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Damage detection and localization for SVI in floating-slab track: a domain adaptation-based method

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Introduction

The steel-spring vibration isolators (SVIs) are critical components of the floating-slab track and are aimed at ensuring a good vibration attenuation performance. Supervised learning, artificial intelligent-based models have been recently developed for the damage detection in these structural parts. As they are mostly trained on simulation datasets, the diagnosis performance of these models is greatly spoiled on real-life datasets due to the so-called domain shift issue.

In this study, a domain adaptation-based methodology is developed for cross-domain SVI damage detection and localization.

Method

In proposed method, two strategies are used for domain adaptation, including domain adversarial training and feature distribution discrepancy regularization. As shown in Fig.1, the domain adaptation neural network is comprised of three modules for: feature extraction, health condition classification, and domain adaptation. The domain adaptation module is linked to the feature extractor, to help the extractor learn domain invariant representations. Algorithm.1 gives the framework for domain adaptation neural network training.

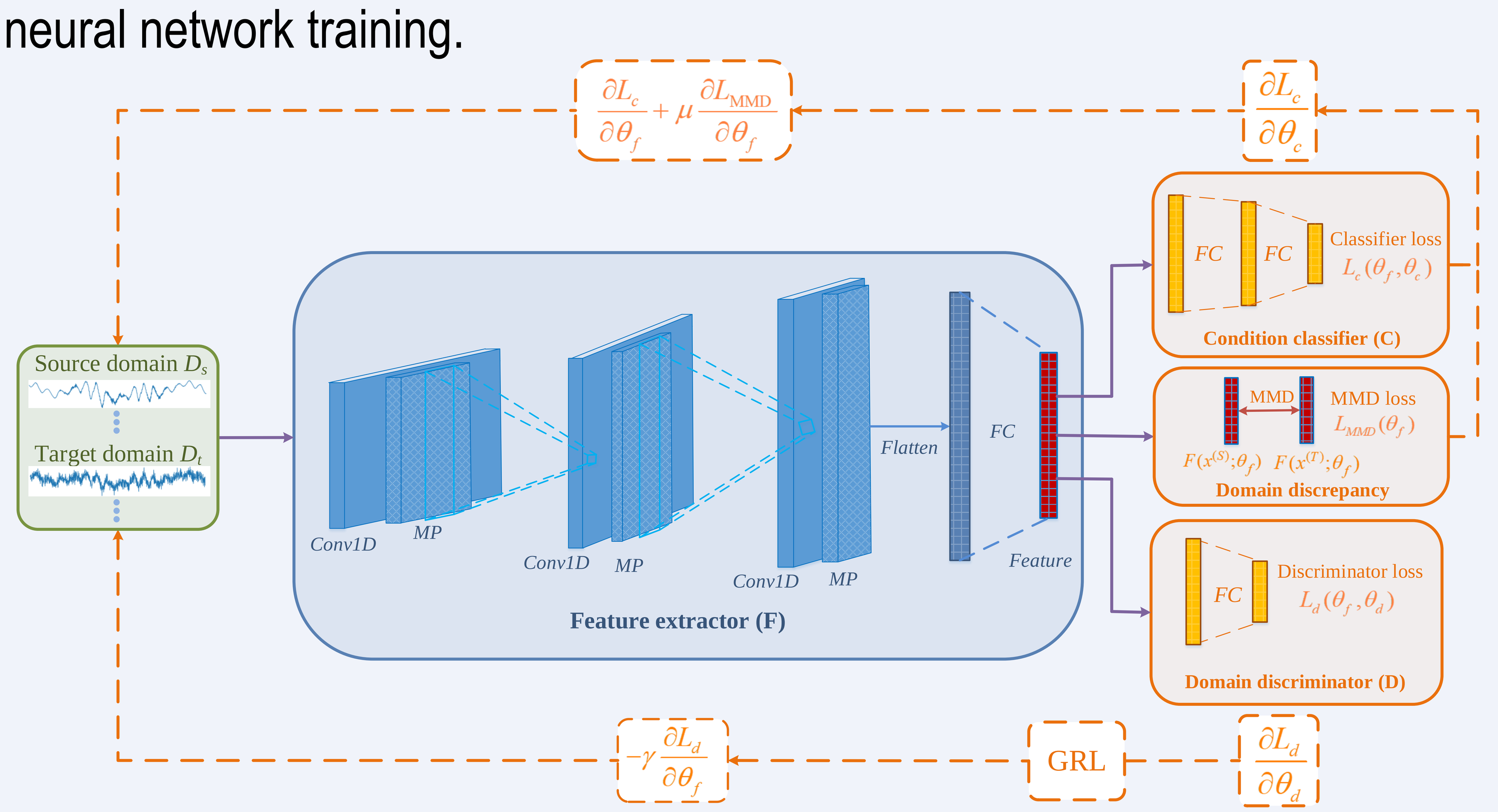


Fig.1. Architecture of the domain adaptation neural network. Here Conv1D, MP and FC respectively denote the one-dimensional convolution layer, the max-pooling layer and the fully connected layer. Solid and dash lines represent the forward propagation of data flow, and the back propagation of gradient regarding the prediction loss.

Algorithm.1 Framework for domain adaptation neural network training

Input:

Labeled source domain dataset $\left\{x_i^{(S)}, y_i\right\}_{i=1}^{N_s}$;

Unlabeled target domain dataset $\left\{x_i^{(T)}\right\}_{i=1}^{N_t}$;

Output:

Trained feature extractor *F* and condition classifier *C*.

Initialize parameters of the subnetworks;

For _ = 1 to n_epochs:

Set the learning rate ε, and loss coefficients μ and γ .

For i = 1 to training_steps:

Sample training data batch $\left\{x_i^{(S)}, y_i\right\}_{i=1}^{batch\_size}$ and $\left\{x_i^{(T)}\right\}_{i=1}^{batch\_size}$

Compute the discriminator loss

Update domain discriminator θ_d and feature extractor θ_f param.

Compute the MMD loss

Update feature extractor θ_f param.

Compute the classifier loss

Update condition classifier θ_c and feature extractor θ_f param.

Endfor

Endfor

Return Trained feature extractor *F* and condition classifier *C*.

Dataset Generation

Vehicle-slab track coupled dynamic simulations are conducted to build the labeled source dataset, allowing for different operational scenarios and SVI health conditions. Then, modeling uncertainties are introduced in relation to model parameters, and signal noise is added to the computed responses in order to mimic real engineering scenarios in the target domain dataset.

