Digital Twin System for Structural Damage Monitoring Based on Lamb Wave Feature Enhancement with Imbalanced Few-Shot Learning and Interactive Transfer

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ABSTRACT

As structural damage patterns and service environments become more complex, digital twin-based structural health monitoring (SHM) with its unique advantages can compensate for the limitations of data-driven methods regarding data dependency and model interpretability. However, it still faces challenges in modeling complexity, simulation accuracy, and discrepancies between real and virtual features. This study proposes a balanced fidelity digital twin for structural damage monitoring based on Lamb wave multilevel feature enhancement and adaptive space interaction. Firstly, multilevel refined features are extracted from few-shot guided wave signals obtained in physical and digital space, and the adversarial synthetic balancing algorithm (ASBA) is proposed for feature enhancement. Additionally, the learning phase of the damage monitoring model based on the feature mapping convolutional network (F-MCN) is driven by virtual samples of readily accessible balanced fidelity in digital space. To reduce the feature distributional difference between the two spaces, an interactive transfer approach is introduced to establish a shared feature digital twin space. Overall, this study provides a feasible technique to enhance the accessibility and generalizability of digital twins for real engineering structures.

1. Introduction

The global aerospace, shipbuilding, and marine engineering industries are evolving toward intelligence, scalability, and sustainability, placing higher demands on structural performance. Structures often endure complex loads and harsh environments, leading to degradation that threatens operational safety [1]. Guided wave–based structural health monitoring (SHM) has emerged to address this challenge. However, traditional physics-based SHM methods struggle with manual feature selection and sensor placement, while purely data-driven approaches often act as black boxes, requiring large datasets and lacking physical interpretability, limiting their reliability in real-world scenarios [2-4].

Digital twin (DT) technology offers a promising solution for SHM by using digital models to represent real-world structures [5-6]. DTs can capture potential damage characteristics and enable flexible, real-time monitoring. Current DT construction approaches fall into two categories: high-fidelity simulation and low-fidelity model calibration. High-fidelity methods use accurate physical modeling to simulate wave propagation and wave–damage interaction, providing detailed insights into crack or corrosion-related damage. However, these simulations are computationally intensive, requiring complex mesh generation and solver tuning, reducing interpretability and responsiveness [7].

To mitigate these limitations, recent research explores computationally efficient alternatives, such as multi-scale modeling and signal feature enhancement using methods like GANs and wavelet transforms [8]. These techniques improve feature diversity in limited data environments but may miss critical microstructural details. Low-fidelity model calibration methods, in contrast, create simplified models and refine

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them using experimental data. While efficient, these models are often constrained by assumptions that neglect nonlinearities or environmental influences [9-10]. Bayesian optimization and joint learning approaches have improved calibration, but struggle to adapt to unseen damage modes or new environments due to weak feature correspondence between digital and physical spaces [11-12].

This study proposes a Lamb wave–based digital twin SHM framework that integrates medium to high fidelity simulated data with scarce but accurate experimental data. The framework leverages transfer learning and physics-informed modeling to bridge the feature gap between digital and physical spaces, enhancing the model's adaptability and robustness in dynamic damage scenarios. The main contributions are as follows: 1) A physics-informed, balanced-fidelity digital model that simplifies Lamb wave propagation mechanisms while preserving essential damage features, achieving a trade-off between accuracy and efficiency; 2) A multi-level feature extraction and adversarial synthetic balancing algorithm that enhances few-shot guided wave signal features from both simulation and experiments. Feature-mapping convolutional networks are introduced to evaluate diagnostic performance under varied data combinations; 3) A hierarchical fine-tuning transfer strategy that enables adaptive communication between physical and digital spaces, facilitating model adaptation to evolving damage patterns.

2. Methodology

In the present study, a guided wave-based digital twin system for structural damage monitoring with balanced fidelity is proposed. The study framework is shown in Figure 1. In digital space, the process includes the following steps: 1) guided wave-based digital modeling, where the finite element technique is used to construct a reasonably simplified digital model that simulates and generates guided wave signals for different damage scenarios; 2) enhancing damage features, where guided wave multilevel feature extraction is applied to simulated and experimental signals, and ASBA is introduced to achieve feature augmentation of imbalanced damaged samples; 3) damage monitoring, where the comprehensive damage feature set obtained after feature enhancement is used as the source domain to train the F-MCN. In physical space, guided wave signals from damaged structures are collected as target domain data using sensing devices, and the trained monitoring model is transferred to this domain.

