Structural Damage Identification Using Physics-Informed Neural Network and Transfer Learning

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ABSTRACT

In structural health monitoring (SHM), finite element models (FEMs) have been used to simulate diverse damage scenarios for training deep learning-based structural damage identification models; however, discrepancies between FEMs and actual structures persist. To bridge this gap, we propose a hierarchical physics-informed domain adaptation (HierPhyDA) approach that synthesizes features from FEMs to mirror those from actual structures and emulates authentic vibration signatures. The proposed solution employs an initial phase of unsupervised anomaly detection using a deep autoencoder approach, followed by a novel physics-informed domain adaptation method that serves as a digital twin of the physical structure. This approach is rigorously evaluated through numerical studies using the ASCE benchmark structure. The results show that the proposed approach outperforms state-of-the-art methods when damage cases from the actual structure are excluded from training and are mutually exclusive from those generated by the FEM.

INTRODUCTION

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Structural damage identification is critical for ensuring the safety and health of civil infrastructures. In this field, data-driven models based on machine learning paradigms have been widely utilized. However, collecting massive amounts of data from an actual structure in various damage scenarios is impractical. Therefore, a digital twin, serving as a virtual representation of the physical structure, can be created using either a FEM or a surrogate model. The FEM can generate the data needed to train the supervised learning model. It is worth noting that supervised learning relies on the assumption that the training and testing datasets have the same data distribution, meaning that the FEM must accurately represent the actual structure [1]. However, the regular model updating technique struggles to obtain a FEM with good generalization due to the ill-posed problem [2]. Mismatches between the FEM and the actual structure are inevitable because of modeling errors, real-world uncertainties, and operational conditions. These mismatches can cause the trained model to fail in predicting damage conditions on the actual structure [3].

Our work introduces the concept of hierarchical physics-informed domain adaptation, a cutting-edge approach designed to bridge the gap between theoretical models and practical applications. By integrating physical and domain-specific knowledge into the learning process, this method not only enhances the detection of structural anomalies through unsupervised learning but also improves the localization of structural damage via supervised learning techniques. Unlike traditional domain adaptation methods that require both healthy and damaged state data from the actual structure, our approach trains the domain adaptation neural network without the need for damaged state data from the actual structure. Unlike traditional physics-informed machine learning (PIML) approaches, we propose a novel method to impose physical constraints on domain adaptation neural networks through weight initialization based on the structure's modal information. Our HierPhyDA approach, which acts as the digital twin of the physical structure, dynamically adjusts to observed data, significantly boosting the reliability and accuracy of structural assessments. Specifically, the approach outperforms existing state-of-the-art methods when the damage cases from the actual structure are excluded from training, and the damage cases from the FEM used for training are mutually exclusive from those of the actual structure. This breakthrough is pivotal for ensuring real-world applicability, enhancing damage identification performance, and prolonging structural lifespan.

METHODOLOGY

In this study, the structure is excited at specific locations using an impact force, which contributes to smart excitation mechanisms and active sensing. The acceleration responses of the structure, subjected to this impact force, are measured and analyzed using the continuous wavelet transform (CWT) for structural damage detection and localization. The proposed HierPhyDA approach comprises six key steps, as summarized in 1. The hierarchical damage identification framework separates structural anomaly detection and structural damage localization into two steps, enhancing the model's adaptability in the domain adaptation process. The domain adaptation process employs an adversarial paradigm through the discriminator-free adversarial learning network (DALN) [4], which includes a feature extractor and a damage predictor. To impose physical con-

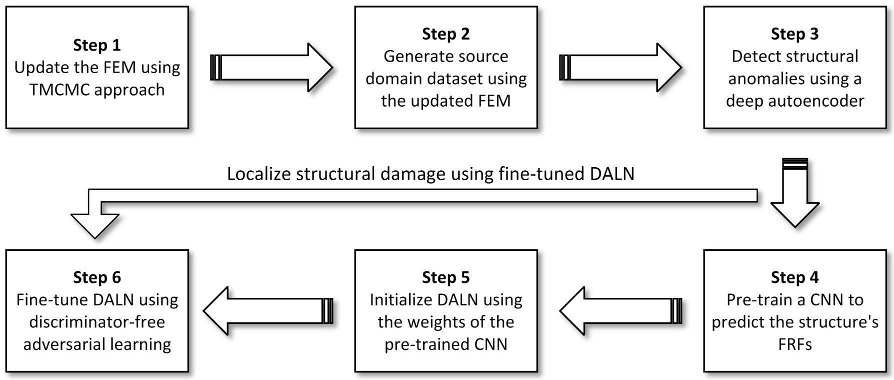

Figure 1. Step-by-step overview of the proposed HierPhyDA approach.

straints, a modal-based weight initialization is applied to the DALN, enabling physics-informed domain adaptation. Specifically, a convolutional neural network (CNN) is pre-trained to predict frequency response functions, which can represent the structure's modal information. The weights from the pre-trained CNN are then utilized to initialize DALN. After the DALN is fine-tuned through discriminator-free adversarial learning, it can be used to localize damage in the actual structure.

