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

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Abstract:

The steel-spring vibration isolator (SVI) is a critical component to ensure a good vibration attenuation performance of the floating-slab track (FST). Supervised learning-based intelligent models have been recently developed for structural damage detection, which are mostly trained on the simulation dataset [4]. The diagnosis performance of these intelligent models will degrade greatly on real-life datasets because of the domain shift issue.

A possible strategy to avoid it, is to train the intelligent models on both the domain datasets aiming to instruct the model to learn ignoring the domain discrepancy, and performing damage detection simultaneously. Transfer learning-based methods can be a good solution in this regard. The intelligent SHM problems can largely benefit from this emerging technology, whose goal is to leverage the diagnostic knowledge learned from the source domain to improve the models classification performance in the target domain. In our study, the source domain represents the dataset generated by dynamic simulations, where numerous damage scenarios can be considered. The target domain denotes instead the real-world dataset collected by online sensors, where the health condition information is unknown.

In this study, the domain adaptation neural network is developed for the cross-domain SVI damage detection and localization, in order to extract damage-sensitive and domain-invariant features from the dynamical responses. Two strategies are used for domain adaptation, including domain adversarial training [1] and feature distribution discrepancy regularization [2], where the adversarial loss calculated by the domain discriminator and the domain distribution discrepancy metric loss are jointly minimized to tune the parameters of the feature extractor. The architecture of the domain adaptation neural network is comprised of three modules: feature extraction, health condition classification, and domain adaptation. Feature extraction aims to automatically learn informative representations from the raw signals and is obtained with a one-dimensional CNN. The health condition classifier identifies SVI health conditions, relying on the learned features from the feature extractor. Two parts are included in the domain adaptation module, which are the domain discriminator and the metric to calculate the discrepancy between the features extracted from the source domain, and target domain. The domain adaptation module is linked to the feature extractor, to help the extractor learn domain invariant representations.

Vehicle-slab track coupled dynamic simulations [3] are conducted for the labeled source domain dataset generation, wherein different operation scenarios and SVI health conditions are considered. Modeling uncertainties are then introduced into the dynamical parameters, and signal noises are added to the calculated responses to provide real engineering signals (target domain dataset). Good detection performances are obtained when evaluating the trained network on the target dataset. Ablation studies and feature visualization are performed, to show the superiority of the proposed method over traditional CNN and other domain adaption methods.

References

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Short biography – The author is currently working toward the Ph.D. degree in vehicle operation engineering at the State Key Laboratory of Traction Power, Southwest Jiaotong University, P. R. China. He is intersted in developing machine learning-based methods for stuctural damage detection in railway engineering.