Chapter 17
Physics-Informed Machine Learning for Advanced Structural Damage Detection and Localization

Zixin Wang, Mohammad R. Jahanshahi, and Shirley J. Dyke

Abstract Structural damage detection and localization are crucial aspects of structural health monitoring. Unsupervised anomaly detection can predict whether the structure is healthy or damaged, but it may face challenges in localizing the damage. In contrast, supervised damage detection can localize damage when the damage diagnosis model is trained with data from a finite element model (FEM) that accurately represents the actual structure. However, mismatches between the FEM and the actual structure are inevitable due to modeling errors, real-world uncertainties, and varying operational conditions. Consequently, a damage diagnosis model trained on the FEM cannot be directly applied to the actual structure because of discrepancies in training and testing data distributions. To bridge this gap, we propose a novel approach using hierarchical physics-informed domain adaptation. Our approach begins by detecting structural anomalies using deep autoencoders and information fusion. If the structure is identified as damaged, physics-informed domain adaptation is then employed to localize the damage. A convolutional neural network (CNN) is pre-trained to predict the frequency response functions of the structure. The weights of this pre-trained CNN model are then used to initialize a domain adaptation neural network, specifically a discriminator-free adversarial learning network (DALN). This modal-based weight initialization imposes physical constraints on the DALN. We evaluate the proposed approach using both numerical and experimental ASCE benchmark setups. The results demonstrate that our approach outperforms existing state-of-the-art methods, even when the damaged state data from the target structure is excluded from training, thereby enhancing the real-world applicability of the proposed solution.

Keywords Structural health monitoring · Structural damage detection · Physics-informed neural networks · Domain adaptation · Deep learning

Introduction

Structural damage detection is critical for ensuring the safety and health of civil infrastructures. Data-driven models based on machine learning have been widely utilized in this field. For example, unsupervised learning uses data in the healthy state of the structure to train a model, which can then be used for structural anomaly detection (i.e., determining whether the structure is damaged). In addition to anomaly detection, damage localization is important for pinpointing the damaged area and retrofitting the structure. Supervised learning requires labeled data in both healthy and damaged states to train a model, which can then be used to predict the damage location. However, collecting massive amounts of data from an actual structure in various damage scenarios is impractical. Therefore, a digital twin, consisting of a physical structure and a corresponding FEM as its virtual representation, can be constructed. 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

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same data distribution, meaning that the FEM must accurately represent the actual structure. However, mismatches between the FEM and the actual structure are inevitable due to modeling errors, real-world uncertainties, and operational conditions. These mismatches can cause the trained model to fail in predicting the damage location on the actual structure.

Domain adaptation, a subset of transfer learning, transfers knowledge from a source domain (e.g., the FEM) to a related target domain (e.g., the actual structure) by learning domain-invariant features through domain-adversarial training. Even though the extracted features from the two domains have close data distributions, the trained model may struggle to extract damage-informative features for damage localization. Additionally, current domain adaptation methods require a large amount of unlabeled data from the target structure to train the model. However, collecting sufficient unlabeled data in various damaged scenarios of the actual structure is infeasible. In this work, we propose a hierarchical physics-informed domain adaptation approach (HierPhyDALN). More specifically, structural anomaly detection is first performed using a deep autoencoder and information fusion, and if the structure is identified as damaged, then physics-informed domain adaptation is employed to localize the damage. Physical constraints are applied to DALN through modal-based weight initialization, which effectively forces DALN to learn damage-informative features. Our approach is rigorously validated using both numerical and experimental ASCE benchmark setups, demonstrating the superior performance of our approach compared to other state-of-the-art methods, even when trained exclusively on data representing the healthy state of the target structure.

Methodology

Intra-class variance evaluates the model's adaptability to a new task, indicating how transferable the model is. Data in damaged states of the structure typically exhibit a larger intra-class variance than data in the healthy state, indicating that the damaged state data is more efficient for domain adaptation. Therefore, hierarchical damage detection is proposed, wherein structural anomaly detection is initially performed using an unsupervised autoencoder and information fusion [1]. If the structure is identified as damaged, physics-informed domain adaptation, which is trained exclusively on the damaged state data, is deployed to predict the damage location. The adversarial paradigm in the form of DALN is adopted for domain adaptation. DALN consists of a feature extractor G and a damage predictor C. The damage predictor C is reused as a discriminator D by incorporating Nuclear-norm Wasserstein discrepancy, which enables feature extractor G to learn domain-invariant features. The loss function used to optimize DALN can be expressed as:

$$\min_{C,G}\left\{\frac{1}{N_s}\sum_{i=1}^{N_s}\mathcal{L}_{ce}\left(C\left(G\left(x_i^s\right)\right),y_i^s\right)+\lambda\max_{C}\left\{\frac{1}{N_s}\sum_{i=1}^{N_s}\left\|C\left(G\left(x_i^s\right)\right)\right\|_*-\frac{1}{N_t}\sum_{j=1}^{N_t}\left\|C\left(G\left(x_j^t\right)\right)\right\|_*\right\}\right\} \tag{1}$$