ILLUSTRATIVE EXAMPLES USING THE ASCE BENCHMARK STRUCTURE

The ASCE benchmark structure is a quarter-scale, four-story steel frame with two bays by two bays. Two FEMs has been developed to simulate the response of the actual structure, including a 12-degree-of-freedom (12-DOF) model and a 120-DOF model [5]. In this numerical study, the source structure is the 12-DOF model, and the target structure is the 120-DOF model. To enhance the representativeness of the 120-DOF model as an actual structure, 5% structural uncertainty and 10% measurement noise are added. Structural damage is simulated by removing one to four braces from each story, resulting in a total of 648 damage scenarios. The approach is trained to detect and localize damage within one of the four stories. To evaluate the generalization capability of the approach, the damage cases of the target structure are excluded from the network training, and the damage cases for the source and target structures are kept mutually exclusive. Our approach is compared with other state-of-the-art approaches, including supervised convolutional neural network (SCNN), discriminator-free adversarial learning network (DALN), hierarchical supervised convolutional neural network (HierSCNN), hierarchical domain adaptation (HierDA), and physics-informed domain adaptation (PhyDA). To consider the randomness of weight initialization during training, each approach is trained and tested 30 times. The effects of modeling errors and impact locations on the approach's performance are systematically analyzed.

In real-world applications, the fidelity of the FEM may be compromised due to modeling simplifications, variability in material properties, and the impacts of the operating environment. To investigate the capability of the HierPhyDA approach under different fidelity levels of the FEM, the 12-DOF model updated using the transitional Markov chain

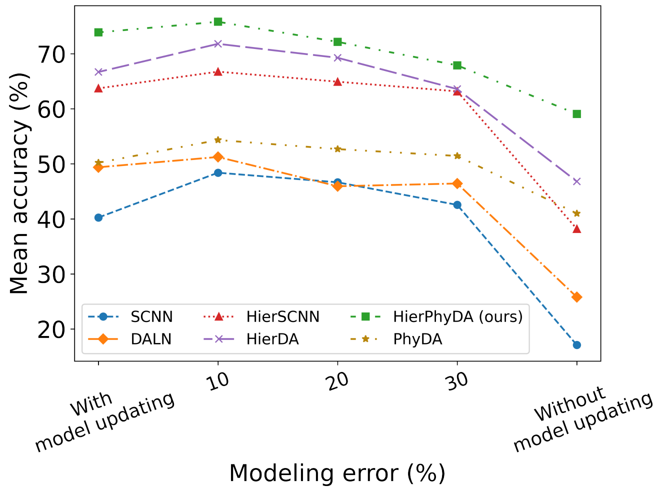

Figure 2. Mean accuracy of the approaches under varying levels of modeling error in the 12-DOF model.

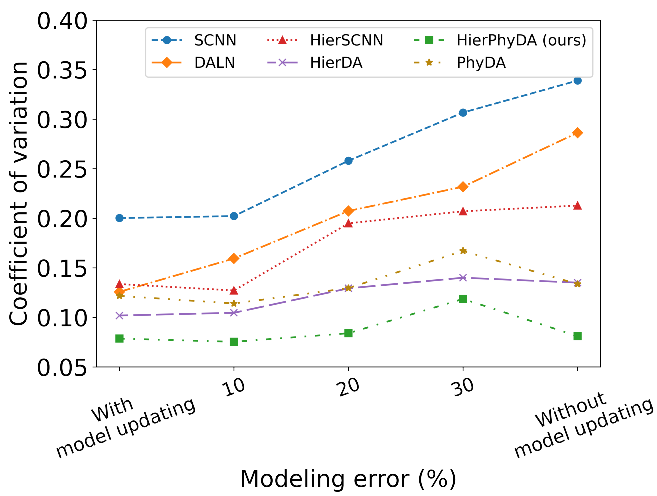

Figure 3. CoV of the approaches under varying levels of modeling error in the 12-DOF model.

