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Structural condition monitoring through information transferring with dimensional expansion

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ABSTRACT: With the rapid development of sensor technologies and computational methodologies, real-time structural health monitoring (SHM) has gained significant attention in the field of civil engineering. Infrastructures, such as long-span bridges and dams, are often equipped with diverse sensor arrays to enable continuous monitoring of their structural conditions. However, conventional SHM typically require extended data collection periods post-sensor installation, which can delay their practical applications. To address this challenge, this study introduces a novel methodology termed information transferring with dimensional expansion, which leverages transfer learning principles to enhance anomaly detection capabilities in newly instrumented structures. By referencing datasets from similar existing infrastructures, this approach mitigates the dependency on extensive initial data while ensuring reliable anomaly detection. Validation through a case study on a long-span bridge in Republic of Kore demonstrates the method's efficiency and accuracy, highlighting its potential to revolutionize SHM practices by enabling immediate operationalization upon sensor deployment. This research contributes to advancing SHM systems, emphasizing scalability and adaptability for diverse structural applications.

KEY WORDS: Structural Health Monitoring; Transfer Learning; Anomaly Detection; Gaussian Process Regression.

1 INTRODUCTION

As sensor technology and computational capabilities have advanced, interest in structural condition monitoring has been steadily growing. In particular, there has been a noticeable shift toward real-time monitoring of infrastructures, such as long-span bridges and dams, utilizing a wide array of sensors including accelerometers, strain gauges, inclinometers, anemometers, thermometers, piezometers, and water level gauges. Consequently, the development of techniques capable of identifying structural anomalies based on sensor data has become important.

Previous studies have proposed various methods for detecting structural anomalies. For instance, Lee et al. (2018) dynamically adjusts anomaly detection criteria by considering environmental conditions' seasonal and daily variations [1]. Lee et al. (2019) integrates information from finite element simulations to build anomaly detection models of structures under construction [2]. Lee et al. (2022) explored the evaluation of railway bridge deflections under high-speed train loads to identify behavioral irregularities [3]. However, a common limitation of these methods is their reliance on extensive data collection before deployment, making them less viable for immediate application following sensor installation.

To address this challenge, our study seeks to develop an anomaly detection model for newly constructed structures by leveraging data from similar existing ones. We adopt the concept of transfer learning [4], enabling knowledge transfer from previously monitored structures to new monitoring applications.

2 METHOD

To develop an anomaly detection model for structural condition monitoring, an information transfer approach with a dimensional expansion can be introduced. Traditional methods require extensive data collection before deployment, while the proposed approach aims to leverage data from existing structures with similar characteristics to enhance anomaly detection in newly instrumented structures. The methodology consists of the following steps:

- Data collection: This process involves acquiring data using sensors, such as accelerometers. A crucial aspect of this step is securing pre-existing sensor data from structural members and physical quantities similar to those of the newly installed target.
- Dimensional expansion: To address the issue of scale differences in data from different sensors, an additional feature via one-hot encoding is introduced, distinguishing data classes while maintaining comparability. For example, when temperature and response data are collected from two difference sensors, the input dimension can be expanded, as shown in Figure 1, distinguishing between different sources of data.
- Transfer learning implementation: Instead of training separate models for each dataset, a unified *super-model*

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that incorporates knowledge frow well-established datasets which fine-tuning for new dataset is constructed.

- Probabilistic anomaly detection: A probabilistic anomaly detection model to identify deviations in structural behavior is constructed using Gaussian process regression, which is non-parametric Bayesian regression methods.

AS-IS

X	Y
Temperature	Response
12.52	30
13.42	32
15.21	40
12.90	31
12.22	10
13.71	12

TO-BE

X1	X2	X3	Y
Temperature	ID 1	ID 2	Response
12.52	1	0	30
13.42	1	0	32
15.21	1	0	40
12.90	1	0	31
12.22	0	1	10
13.71	0	1	12

Figure 1. Dimensional expansion via one-hot encoding

3 RESULTS

The approach was validated using real-world bridge monitoring sensors: two accelerometers installed on the cables of an operational cable-stayed bridge. One accelerometer had been measuring data for two weeks in advance, while the other began recording approximately two weeks later, leaving only on day of available data for anomaly detection model construction. The acceleration measurements from the two sensors differed in scale by approximately 2 cm/s^2. The objective was to detect anomalies in the sensor data over the subsequent 10-day period (Figure 2).

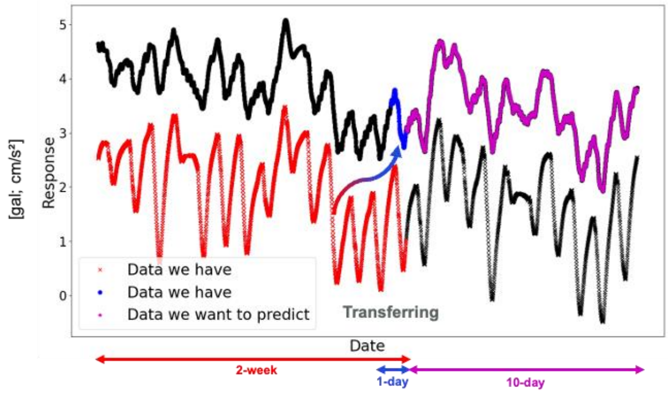

Figure 2. Dataset utilized to validate the approach

First, Figure 3 presents the anomaly detection results obtained using only one day of data without applying transfer learning. Although the 10-day prediction period corresponds to a normal state with no actual anomalies, the model incorrectly identifies multiple data points as anomalies. In contrast, Figure 4, which applies the proposed approach, successfully distinguished the normal state, even though the model was built with limited data from a newly installed sensor. This demonstrates that the proposed approach enables the construction and deployment of an anomaly detection model from the early stages of sensor installation.

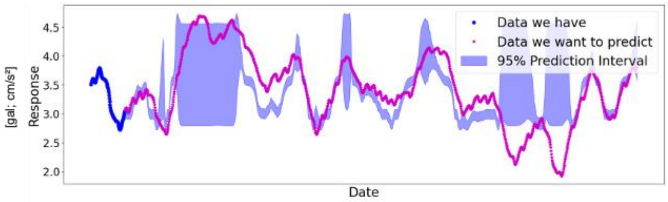

Figure 3. Anomaly detection without transferring information

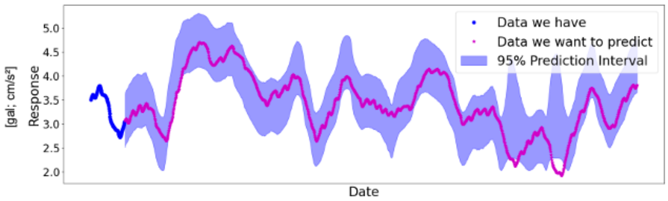

Figure 4. Anomaly detection with transferring information

4 CONCLUSION

This study demonstrates the effectiveness of a transfer learning-based approach for structural anomaly detection in newly monitored structures. Traditional anomaly detection methods require a substantial data collection period before deployment, limiting their immediate applicability. To address this challenge, leveraging pre-existing sensor data from similar structural members can be considered to enhance anomaly detection for sensors with limited initial data.

The results show that models built using only one day of data without transfer learning tend to misclassify normal conditions as anomalies. In contrast, the proposed method effectively distinguishes normal states, even when applied to a newly installed sensor. This confirms that transfer learning can improve anomaly detection accuracy from the early stages of sensor deployment.

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