Satellite-Based Damage Identification by Distributed Displacement Responses from SAR Images

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**Abstract.** Identification of structural damage in civil structures is essential for ensuring safety and minimizing economic losses. Traditional methods for identifying damaged areas within the realm of structural health monitoring (SHM) often require complex numerical models and extensive sensor networks, which are costly and challenging to implement. This study introduces innovative applications of satellite remote sensing, specifically utilizing synthetic aperture radar (SAR) imagery combined with unsupervised learning, to address these challenges. This research highlights the role of distributed displacement responses from scatterer points in interferometric SAR methodologies as crucial indicators for damage identification. By analyzing all displacement responses of scatterer points. Unsupervised distance-based anomaly detection models are developed to identify damaged areas in civil structures. Scatterer points that yield anomaly scores exceeding a predefined threshold indicate potential damage. The effectiveness and practicability of this method are demonstrated through limited SAR-extracted displacement samples from a historic masonry bridge that suffered partial collapse. Results suggest that this approach is not only practical and efficient but also effective in SHM applications.

**Keywords:** Damage Localization, Satellite Remote Sensing, SAR Image, Unsupervised Learning, Displacement.

1. Introduction

To safeguard civil structures, structural health monitoring (SHM) has become a practical process by using sensory and simulated data from experimental and numerical modeling programs and advanced computational techniques. This technology is necessary for every society due to early detection of structural damage, prevention of catastrophic failures, reductions in maintenance costs, and extension of the service life of civil structures [1,2]. The underlying SHM methods can be broadly categorized into model-based and data-based approaches. The former relies on creating accurate mathematical or numerical models of the structure being monitored, which are then compared with real-time sensor data to diagnose damage. These methods often involve finite element model updating and modal analysis [3]. On the other hand, data-based methods utilize machine learning and statistical techniques to analyze raw measured datasets collected from sensors [4]. Using model-based techniques, it is possible to perform all levels of SHM including early damage detection, damage localization, and damage quantification, while data-based solutions are only able to operate in the first two levels [5].

Damage localization is a critical aspect of SHM as it provides precise information about where damage has occurred within a civil structure [6]. This enables civil engineers to perform targeted maintenance and repair efforts. Accurate localization is essential for ensuring the safety and reliability of structures, as it allows engineers to address specific areas of concern before damage propagates and leads to catastrophic failure. Although model-driven damage localization is a common approach to SHM, this solution encounter different challenges such as high dependency on accurate numerical models of real civil structures, sensitivity to modeling errors, computational costs, and problematic scalability to large-scale civil structures with complex interactions and behavior.

Data-driven damage localization offers several distinct advantages over model-based methods within the framework of SHM. Primarily, data-driven approaches are highly adaptable, capable of handling complex and unpredictable environments without the need for extensive pre-existing models of the structure. Unlike model-based damage localization techniques, which require detailed and often labor-intensive development of accurate physical models, data-driven solutions leverage the power of machine learning and statistical analysis to learn directly from sensory data [7-12]. This allows them to continuously update and refine their understanding based on new information, improving their accuracy and reliability over time.

Sensor networks play an indispensable role in data-driven damage localization by providing the critical spatial data necessary for accurate assessments [7]. The spatial distribution of sensors allows for the detailed mapping of physical phenomena, enabling the detection of anomalies at specific locations. In this context, sensor locations close to damaged areas have different statistical characteristics or machine learning outputs compared to other sensors located in undamaged areas [10,7]. Despite such benefits, the accuracy of these methods heavily depends on the number, type, and placement of sensors. Poor sensor distribution can result in blind spots where damage cannot be detected or localized. Data-driven methods, particularly those are based on supervised learning, require large amounts of labeled training data to learn meaningful patterns [13,14]. However, obtaining labeled damage data is challenging because real structures rarely experience severe damage under controlled conditions.