To enforce DALN to learn damage-informative features, we propose a physics-informed neural network using modal-based weight initialization. Specifically, a CNN containing a feature extractor G and a modal predictor M is pre-trained to predict the FRFs of source and target structures. Note that the modal predictor M and the damage predictor C share the same architecture, except for their output layers. The weights from the pre-trained CNN are then utilized to initialize DALN, thereby imposing physical constraints on DALN and enabling it to learn modal-related features such as natural frequencies and mode shapes, which are conducive to damage localization. DALN is fine-tuned using labeled data from the source domain and unlabeled data from the target domain. In this study, the input to the data-driven models is the continuous wavelet transforms of acceleration signals. Fig. 1 provides an overview of the proposed approach.

Numerical Study: ASCE Benchmark Models

The benchmark structure is a four-story, two-bay by two-bay quarter-scale steel frame constructed at the University of British Columbia. A 12-degree-of-freedom (DOF) model and a 120-DOF model, as shown in Fig. 2, are built to generate simulated response data [2]. Though the model parameters of the 12-DOF model are updated using the transitional Markov chain Monte Carlo (TMCMC) approach to match the modal properties of the 120-DOF model, domain discrepancies between the two models still exist. To predict the damage categories on the target structure, domain adaptation is performed between the 12-DOF model (the source structure) and the 120-DOF model (the target structure). Structural damage is emulated by removing the braces on each story, resulting in five categories, including one healthy category and four damaged categories with each story being damaged. A hammer is used to excite each floor and the corresponding vibration responses are calculated. For each damage category, 80 samples are generated with each sample containing 16 sensor signals. Since the

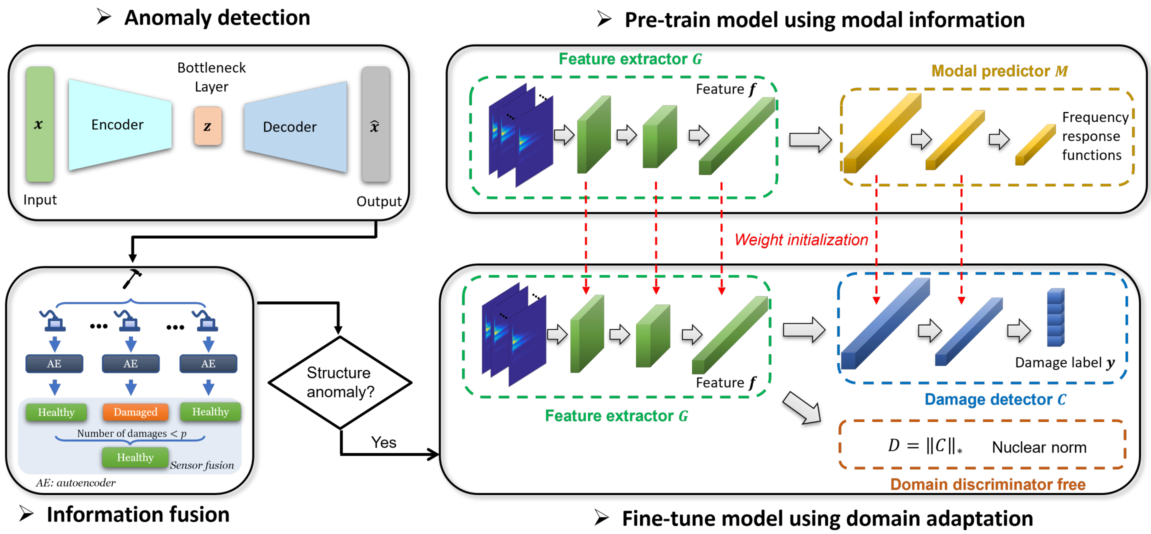
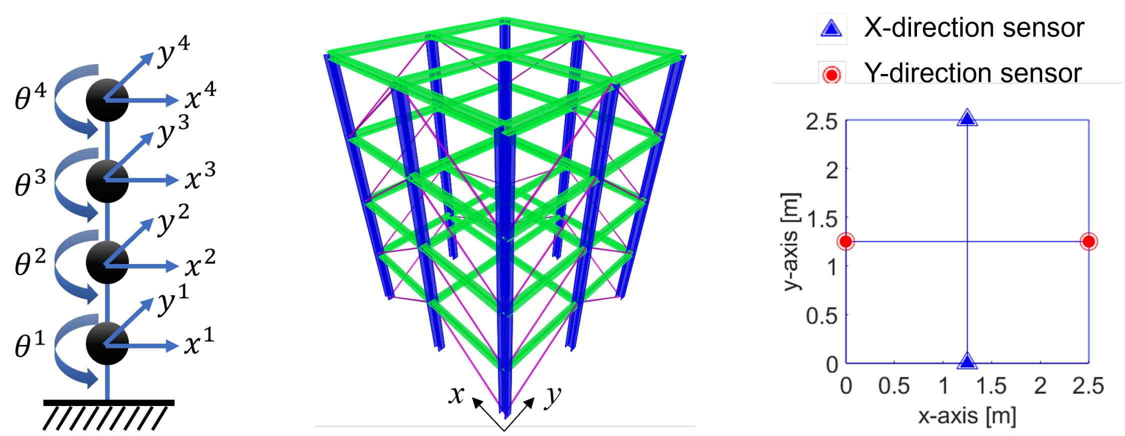


