



# Damage Detection of Rail Fastening System Through Deep Learning and Vehicle-Track Coupled Dynamics

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**Abstract.** Owing to the rapid development of the rail transportation, the health monitoring of the track structure becomes a challenging problem. This article presents a novel approach to carry out damage detection and localization of fastening systems along the rail based on deep learning and vehicle-track coupled dynamics analysis. A convolutional neural network (CNN) is designed to learn optimal damage-sensitive features from the rail acceleration response automatically and identify the damage location of fastening systems, leading to a high detecting accuracy. The vehicle-track coupled dynamics model incorporating different damage level of fastening systems is adopted to generate labeled dataset to train the proposed network. The advantage of this approach is that CNN learns to extract the optimal damage-sensitive features from the raw dynamical response data automatically without the need of computing and selecting hand-crafted features manually. T-SNE is applied to manifest the super feature extraction capability of CNN. Thereafter, the trained network is estimated on the testing dataset to validate its generation capability. The results reveal a good performance of the proposed method.

**Keywords:** Vibration · Damage detection · Convolutional neural network · Vehicle-track coupled dynamics

## 1 Introduction

The health monitoring of larger-scale operating railway network has been an essential challenging task for railway engineers and researchers, especially for the early-stage damage detection for the key components of railway structures [1]. Vision-based method is popular for structural damage detection. Image analysis [2] is applied to find the clip missing position along the track. An object detection model through CNN [3] is established to detect and localize the crack of the structure. The limitation of this sort of method is to identify early-stage failure and invisible flaw of the structure, such as the aging of the rubber pad and the invisible crack of fastening clip in the fastening system. Since the change of the structural property has a direct impact on the dynamic response, it's reasonable to suppose the variation of response as a sign of the structural damage. Therefore, Vibration-based damage detection can address the drawback of the

Image-based method to a great extent, and intelligent diagnosis method based on dynamic response is a hot topic in structural damage detection field in the recent years.

Generally, intelligent diagnosis method, in which artificial neural network (ANN), and support vector machine (SVM) are the most widely applied, includes two main process: feature extraction and damage identification. A neural network-based damage detection method using the modal properties is presented [4]. Wavelet packet transform is adopted to extract damage-sensitive feature from the dynamical response of a bridge, ANN is then applied to achieve damage detection based on the extracted feature [5]. Although partial successes were obtained, its performance is influenced by the hand-crafted features from the raw data greatly.

The main purpose of this article is to demonstrate the feasibility of application of 1-D CNN on the damage detection of railway system. In light of CNN's capability to extract optimal damage-sensitive feature [6, 7], a novel approach is proposed in this study, aiming to identify the early-stage damage presence and location of the fastening system along the rail effectively. Based on the dataset containing different health conditions of the fastening system generated by the vehicle-track coupled model, a customized CNN is designed and trained to carry out feature extraction and damage location.

## 2 Dataset Generation Model

In this section, a vehicle-track vertical coupled dynamics model is established with a combination of the vehicle subsystem, the track subsystem and the wheel-rail interactive model [8]. Specifically, dynamical parameters of a kind of high speed train and ballasted track are adopted in this model. An explicit integration method [9] is employed to compute the system response.

Since the fastening system is simplified as a spring in the dynamical model, stiffness reduction in varying degree is regarded as the simulation of different health condition of the fastening system. As shown in Fig. 1, ten consecutive fastenings of the rail are selected randomly to make damage cases in multiple degrees. Excited by various kinds of rail irregularities, the acceleration responses of the rail position corresponding to the fastenings can be collected as the dataset. Each case is sampled to 1500 data points. Concretely, the dynamic response considering stiffness reduction of 5 extents: 100%, 70%, 50%, 30%, 10% and the intact condition for each selected position is calculated under the excitation of 44 different rail irregularities. The whole dataset comprises of 11 categories, no.0 to no.9 representing damage location of the fastening system on no.0 to no.9, and no.10 representing the intact condition. There are 44 samples for the intact case, while the number of other cases is 220 (44 excitations  $\times$  5 damage levels). The intact samples are duplicated 5 times to generate a category-balanced dataset. Therefore, the generated dataset contains 2,420 samples (220  $\times$  11 categories). After shuffling the dataset for each category, 1,694 samples (154  $\times$  11) are used as training dataset, 242 samples (22  $\times$  11) are used as validation dataset, and the rest 484 samples as testing dataset.

The dataset is normalized to a distribution with a mean of 0 and a variance of 1 to expedite the convergence of the network training process. Then, data augmentation is implemented on the dataset to gain more data, which will be beneficial for the training and generalization of the network.