This study aims to leverage the benefits of satellite remote sensing and unsupervised distance-based models for identifying damaged locations in civil structures. Satellite remote sensing offers transformative benefits for damage localization, particularly for large-scale or difficult-to-access structures. Satellite systems can routinely capture images over the same area at regular intervals, allowing for systematic monitoring without the logistical challenges of deploying ground-based sensors or conducting manual inspections [15,16]. In particular, SAR technology is capable of penetrating clouds and is unaffected by lighting conditions, providing reliable data acquisition regardless of weather conditions or time of day [15]. For these reasons, a few SAR images from satellite remote sensing can be used to extract structural displacement responses at different areas of civil structures. Such SAR-extracted displacement responses serve as the main structural features for damage localization. On the other hand, unsupervised distance-based models based on the Mahalanobis-squared distance (MSD) [17] and Euclidean-squared distance (ESD) are exploited to develop anomaly detectors for identifying the damaged areas based on displacement data from satellite remote sensing. A masonry bridge structure suffered from partial collapse at the bridge deck is used to validate the proposed data-driven method. In this case study, a few SAR images from TerraSAR-X were considered to extract bridge displacement responses at seven locations (i.e., scatterer points in the interferometric SAR methodology).

1. Proposed Data-Driven Damage Localization

The proposed data-driven method for damage identification combines the applications of satellite remote sensing and InSAR methodology with unsupervised learning to derive a practical and innovative solution to identifying damaged areas. The application of satellite remote sensing in damage identification begins with the acquisition of SAR images of the structure of interest, in this case, a full-scale bridge. These images are collected over a series of time points to capture the ongoing state of the bridge. An InSAR technique is then applied to measure the phase differences between successive SAR images taken at different times from some scatterer points considered on the bridge surface. These points are chosen based on their expected stability and visibility in SAR images, ensuring they provide robust data. Each of the scatterer points acts as a marker whose displacement is tracked over time.



**Fig. 1**. Graphical representation of distributed SAR-extracted displacement data for damage localization from satellite remote sensing

Once the scatterer points are established, the displacement responses of these points are meticulously extracted from the interferograms. This involves detailed digital image processing and phase unwrapping techniques to convert phase information into actual displacement measurements. These displacement responses are then compiled into a comprehensive dataset that reflects the movement of each point over the monitoring period. For simplicity, **Fig. 1** depicts the graphical representation of applications of satellite remote sensing, SAR images, and InSAR methodology to providing distributed displacement samples for damage identification.

Suppose that **X**∈ℜ*p*×*n* denotes the distributed displacement matrix from *p* scatterer points and *n* instances (*n* times capturing SAR images) associated with the undamaged structural state. This dataset is exploited to train unsupervised distance-based anomaly detectors for damage identification. These detectors are established from the main statistical characteristics of the training matrix **X**, which are included the mean vector **μ***tr*∈ℜ*p*×1 and covariance matrix **Σ***tr*∈ℜ*p*×*p* of the distributed displacement dataset. The mean vector is composed of np mean values of the displacement samples and the covariance matrix comprises *p*×*p* elements, representing the variance and covariance between each pair of points within the dataset. Each element of the covariance matrix quantifies the degree to which two displacement samples vary together, providing a measure of their joint variability relative to their respective means. From a machine learning perspective, the mean vector and covariance matrix are the main components for training the distance-based anomaly detectors. On this basis, the displacement instances of the training and testing datasets are fed into these models to compute anomaly scores for damage identification.

The anomaly detection models are developed from the MSD and ESD. For the MSD-based anomaly detector, one can express:

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where *i*=1,…,*n* and *j*=1,…,*p*. Given the only mean vector, the ESD is given by:

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For the testing samples in the matrix **Z**∈ℜ*p*×*m*, it suffices to replace *zij* with *xij* in Eqs. (1) and (2) to determine the anomaly scores of the *p* scatterer points in the testing phase. Using the MSD and ESD values in the training phase, it is necessary to establish a threshold limit for damage localization. However, since the number of scatterer points is limited, determining a well-defined threshold using only a few distance values can be challenging. To address this issue, the threshold estimation technique proposed by Entezami et al. [10], which is suitable for small datasets, is employed to calculate the threshold for damage identification. According to this approach, the distance values obtained during the training phase, which correspond to the undamaged structural state, should not exceed the estimated threshold limit. During the testing phase, if any distance value surpasses this threshold, it indicates that the scatterer point associated with that distance value is located in the damaged area.