Fig. 1 An overview of the proposed approach.

120-DOF model represents the actual structure, 5% structural uncertainty and 10% measurement noise are introduced to the model.



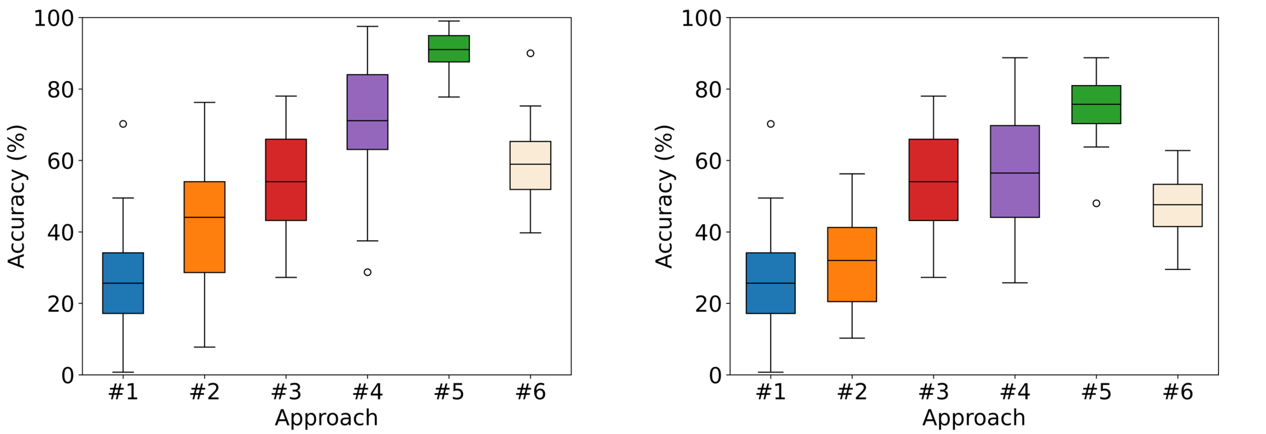
(a) 12-DOF model (source structure)
(b) 120-DOF model (target structure)
(c) Sensor location (top view)

Fig. 2 ASCE benchmark models.

We compared our proposed approach (HierPhyDALN) with other state-of-the-art methods, as summarized in Table 1. Each approach is trained 30 times to consider the randomness of weight initialization during training. Damage detection results on the 120-DOF model using different approaches are presented in Fig. 3. The results demonstrate that hierarchical damage detection, which includes anomaly detection followed by damage localization, can significantly enhance accuracy. This improvement is attributed to the larger intra-class variance of the damaged state data, which enhances the adaptability of the DALN trained exclusively on the damaged state data. Furthermore, the physics-informed DALN outperforms the pure DALN. This is because the modal-based weight initialization constrains DALN from learning damage-informative features, which is conducive to damage localization. It is worth noting that collecting data in different damaged scenarios on the actual structure is impractical. However, our proposed approach can achieve promising performance even when the damaged state data from the target structure is excluded from the training (Fig. 3(b)).