Monte Carlo (TMCMC) method [6] is adopted as the baseline. Subsequently, modeling errors of 10%, 20%, and 30% are introduced to this updated 12-DOF model to simulate varying levels of fidelity. According to Figures 2 and 3, as the modeling error increases, there is a noticeable decline in the mean accuracy of the approaches, accompanied by a rise in the coefficient of variation (CoV), which reflects increased uncertainty in performance. Notably, the proposed HierPhyDA approach achieves the highest mean accuracy and the lowest CoV across various levels of modeling error compared to other methods.

Targeted excitation, achieved by applying impact forces at specific locations near the damage site, enhances damage identifiability, leading to improved damage localization performance. Specifically, excitation on the i^{th} floor is used to detect damage on the corresponding i^{th} story (i $\in$ 1,2,3,4). According to the results in Table I, targeted excitation improves the performance of the proposed HierPhyDA approach, increasing accuracy from 87.6% to 99.4% when healthy cases are included in the testing dataset, and from 84.5% to 98.7% when they are excluded. In real-life applications, the targeted excitation strategy can be implemented by systematically exciting potential damage locations and only accepting results where the predicted damage location aligns with the actual impact site.

TABLE I. Accuracy of different approaches with and without targeted excitation.

Approach	Without targeted excitation (excite random floor to detect i^{th} story damage)		With targeted excitation (excite i^{th} floor to detect i^{th} story damage)	
	Include healthy cases	Exclude healthy cases	Include healthy cases	Exclude healthy cases
SCNN	62.6%	78.3%	45.8%	94.7%
DALN	68.0%	72.5%	56.1%	62.7%
HierSCNN	83.5%	79.4%	91.6%	82.7%
HierDA	82.9%	78.6%	94.8%	89.3%
HierPhyDA (ours)	**87.6%**	**84.5%**	**99.4%**	**98.7%**
PhyDA	69.0%	80.0%	50.7%	78.0%

CONCLUDING REMARKS

To bridge the gap between theoretical models and practical applications, we introduce HierPhyDA, a novel PIML approach for structural damage identification. This approach serves as a digital twin of the physical structure by synthesizing features from the FEM to accurately emulate authentic vibration signatures. Based on an extensive study using the ASCE benchmark structure, the following conclusions can be drawn:

- Hierarchical damage identification, which first employs unsupervised anomaly detection followed by damage localization, outperforms All-in-One damage identification.
- Integrating targeted excitation into the proposed HierPhyDA approach by applying impact forces close to the damage site enhances damage identifiability, thereby improving damage localization accuracy.
- Modal-based weight initialization, which imposes physical constraints on DALN, enhances the generalization and extrapolation capabilities of DALN. As a result, even without training on damaged state data from the actual structure, HierPhyDA effectively generalizes to detect and localize damage within the actual structure.
- The proposed approach demonstrates greater robustness against modeling errors. The results indicate that HierPhyDA outperforms other state-of-the-art methods in the presence of modeling errors.

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REFERENCES

1. Pan, S. J. and Q. Yang. 2010. “A Survey on Transfer Learning,” *IEEE Transactions on Knowledge and Data Engineering*, 22(10):1345–1359, doi:10.1109/TKDE.2009.191.
2. Bao, Y. and H. Li. 2021. “Machine learning paradigm for structural health monitoring,” *Structural Health Monitoring*, 20(4):1353–1372, doi:10.1177/1475921720972416.
3. Ge, L. and A. Sadhu. 2024. “Domain adaptation for structural health monitoring via physics-informed and self-attention-enhanced generative adversarial learning,” *Mechanical Systems and Signal Processing*, 211:111236, ISSN 0888-3270, doi: https://doi.org/10.1016/j.ymssp.2024.111236.
4. Chen, L., H. Chen, Z. Wei, X. Jin, X. Tan, Y. Jin, and E. Chen. 2022. “Reusing the Task-Specific Classifier as a Discriminator: Discriminator-Free Adversarial Domain Adaptation,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 7181–7190, doi:10.48550/arXiv.2204.03838.
5. Johnson, E. A., H. F. Lam, L. S. Katafygiotis, and J. L. Beck. 2004. “Phase I IASC-ASCE Structural Health Monitoring Benchmark Problem Using Simulated Data,” *Journal of Engineering Mechanics*, 130(1):3–15, doi:10.1061/(ASCE)0733-9399(2004)130:1(3).
6. Ching, J. and Y.-C. Chen. 2007. “Transitional Markov chain Monte Carlo Method for Bayesian Model Updating, Model Class Selection, and Model Averaging,” *Journal of Engineering Mechanics*, 133(7):816–832, doi:10.1061/(ASCE)0733-9399(2007)133:7(816).