are relatively slight and easily confused with other damage types.

The RF-SVM model exhibited good damage classification performance on the test set, with an overall accuracy of 82.5% for the test samples. This indicates that the model can effectively learn and distinguish different types of damage in PC structures. The model has the highest discriminative accuracy for undamaged samples, with 9 out of 10 undamaged samples correctly identified and only 1 misclassified as joint connection damage. This may be because the vibration response features of undamaged samples differ greatly from other damage types and are therefore more easily correctly distinguished by the model. The model also has high discriminative accuracy for beam/column cracking and slab cracking damage, indicating that the RF-SVM model can better capture the changes in vibration response features caused by beam/column and slab cracking.

From the off-diagonal elements, the model's misclassifications are mainly concentrated in misclassifying joint connection damage as other types and misclassifying other types as joint connection damage. It is worth noting that the model's discriminative accuracy for joint connection damage is relatively low, possibly because the changes in vibration response caused by joint connection damage are relatively slight, and its features are more easily confused with other damage types.

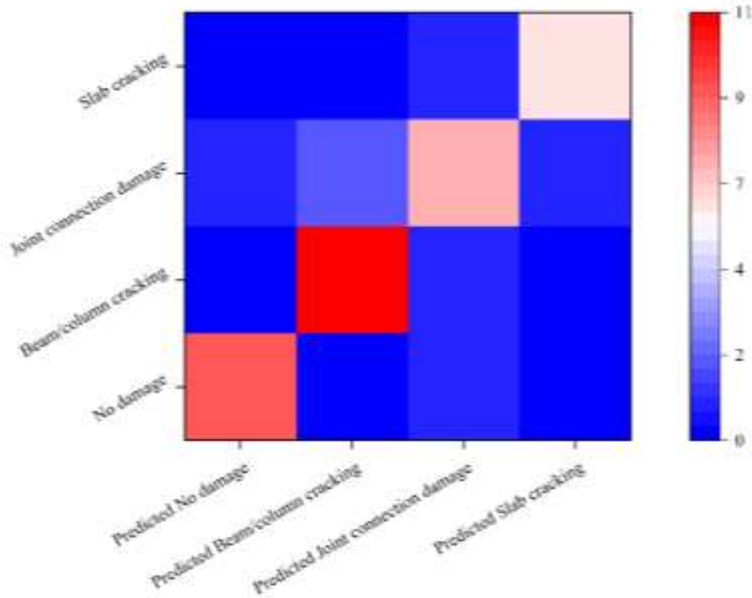

Fig. 3. Random Forest Training Node Schematic.

3 Conclusion

This paper proposes a hybrid machine learning method combining RF and SVM for damage detection and classification of PC structures. The method aims to overcome the limitations of traditional damage assessment methods and improve the accuracy and efficiency of damage recognition. To verify the effectiveness of the proposed method, a simplified PC frame structure finite element model was constructed using OpenSEES, and vibration response data under different damage scenarios were generated through numerical simulation. The performance of the RF-SVM method in damage detection and classification tasks was evaluated through model training and testing.

The proposed RF-SVM hybrid method can more effectively integrate the advantages of different models and achieve better results in feature selection, damage classification, and nonlinear decision boundary fitting. By introducing damage-sensitive features such as energy features, statistical features, and singular value features, the RF-SVM model can capture the key damage information contained in the vibration response data of PC structures, thereby improving the accuracy of damage detection and classification. Unlike other traditional methods that require a large amount of damage scenario data, the RF-SVM method only needs to use baseline data for training, simplifying the data preparation process and reducing computational complexity and operating costs.

The model achieved an overall accuracy of 82.5% on the test set and can well capture the changes in vibration response features caused by undamaged conditions and beam/column cracking. It can also better recognize the patterns of changes in vibration response caused by slab cracking, but the discrimination of joint connection damage type features is easily confused with other damage types.

It is undeniable that this study still has some limitations. For example, due to the lack of sufficient damage location and severity information in the training data, the model's ability in damage localization and quantification needs to be further improved. In addition, this paper uses a simplified PC frame structure model and has not yet considered the complexity and uncertainty factors of actual structures.

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