Special Issue Editorial: “Remote Sensing in Structural Health Monitoring”

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Editorial

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Remote Sensing in Structural Health Monitoring

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Editorial

Special Issue Editorial: "Remote Sensing in Structural Health Monitoring"

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1. Introduction

Structural Health Monitoring (SHM) plays an indispensable role in ensuring the safety and longevity of critical infrastructure, including bridges [1,2], tunnels [3,4], wind turbines [5,6], and skyscrapers [7,8]. As global infrastructure ages, the risk of damage and deterioration significantly increases. Traditional structural maintenance methods rely on regular manual inspections, which are time-consuming and costly, and often fail to detect early-stage damage, only identifying issues once they have escalated. This limitation is especially pronounced for remote or difficult-to-access infrastructure where frequent maintenance is challenging. Consequently, SHM systems based on sensor networks and data analysis have emerged as a preferable alternative. These systems enable real-time, continuous monitoring, allowing early detection of structural damage in its nascent stages and thus preventing major accidents. This proactive approach is essential for extending infrastructure lifespans, reducing maintenance costs, and enhancing public safety.

Despite substantial theoretical and practical advancements, SHM systems still face several challenges. Firstly, sensor accuracy remains a critical technical obstacle. The precision, stability, and reliability of sensors directly impact data accuracy. Over prolonged monitoring periods, sensors may experience drift, aging, or other issues, causing data deviations. Secondly, environmental factors such as temperature, humidity, and wind speed can interfere with monitoring data, complicating the accurate assessment of structural conditions. Additionally, the complexity of infrastructure itself—such as the nonlinear vibration responses of bridges, the multi-material composition of tunnels, and the dynamic loads on wind turbines—requires higher standards for SHM implementation. Consequently, achieving high-precision damage detection and assessment within complex structural systems has become a central focus in current SHM research.

In response to these challenges, researchers have proposed a variety of innovative structural health monitoring (SHM) methods that leverage statistical analysis, deep learning algorithms, and remote sensing to overcome the limitations of existing techniques and advance SHM capabilities. Bridges, as a critical type of infrastructure, are affected by natural environmental factors such as temperature and by traffic loads, making SHM crucial to their safety and durability. Recently, with the rapid advancement of intelligent algorithms, methods based on deep convolutional networks have gained significant attention in bridge health monitoring. Huang et al. [9] proposed a spatiotemporal nonlinear modeling method for temperature-induced pier displacement in long-span single-pier rigid-frame bridges. This method combines elastic modulus fusion, deep convolutional neural networks (DCNNs), and long short-term memory (LSTM) networks to enable real-time,

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accurate monitoring of temperature-sensitive pier displacement, providing a scientific basis for the early warning of excessive displacement in long-span bridges. This non-destructive method greatly enhances the convenience and reliability of bridge health monitoring, highlighting a crucial direction for future research. Similarly, bridge modal parameter identification [10] is a core SHM technology; accurate identification of these parameters is essential for damage assessment and informs maintenance-related decision-making.

SHM for building structures has also seen notable breakthroughs. For example, probability density evolution analysis of random vibration responses [11] enables efficient, precise damage assessment in complex building systems. In the wind energy sector, the health monitoring of wind turbine towers has gained attention. Given their long-term exposure to harsh conditions, turbine towers and blades are prone to fatigue damage. Optimal fractional statistical moment-based vibration signal analysis [5] has been introduced, capturing subtle variations in tower vibration signals through high-order statistics. This method offers a novel approach to the long-term monitoring of turbine towers, and is especially valuable for early damage detection and preventive maintenance. Furthermore, computer vision methods [12,13] now support SHM by enabling automated surface damage recognition and evaluation through the integration of remote sensing and image processing algorithms.

While existing SHM methods are effective, they often face limitations such as restricted monitoring scope, sensitivity to environmental conditions, and difficulty in covering extensive or remote areas. Remote sensing, by contrast, can capture surface information from a distance, offering broad spatial coverage, rapid data collection, and a solution to the constraints of ground-based sensor networks. These capabilities make remote sensing an increasingly valuable asset in SHM [14,15], particularly for applications where traditional methods fall short.

2. Overview of Published Articles

This Special Issue includes 11 original research articles and 1 review article, each showcasing innovative applications of remote sensing technology in structural health monitoring (SHM). These studies cover a wide range of topics, including damage detection, deformation monitoring, defect identification, precise localization, and vibration analysis. Furthermore, these articles discuss the advantages and challenges, of various remote sensing methods in SHM and future prospects for their application. The following is an overview of the key contributions presented in this Special Issue.

Feng et al. [Contribution 1] introduce a novel method for the remote three-dimensional displacement monitoring of civil structures using stereo Digital Image Correlation (DIC). Their approach enhances control point matching accuracy through image correlation algorithms and establishes an adaptive external parameter calibration method based on epipolar geometry, monotonicity, and Euclidean transformation. Validated on a 2 MW wind turbine blade, the system effectively monitors both in-plane and out-of-plane displacements, demonstrating great potential for large-scale SHM applications.