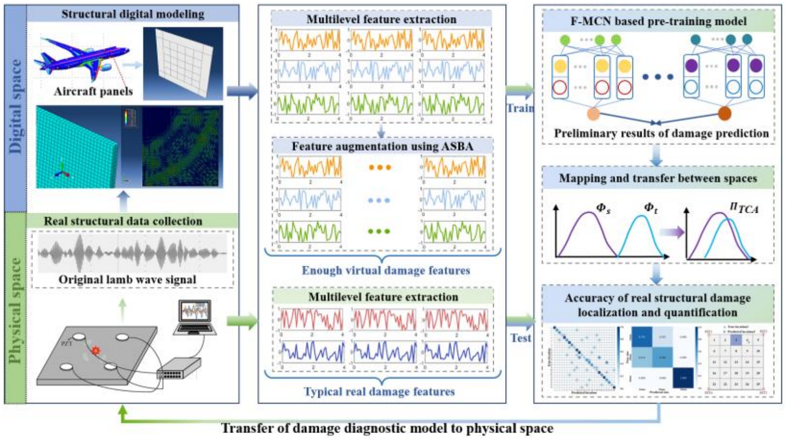

Figure 1. Schematic diagram of the holistic monitoring approach.

2.1 Guided wave-based digital simulation model

The first step in constructing a guided-wave-based balanced-fidelity digital model is to calculate the wave propagation characteristics in the structure using the semi-analytical finite element (SAFE) method. The second step introduces the amplitude decay equation and the Rayleigh damping model to characterize the effects of damage, ultimately generating dynamic displacement data that include damage features. This reasonably simplified modeling process provides reliable data support for the interaction between digital and physical spaces, ensuring accurate simulation results and achieving an optimal balance between reproducing physical laws and modeling efficiency in the digital twin system.

The dynamic behavior of guided wave propagation can be described by the two-dimensional fluctuation Equation (1).

$$\frac{\partial^2 u(x,y,z,t)}{\partial t^2} = \frac{1}{\rho}(\nabla \cdot (C : \nabla u(x,y,z,t))) \tag{1}$$

where the displacement vector $u(x,y,z,t)$ represents the displacement at any given point and time. ρ is the material density, and C is the elasticity tensor, reflecting the material's rigidity. ∇ is the gradient operator, representing spatial variations in the x, y, and z directions.

The total displacement amplitude at any point in space can be calculated using Equation (2).

$$\begin{aligned} |u(t)| = {} & A_d(x,y,z) \cdot e^{-\sigma(x,y,z)t} \\ & \cdot \sqrt{u_{x0}^2(x,y,z,t) + u_{y0}^2(x,y,z,t) + u_{z0}^2(x,y,z,t)} \end{aligned} \tag{2}$$

where $A_d(x,y,z)$ denotes the initial amplitude in the undamaged region. u_{x0}， u_{y0} and u_{z0} are the three displacement components, representing the dynamic response under the influence of structural damage.

2.2 Feature enhancement strategy in digital space

The feature enhancement strategy in this study aims to construct a comprehensive damage feature set in digital space. The first phase involves multilevel feature extraction of the simulation signals from Section 2.1 and the experimental signals, enabling hierarchical analysis and mining of the features from these signals. The second phase introduces the adversarial synthetic balancing algorithm (ASBA) to further augment and balance the damage features, enhancing the generalizability of the samples across diverse damage scenarios. This strategy reduces the dual costs of both simulation and experimental data acquisition while providing more discriminative and adaptable feature support for the damage monitoring model.

The generator and discriminator update their respective parameters through adversarial training, such that the generated samples progressively approximate the real distribution. The optimization objective is expressed in Equation (3).

$$\min_{G}\max_{D}[\mathbb{E}_{x\sim P_r}[D(x)] - \mathbb{E}_{z\sim P_z}[D(G(z))] - \mathrm{GP}((U(d)))] \tag{3}$$

where U(d) denotes the oversampled data generated by SMOTE.

The training process of ASBA concatenates features belonging to the same damage path and inputs them into the model as a complete feature set. In this way, the model not only captures the multi-scale details and global associations of damage features more comprehensively but also reduces model training time and algorithm complexity.

