Doctoral Dissertation
Doctoral Program in Civil and Environmental Engineering (38th Cycle)

Online Joint Identification of Structural Dynamic Response Anomalies and Structural Damage Using Limited Data

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Summary

Structural Health Monitoring (SHM) systems aim to enable real-time assessment of structural conditions by continuously collecting structural response data through sensor networks, while leveraging advanced techniques for data processing and analysis. However, their practical application remains hindered by several challenges: sensor faults frequently degrade data reliability; the lack of adaptive model updates restricts performance under changing environmental and operational conditions; and accurate damage diagnosis is often impeded by the scarcity of labeled damage data, which limits model generalizability and diagnostic accuracy.

To address these challenges, this thesis proposes a limited-data-driven framework for the online joint identification of structural response anomalies and structural damage. The research includes four main components:

(1) To address the limitations of current sensor fault diagnosis methods, particularly their poor performance under limited labeled data and lack of online adaptability, an online meta-learning approach is proposed for sensor fault diagnosis using limited data. A 1D convolutional neural network (1D-CNN) is employed to detect and locate faulty sensors, with initial weights optimized via model-agnostic meta-learning to enhance adaptability across sensor fault classification tasks. After detecting and locating the faulty sensors, an online updating algorithm based on a dual Kalman filter is used to estimate the severity of sensor faults and structural states simultaneously. The effectiveness of the method is validated through both numerical simulations and the Canton Tower benchmark, showing superior performance over conventional deep learning approaches.

(2) To balance identification accuracy and computational efficiency, this study proposes a hierarchical damage identification approach that integrates Bayesian model selection with meta-learning. At the coarse identification stage, potential damaged substructures are detected by generating candidate models and computing their posterior probabilities based on the Bayesian information criterion. At the fine-grained identification stage, a meta-learning-based artificial neural network is employed to locate specific damaged elements and estimate their severity. The effectiveness of the proposed method is demonstrated through numerical simulations and a benchmark application on the Canton Tower, showing superior performance compared to conventional deep learning techniques.

(3) To effectively distinguish between sensor fault- and structural damage-induced anomalies, this study develops a novel meta-learning-based classification model. Damage-sensitive features are extracted using autoencoders, while fault-sensitive features are computed using a set of metrics, including Euclidean distance, mean absolute percentage error, Mahalanobis distance, Pearson correlation, and dynamic time warping. These features are then integrated and fed into a meta-learning-based deep neural network to classify the anomalies. The proposed model successfully differentiates between the sources of anomalies and demonstrates strong robustness across both shear-building simulations and the Qatar University benchmark structure.

(4) To overcome the inherent inflexibility of threshold-based anomaly detection, an adaptive

Bayesian inference framework is proposed for real-time simultaneous anomaly detection and system identification. Statistical models for random and gross errors are introduced to represent typical measurement anomalies, and Bernoulli random vectors are used for anomaly detection. An adaptive Bayesian scheme updates both the Bernoulli and model parameters, allowing for real-time simultaneous anomaly detection and system identification. The effectiveness of the method is demonstrated through numerical simulation, laboratory experiment, and practical implementation in the Canton Tower monitoring system.

Overall, this thesis presents a framework based on meta-learning and Bayesian inference, capable of achieving accurate, adaptive, and efficient online joint identification of structural dynamic response anomalies and structural damage using limited training data.