Table 1 State-of-the-art approaches used for structural damage detection and comparison in this study.

Approach	DALN	Physics-informed NN	Hierarchical damage detection
#1: SCNN	×	×	×
#2: DALN	✓	×	×
#3: HierSCNN	×	×	✓
#4: HierDALN	✓	×	✓
#5: HierPhyDALN (ours)	✓	✓	✓
#6: PhyDALN	✓	✓	×



(a) Unlabeled data in damaged states of the 120-DOF model are **included** in the training.

(b) Unlabeled data in damaged states of the 120-DOF model are **excluded** from the training.

Fig. 3 Damage detection results on the 120-DOF model using different approaches.

Experimental Study: ASCE Benchmark Structure

In this section, we validate our approach using the actual benchmark structure (the target structure) and the 120-DOF model (the source structure), as shown in Fig. 4. The model parameters of the 120-DOF model are updated using the TMCMC approach to match the modal properties of the actual structure, yet the source and target domains still exhibit different data distributions. In the target domain, 7 samples for the healthy category are collected from the actual structure subjected to hammer impact, with each sample containing 12 sensor signals. Additionally, three damage categories are implemented on the actual structure: (i) brace damage on the east face; (ii) brace damage on the east and north faces; and (iii) brace damage on all faces, with 24, 6, and 18 samples collected for each damaged category, respectively. In the source domain, 96 samples are generated using the 120-DOF model for the healthy category, and 384, 96, and 288 samples are generated for the three damaged categories, respectively. The damage detection results using different approaches, excluding the damaged state data of the actual structure from training, are shown in Fig. 5. We also perform t-tests on the results obtained by our proposed approach versus other approaches, as listed in Table 2. All p-values are below 0.05, indicating that our approach has statistically significant improvements compared to other state-of-the-art methods, even with limited data from the actual structure.

Table 2 T-test on the results obtained by the proposed approach versus other state-of-the-art methods.

Approach	P-value
#1 vs #5	4.15×10^{-17}
#2 vs #5	2.32×10^{-12}
#3 vs #5	5.18×10^{-12}
#4 vs #5	1.99×10^{-9}
#6 vs #5	4.34×10^{-2}

(a) 120-DOF model (source structure)

(b) Actual benchmark structure (target structure)

(c) Sensor location (top view)

Fig. 4 ASCE benchmark structure.

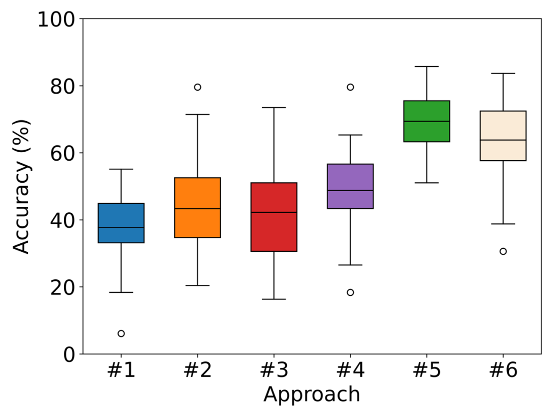


Fig. 5 Damage detection results on the actual structure.

Conclusion

This study proposes a hierarchical physics-informed domain adaptation approach (HierPhyDALN) to address the domain shift between the FEM and the actual structure in supervised damage detection. Hierarchical damage detection leverages the larger intra-class variance of the damaged state data to enhance the adaptability of DALN. The physical constraints through modal-based weight initialization enable DALN to learn damage-informative features. Results from both numerical and experimental ASCE benchmark setups indicate that our approach outperforms other state-of-the-art methods, even when the damaged state data from the target structure is excluded from training, thus enhancing the real-world applicability of the proposed solution.

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References

1. Wang, Z., Jahanshahi, M.R., Bilionis, I., Fu, Y., Maghareh, A., and Dyke, S.J. Unsupervised Structural Damage Detection on Extraterrestrial Habitats using Information Fusion and Autoencoders. The 14th International Workshop on Structural Health Monitoring (IWSHM), September 12–14, 2023, Standford University, California.
2. Johnson, E.A., Lam, H.F., Katafygiotis, L.S., and Beck, J.L. 2004. "Phase I IASC-ASCE structural health monitoring benchmark problem using simulated data." *Journal of Engineering Mechanics*, 130 (1): 3–15.