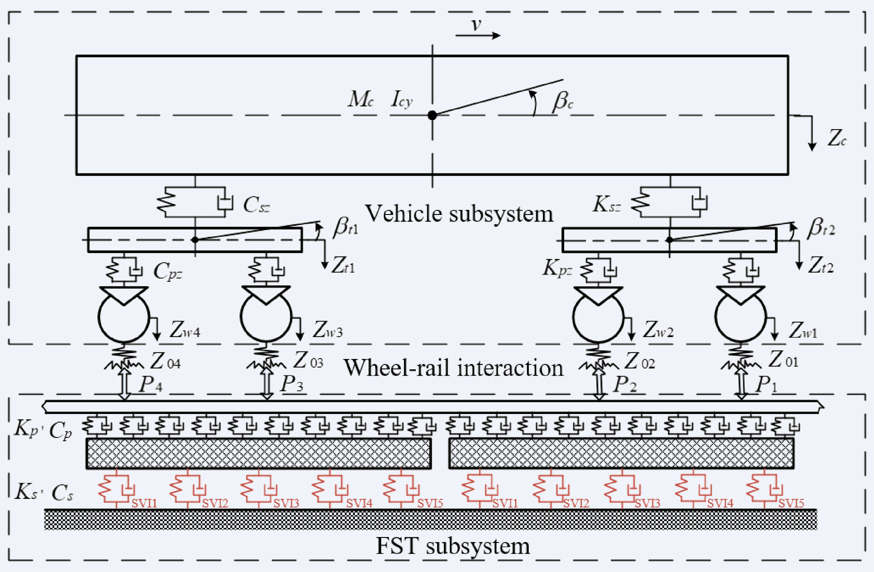


Fig. 2. Vehicle-floating slab track coupled dynamics model

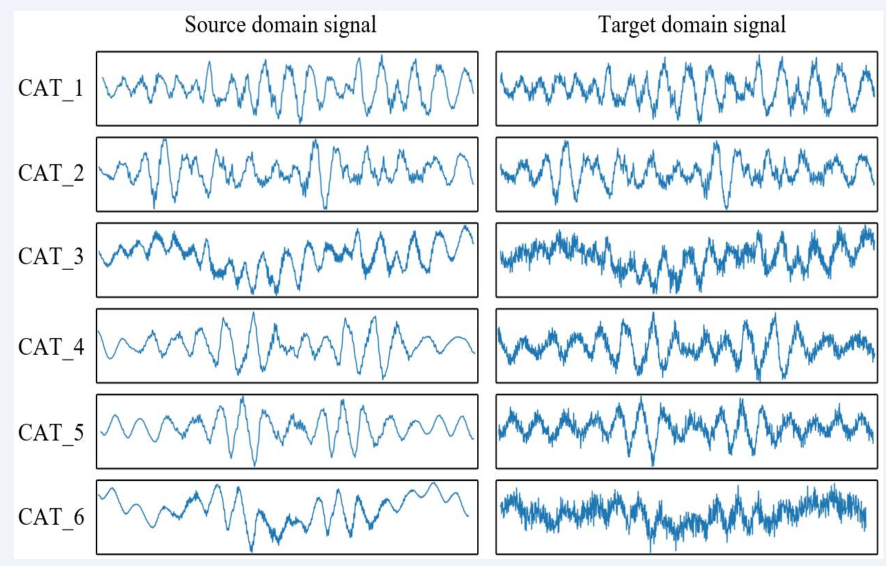


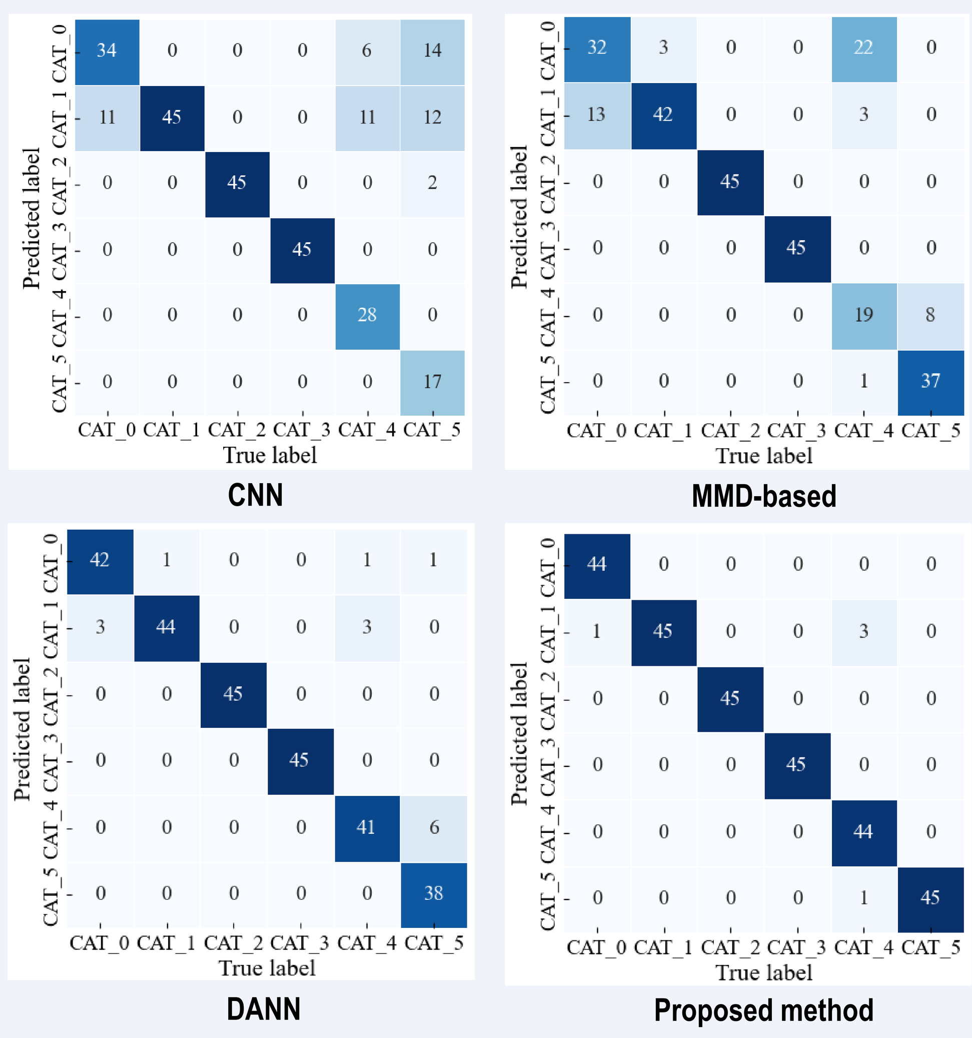
Fig.3. Exemplary signal samples

Results and Conclusion

Good detection performances are obtained when evaluating the trained network on the testing dataset, with an accuracy of 99.63% on the source domain, and 99.26% on the target domain.