2.3 Damage monitoring model across space

The interactive mapping between physical space and digital space is based on the correlation between experimental signal features and the signal features generated in Section 2.2. The signal features of digital space serve as source data, and those of physical space serve as target data, respectively, jointly driving knowledge transfer and collaborative optimization. The source domain features are used as pre-training data for the damage monitoring model. A portion of the target domain features is employed for fine-tuning and optimizing the model, while the remaining portion is used to assess the model's diagnostic capability in novel physical tasks, thereby achieving cross-space interactive transfer.

the fine-tuned model performs damage identification on the target domain data Φ_t in the shared feature space. Since the features are already aligned, the model utilizes the lower-layer general feature extractor to process the underlying features of the target domain, while the fine-tuned higher-layer weights adapt to the specific damage patterns of the target domain. The damage identification process is expressed in Equation (4).

$$\hat{\gamma}_{t,i} = f_{\text{F-MCN}}(\phi_{t,i}; \theta_{\text{low}}^{\text{target}}, \theta_{\text{high}}^{\text{target}}) \tag{4}$$

where $\hat{\gamma}_{t,i}$ represents the predicted damage label.

Through the iterative fine-tuning process described above, the proposed method improves the accuracy of damage identification, even under conditions of limited sensor availability and low-fidelity simulations. This approach successfully achieves transfer from physical space to digital space, demonstrating the significant advantages of the balanced-fidelity digital twin system in terms of adaptability and precision.

3. Case study

To verify the effectiveness of the proposed method in the digital twin system for structural damage monitoring, a typical component of an aircraft fuselage panel is analyzed as a case study. The carbon fiber reinforced plastic (CFRP) structure used in the component is composed of eight layers of T300 carbon-fiber woven fabric, with dimensions of 280mm × 280mm × 1.6mm.

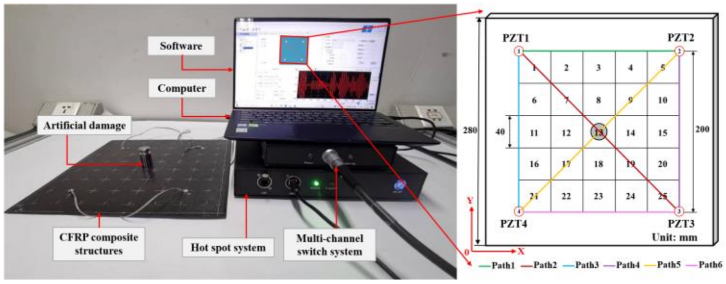

Figure 2. Experiment set-up and sensor array in physical space.

In physical space, the experimental system consists of a CFRP plate, a piezoelectric (PZT) sensor array, an ultrasound detector, and an upper computer, as shown in Figure 2. The sensor array comprises four PZT sensors with a diameter of 8 mm and a thickness of 0.1 mm, forming six sensing paths. A five-cycle sinusoidal wave modulated by a

Hanning window with a center frequency of 160 kHz is selected as the excitation signal. The sensor coverage area serves as the structural damage monitoring region, which is divided into 25 regions. The position and size of each artificial damage are varied, and 72 GW guided wave signals are collected using an ultrasonic guided wave monitoring system with a sampling frequency of 12 MHz.

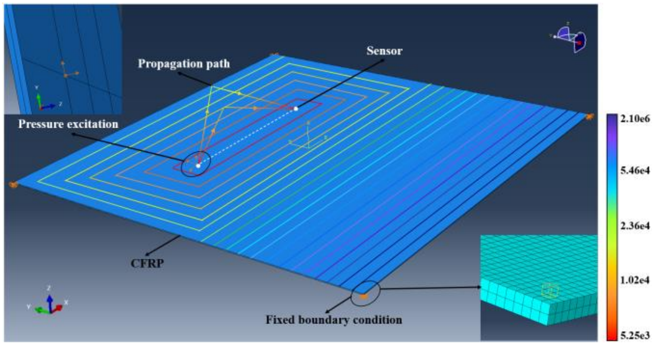

Figure 3. The FE model for Lamb waves simulation with mesh details.