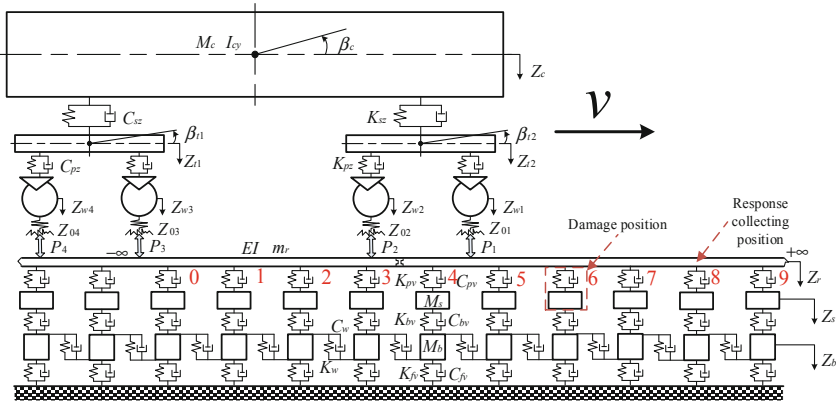


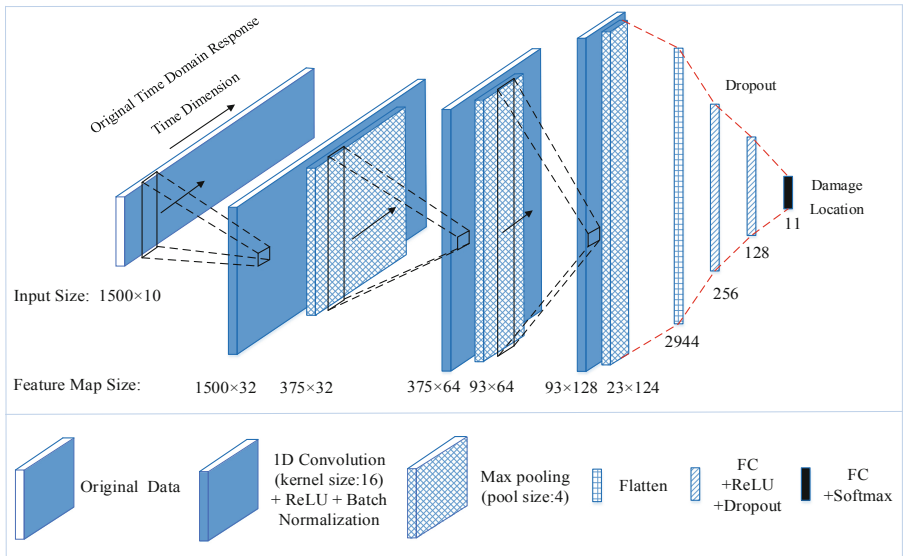
Fig. 1. Vehicle-track coupled dynamics model for dataset generation.

### 3 Damage Detection Method

Compared to traditional artificial neural network, there are three main traits of CNN, which are, local field, weight sharing and subsampling. Taking advantage of these configuration, CNN not only gets a shift invariance property, leading to the model robustness, but also has less trainable parameters, decreasing the risk of overfitting. Stack of convolution and pool operation makes CNN to learn hierarchical feature from the raw data.

In this section, a 1-D CNN is designed to extract optimal damage-sensitive feature and identify the fastening system health condition. As illustrated in Fig. 2, the structure of the designed CNN can be divided into two parts: convolution block for feature extraction and FC block for classification. In the convolution block, the input time series data is followed by a convolutional layer with nonlinear activation, then a max pooling layer is added. The similar substructure is stacked twice to get a hierarchical representation of the raw data. Specifically, the filter size of the convolutional layer and the pooling size is set as 16 and 4, respectively. Batch Normalization layers [10] are inserted after each convolutional layer to solve the so-called internal covariate shift problem, thus accelerating the convergence of network training process. In the FC block, the output of the last pooling layer is flattened to a 1-D vector. Three full connected layers (FC) and a Softmax layer are then used to carry out feature transformation and classification. Tricks called dropout are employed in the FC layers to relieve the overfitting problem of the network. The training and testing process of the CNN are implemented through Tensorflow [11] developed by Google.

Totally, there are 958,315 (958,867 trainable) parameters and 6 nonlinear layers involved in the designed CNN. The configuration of the network is determined by trial and error process to achieve a good performance. The parameters of the designed CNN are updated through the Adam Stochastic optimization algorithm [12] to minimize the loss function, namely cross-entropy which estimates the divergence between the distribution of the network output and the ground truth.