Zuo et al. [Contribution 2] address the challenge of time-domain nonlinear damage identification by proposing a method based on the Kullback–Leibler (KL) distance of time-domain model residuals. Using an autoregressive (AR) model with the autocorrelation function (ACF) and Akaike Information Criterion (AIC) for order selection, the KL distance serves as a damage indicator, successfully localizing structural damage in complex, multi-degree-of-freedom structures. This method's robustness to environmental noise and minor damage makes it highly applicable in real-world SHM.

Chen et al. [Contribution 3] present an innovative signal reconstruction algorithm designed to extract the modal shapes of structures subjected to low-amplitude vibrations caused by environmental excitations. Their vision-based SHM approach, validated on a cantilever beam, can accurately identify the first two modal shapes at vibration amplitudes as low as 0.01 mm, extending the limits of traditional vibration analysis techniques.

Semih et al. [Contribution 4] propose a hybrid SHM method for bridge structures that combines traditional accelerometer data with vision-based measurements for vibration damage detection. Their approach demonstrates improved accuracy and resistance to noise, even in cases where conventional acceleration measurements fail. The method was validated using a simply supported bridge model, highlighting its potential for enhancing vibration-based SHM methods.

Ji et al. [Contribution 5] developed a three-dimensional laser point cloud positioning method for improving the accuracy of seam localization in shield tunnels. By dividing tunnel sections into circular and mileage regions, their approach achieves high precision in seam positioning, with average deviations of only a few millimeters. This method holds significant promise for tunnel safety monitoring and inspection.

Qin et al. [Contribution 6] propose a novel temperature compensation method based on long short-term memory (LSTM) networks and Particle Filters (PFs) to address the effects of temperature variation on long-term SHM data. The LSTM-PF model effectively compensates for both linear and nonlinear temperature effects while filtering out outlier data. Validated with real-world deflection data from a suspension bridge, this method offers an enhanced approach to temperature compensation in SHM systems.

Li et al. [Contribution 7] focus on monitoring the dynamic characteristics of wind turbine blades using a target-free Discriminative Scale Space Tracker (DSST) visual algorithm integrated with drones. Their study introduces a displacement compensation method to address drone hovering drift, enabling the accurate extraction of dynamic characteristics. This approach offers a new perspective for monitoring large wind turbine blades using remote sensing technologies.

William et al. [Contribution 8] present a method for large-scale structural deformation measurement using 3D point cloud imaging from photogrammetry. Their geometric analysis of point clouds captures bridge deformations during static load testing, providing valuable insights into the integration of remote sensing data with finite element models.

Yuan et al. [Contribution 9] introduce the SDS-Network, a lightweight disaster classification model optimized for high-resolution remote sensing imagery. Their method incorporates a spatial attention mechanism and depthwise separable convolutions to improve classification accuracy while reducing computational complexity. The SDS-Network outperforms classical models such as ResNet and VGG in terms of both accuracy and computational efficiency, highlighting its applicability in remote sensing tasks.

Yang et al. [Contribution 10] provide a comprehensive review of SHM systems for super high-rise buildings, focusing on wireless sensor networks and cloud platforms. The review examines key technologies, case studies, and future challenges in SHM for super high-rise structures, underscoring the importance of integrating remote sensing techniques into these systems.

Kwasi et al. [Contribution 11] propose an innovative workflow for creating 3D models of bridges from 2D drawings using corner detection image processing. Their method reconstructs partial 3D point clouds and merges them to create scaled 3D objects, providing a new approach to supplementing real-world laser scan or camera data for bridge inspections.

Finally, Yang et al. [Contribution 12] systematically compare various Time of Flight (ToF) algorithms and propose an automatic diagnostic method based on the Defect Peak Tracking Model (DPTM). This method, applied for the first time in ultrasonic echo signal processing, achieves high accuracy in defect localization and offers potential for future integration with AI-based SHM systems.

3. Conclusions

This Special Issue highlights the broad application and significant potential of remote sensing technology in structural health monitoring (SHM). The featured studies demonstrate how remote sensing enhances SHM in terms of accuracy, spatial coverage, and data acquisition speed across various infrastructures, including bridges, tunnels, wind turbines, and skyscrapers. By integrating high-resolution imaging, LiDAR point clouds, and time-domain analysis, researchers have successfully achieved precise damage detection and real-time monitoring of complex structures, significantly improving the efficiency and practicality of SHM. However, this Special Issue also identifies key challenges, such as the complexities of large-scale data processing, the need for further improvements in monitoring accuracy, and addressing sensor interference under diverse environmental conditions. These challenges mark important directions for future research.

Future SHM systems should focus on the integration of remote sensing technologies with artificial intelligence (AI), the Internet of Things (IoT), and cloud computing to enhance monitoring intelligence and remote control capabilities. AI and machine learning will play a pivotal role in processing remote sensing data and identifying structural damage, while cloud-based centralized monitoring and extensive sensor networks will overcome geographic and temporal limitations, enabling continuous, real-time SHM. Additionally, the development of low-cost, lightweight remote sensing solutions and multi-modal data fusion technologies will broaden the scope of SHM applications across a wider range of infrastructure types. By integrating these emerging technologies, remote sensing is set to become an essential tool for ensuring the long-term safety and sustainability of global infrastructure.

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