In digital space, a three-dimensional FEM analysis is performed in ABAQUS, utilizing eight-node linear reduced integration hexahedral elements (C3D8R), and setting the mesh size to 1 mm. Four surface-mounted PZT sensors, with the same dimensions as those used in the experiment, are modeled, and the encastre boundary condition is used. Considering the propagation characteristics of guided wave in CFRP structures, an exponentially increasing Rayleigh damping is introduced in this study to simulate the behavior of the Lamb wave at the boundaries. The Rayleigh damping incrementally increases from the non-damping area outward, effectively suppressing boundary reflections of the guided wave, as detailed in Figure 3.

4. Results and Discussions

To explore the capability of the constructed digital twin system in damage monitoring, five scenarios involving different combinations of data sources and training methods are discussed in this section. The accuracy and F1 scores of damage diagnosis are shown in Figure 4. S1 and S2 represent scenarios where the diagnostic model is trained using only physical space experimental samples and only digital space simulation samples, respectively. In S3, the training samples are directly fused from experimental and simulation samples. S4 introduces ASBA, using feature-enhanced samples to train the model. S5 is the scenario where digital space and physical space interaction is achieved through fine-tuning.

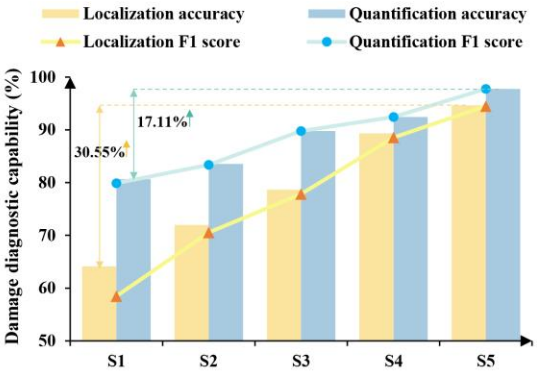

Figure 4. The accuracy and F1 scores of damage diagnosis for each scenario.

Among all scenarios, S5 demonstrates the highest diagnostic capability, with localization and quantification accuracies reaching 94.67% and 97.78%, respectively. Figure 5 illustrates instances of localization errors in the test results. It is evident that the localization regions of the erroneous samples are generally adjacent to the actual damage locations, further validating the system's high-precision diagnostic capability in this scenario. This is attributed to the effective communication between the two spaces, where the fusion of virtual and real data leverages their respective advantages, enhancing the adaptability and flexibility of F-MCN. Moreover, this result also demonstrates that even without developing a high-fidelity digital model, the diagnostic accuracy still rivals that of pure physical space with a sufficient sample size.

Overall, the localization and quantification accuracies in S5 are improved by 30.55% and 17.11%, respectively, compared to S1 with the same number of experimental samples. This significant enhancement proves that the constructed digital twin system can successfully overcome the problems of low simulation fidelity and limited sensor availability, as well as quickly adapt to new damage features and environmental changes.

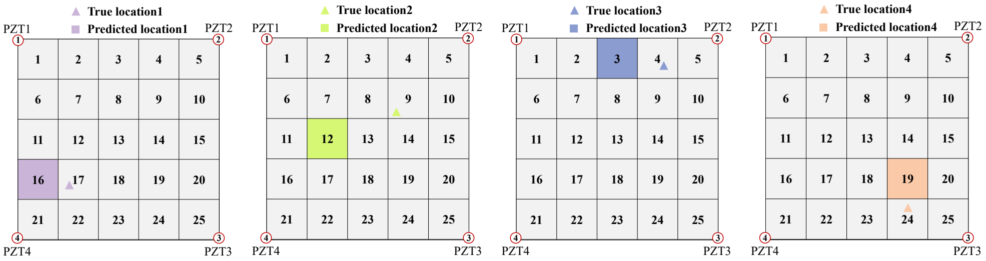

Figure 5. The instances of localization errors in the test results.

5. Conclusions

The proposed methodology is verified through a case study of damage diagnosis for typical aircraft fuselage panel components, and the main conclusions are as follows.

1. From the perspective of system modeling, the physics-informed balanced fidelity digital model achieves a reasonable trade-off between model fidelity and simulation cost, improving the accessibility of the DT system.

2. In terms of damage monitoring, F-MCN is adaptively updated according to changes in damage patterns by combining multi-source data fusion with hierarchical

fine-tuning transfer learning methods, thus enhancing the robustness of the system in the actual damage monitoring tasks.

3. The results of the case study show that the damage localization accuracy of this digital twin system is increased by 22.67%~30.55% and the quantification accuracy by 14.23%~17.11% compared to a single space with a limited number of experimental samples.

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