**Fig. 2.** One-dimensional convolutional neural network architecture

As depicted in Fig. 3, the proposed damage detection method can be divided into two phases: training phase and testing phase. In the training phase, the loss is computed by the constructed network with the input training data, and the training parameter updating process is carried out w.r.t the calculated loss. In the testing phase, the trained CNN can be used to predict the damage presence and location only with the dynamical response signals as input. Furthermore, evaluation of the CNN performance can be conducted by calculating the predicting accuracy through comparing the predicted logits and the true label.

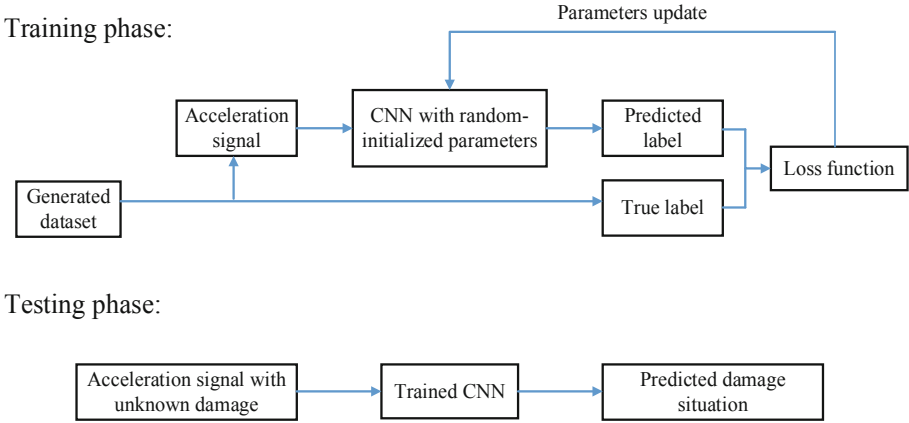


Fig. 3. Scheme of the proposed damage detection method

### 4 Results and Conclusion

In this section, t-SNE [13] is adopted for the visualization of the extracted features in the last layer of CNN. Figure 4 shows the 2D and 3D features of the testing samples. Clear inter-category distance can be found, which indicate excellent ability of CNN for feature extraction.

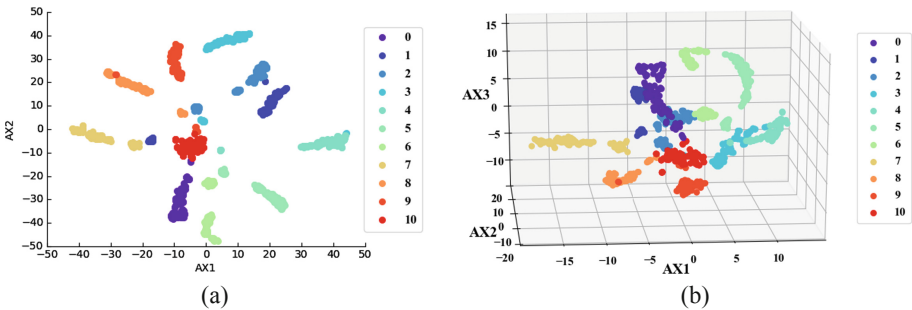


Fig. 4. Visualization of the learned features: (a) 2D features and (b) 3D features

The damage detection performance of the CNN is evaluated on the generated testing dataset. Table 1 gives the confusion matrix of the designed network on the testing dataset. It shows the identification results of all patterns specifically. Each element in the matrix is the number of a certain real pattern to be identified. More specifically, the elements in the diagonal are the number of cases classified accurately. And the identification accuracy for each pattern are shown in the right side of the table. Obviously, the result reveals a high detection accuracy of CNN. In conclusion, the proposed method shows great potential for the automatic damage detection in the early stage of the fasten system, relieving the labor of the workers.

**Table 1.** The detection accuracy on the test dataset.

Counting results		Predicted damage location												Total	%
		0	1	2	3	4	5	6	7	8	9	10			
Ground truth label	0	85	0	0	0	0	0	0	0	0	0	0	3	88	96.6
	1	1	86	0	0	0	0	0	0	0	0	0	2	88	97.7
	2	0	0	86	2	0	0	0	0	0	0	0	0	88	97.7
	3	0	0	0	88	0	0	0	0	0	0	0	0	88	100
	4	0	0	0	0	85	3	0	0	0	0	0	0	88	96.6
	5	0	0	0	0	0	86	0	0	0	0	0	2	88	97.7
	6	0	0	0	0	0	0	88	0	0	0	0	0	88	100
	7	0	0	0	0	0	0	1	86	1	0	0	0	88	97.7
	8	0	0	0	0	0	0	0	0	85	3	0	0	88	96.6
	9	0	0	0	0	0	0	0	0	2	86	0	0	88	97.7
	10	0	0	0	0	0	0	0	0	0	0	88	0	88	100
	Total	86	86	86	90	85	89	89	86	88	89	95	968	Overall:97.5	

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