1. Real-World Verification

This section exploits the SAR-extracted displacement responses of a historical masonry bridge called the Tadcaster Bridge located in United Kingdom, to verify the effectiveness and practicability of the proposed data-driven damage localization method. This bridge has approximately 100 meters long and 10 meters wide that facilitates traffic flow across the town by providing a lane for vehicles in each direction and pedestrian pathways on either side. In recent times, especially before its collapse, the bridge experienced underwater inspections to check for potential scour from riverbed movement due to floods. However, a partial collapse events occurred on December 29, 2015, due to floods from Storm Eva. The bridge was then rehabilitated and reopened on February 3, 2017. **Fig. 2**(a) shows a picture of the Tadcaster Bridge and the damaged area due to the partial collapse.

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| **(a)** | **(b)** |
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**Fig. 2**. (a) A picture of the bridge and the damaged area, (b) the graphical schematic of the Tadcaster bridge along with the damaged area and the locations of the scatterer points emanated from Selvakumaran et al. [18].



**Fig. 3**. SAR-extracted displacement responses (*D*) of the scatterer points 1-7 of the Tadcaster Bridge

In the lead-up to the collapse, a study was conducted using 45 SAR images from TerraSAR-X taken from March 9, 2014, to November 26, 2015. These images, which provided a ground resolution of 3×3 meters, were the last recorded before the bridge failure and were generally taken every 11 days. The differential interferometric SAR methodology and the small baseline subset technique were applied to extract the distributed displacement responses from seven scatterer points, as shown in **Fig. 2**(b). In this regard, **Fig. 3** illustrates the evolution of the displacement samples at these points.



**Fig. 4**. Damage identification by MSD: (a) the training phase, (b) the testing phase



**Fig. 5**. Damage identification by ESD: (a) training phase, (b) testing phase

The displacement samples are divided into two datasets for generating the training and testing matrices. Using the ratio 80-20, the first 36 displacement instances of the seven scatterer points are collected to make the training matrix **X**, where *p*=7 and *n*=36. This means that the distributed displacement samples between March 2014 to July 2015 are considered as the training instances, when no damage occurred in the bridge structure. Moreover, the remaining samples are gathered to generate the testing matrix **Z**, where *m*=9. In this case, the distributed displacements between July 2015 to November 2015 are labeled as the testing points. An important note is that the initial signs of abnormal conditions of the Tadcaster Bridge emerged on November 15, 2015 and November 26, 2015 a few days before the occurrence of the partial collapse. Indeed, the large deviation in the two last displacement samples regarding the scatterer point #2 belongs to these dates as can be seen in **Fig. 3**.

The results of damage identification via the MSD- and ESD-based anomaly detectors are shown in **Fig. 4** and **Fig. 5**, respectively. In both figures, the horizontal lines depict the threshold limits derived from the anomaly scores of the training samples. As illustrated in **Fig. 4**(a) and **Fig. 5**(a), the distance values of the training phase are below the threshold, which mean that the bridge structure still operated normally until July 2015 and there is no damaged area in this bridge. However, as the testing matrix includes the displacement variations caused by abnormal behavior of the bridge in the vicinity of the scatterer point 2, the anomaly detection models correctly identify the location of this point as the damaged area in the Tadcaster Bridge. From **Fig. 4**(b) and **Fig. 5**(b), it is seen that the distance values of the scatterer point #2 exceed the threshold limits, while the distance quantities of the other scatterer points are under the thresholds.

1. Conclusion

This research has introduced a new application of satellite remote sensing for damage identification in civil structures. Building on this foundation, a data-driven damage localization method has been proposed, utilizing distributed displacement responses from selected scatterer points in InSAR techniques. SAR-extracted displacement samples from the undamaged structural state during the training phase have been used to develop unsupervised anomaly detectors based on MSD and ESD. The Tadcaster Bridge, which experienced partial collapse, has served as a case study to validate the proposed method.

The results have demonstrated that the proposed data-driven method leveraging SAR-extracted displacement responses could identify the damaged location in the bridge before its collapse occurrence. Both the MSD- and ESD-aided anomaly detectors could find the potential collapse area. Notably, these models have precisely localized damage at the scatterer point #2, where significant deviations in displacement data were observed right before the bridge partial collapse. These deviations have temporally been aligned with the initial signs of structural failure, highlighting the potential of SAR-based methodologies for timely and precise damage detection in civil infrastructure monitoring.

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