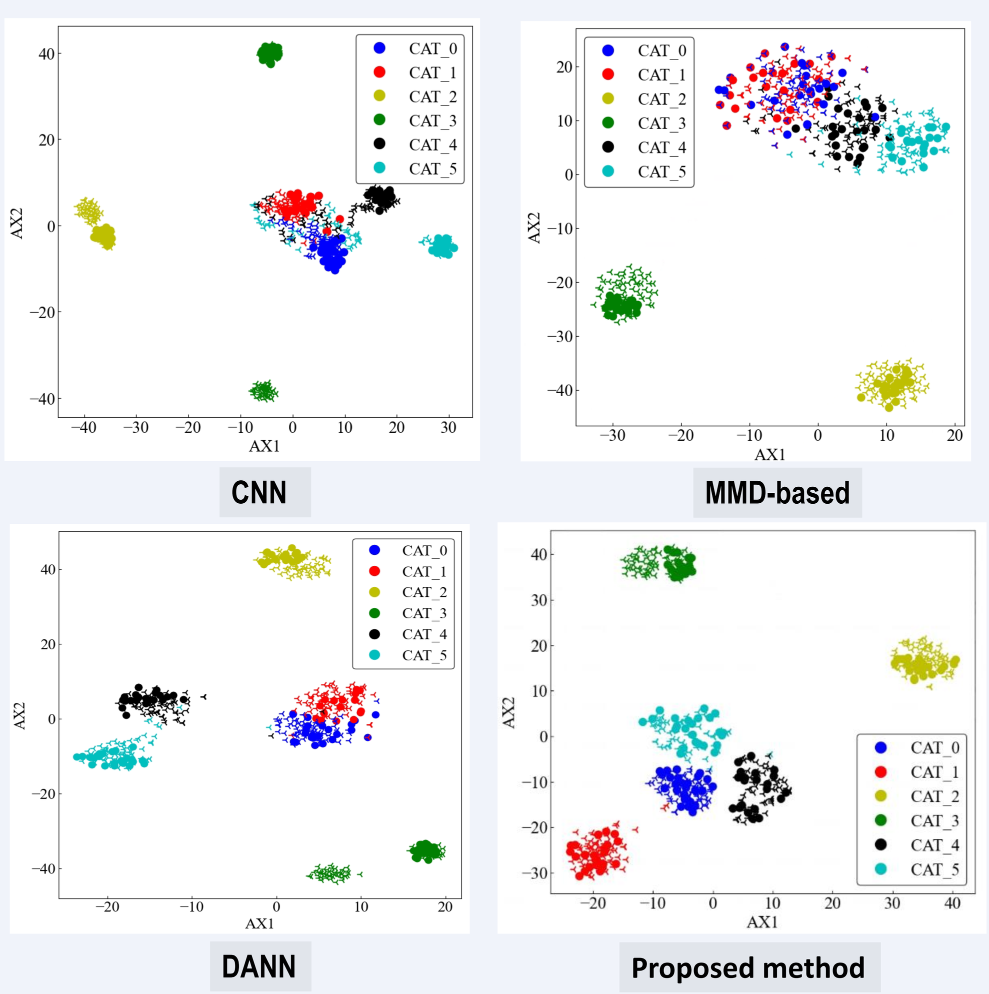
Ablation studies and feature visualization are performed, to show the superiority of the proposed method over traditional CNN and other domain adaption methods.

Confusion matrices



The proposed method accurately classifies almost all the data samples from every category. CNN and MMD-based domain adaptation method fail to identify the proper category for samples from CAT_0, CAT_4 and CAT_5. The DANN method has a classification performance slightly worse than that of the proposed method, regarding samples from CAT_0, CAT_4 and CAT_5.

Feature visualization



CNN, MMD-based and DANN-based domain adaptation methods, show entangles between samples from CAT_0, CAT_4 and CAT_5. The feature distribution of our method seems to be excellent, with samples in the similar category but from different domains clustered together, and samples from different categories moved apart.

Results here reported have demonstrated that the proposed method outperforms the traditional CNN and also other domain adaptation methods.