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Large-Scale Structural Anomaly Detection During Seismic Events Using Optical Flow and Transfer Learning from Video Data

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ABSTRACT: Civil structures inevitably experience anomalies and damage, especially during disasters like earthquakes, tsunamis, and hurricanes, causing performance degradation or even collapse. Identifying such anomalies plays an extremely critical role in the maintenance and life extension of civil structures. This study proposes a novel approach based on video data due to its accessibility and rich temporal-spatial information for anomaly detection in large-scale civil structures by integrating transfer learning (TL) techniques with optical flow. Given the low importance of structural Region-of-Uninterest (RoU) like windows and doors, TL with BEIT+UPerNet pre-trained models identifies them. The extended node strength network then leverages video data to focus on structural components and detect disturbances in the nonlinearity vector field. The approach was validated using open video data from E-Defense, capturing two large-scale structural shaking-table tests that featured both pronounced shear cracks and tiny cracks. The detection and quantitative analysis results confirmed the method's effectiveness in detecting structural anomalies and improved computational efficiency by approximately 10%, with a positive correlation observed between this efficiency gain and the proportion of structural RoUs in the video. This study advances anomaly detection in large-scale structures, offering a promising approach to enhancing safety and maintenance practices for critical infrastructure.

KEY WORDS: Anomaly detection; Optical flow; Transfer learning; Video data; Node strength network; Shaking-table test

1 INTRODUCTION

Engineering structures often sustain damage throughout their service life, deteriorating over time due to various environmental and mechanical factors. Both immediate and prolonged damage contribute to the aging of structures and a subsequent reduction in their service life, highlighting the importance of the structural health monitoring (SHM) process [1].

In recent years, the traditional reliance on manual inspection and scheduled maintenance has evolved with the integration of advanced imaging technologies and machine learning (ML) [2]. For instance, Ji et al. [3] proposed vision-based measurement methods for deformation estimation and cracks identification and demonstrate much higher efficiency and provide more useful information than the traditional measurement techniques. Wu et al. [4] developed an improved algorithm based on YOLOv5s which made mAP@0.5 (mean Average Precision when IoU equal 0.5) values improve by around 10%. Furthermore, Xiong et al. [5] proposed a novel computer vision model based on YOLOv8 for automated concrete bridge crack detection. Structural cracks, as a representative form of anomaly event, can serve as indicators of the deterioration in structural service performance.

The authors previously conducted research on anomaly event detection, focusing on nonlinear occurrences, and validated the efficiency of their proposed methods through a small-scale frame model shaking table test [6]. This method detects nonlinearity in structural vibrations using video data, with feature extraction performed via optical flow techniques. However, a significant challenge persists across the field: the high computational costs associated with the analysis process. Addressing this issue is crucial for advancing SHM technologies and methodologies.

This study introduces a novel method for detecting anomalies due to structural nonlinearity in video data, validated through a 3-D full-scale shaking table test conducted by NIED. The method involves extracting nonlinear disturbances from anomaly events in the velocity vector field estimated by optical flow, constructing an extended node strength network, and applying a morphological opening operation for feature extraction and enhancement. This study presents two key advancements for applying the method to general video data. First, the developed algorithm, which was previously applied only to small-scale experimental models, is now tested on large-scale engineering structures to assess its effectiveness in real-world scenarios. Second, to address the challenge of excessive computational time, we integrate a transfer learning (TL) algorithm to initially identify and filter out the Region-of-Uninterest (RoU), thereby enhancing identification efficiency.

The remainder of this extended abstract is organized as follows: Section 2 presents the framework of the proposed algorithm, while the detailed mathematical formulations are omitted due to the page limit of the extended abstract. Section 3 describes the 3D large-scale shaking table tests, including concrete and wooden building tests, followed by the identification results of TL for structural RoU. It also compares visualization results before and after anomaly events (pronounced shear cracks and tiny cracks) to demonstrate the feasibility of the proposed method. Additionally, a morphological opening operation is introduced to enhance features and denoise visualization results. Computational efficiency, with and without TL, is also compared in Section 4. Finally, conclusions are presented in Section 5.

2 METHODOLOGY

The proposed method for detecting structural anomaly events during earthquakes, relying solely on video data, integrates TL with an extended node strength network. Figure 1 illustrates the framework of this method and the flowchart detailing the subsequent steps.

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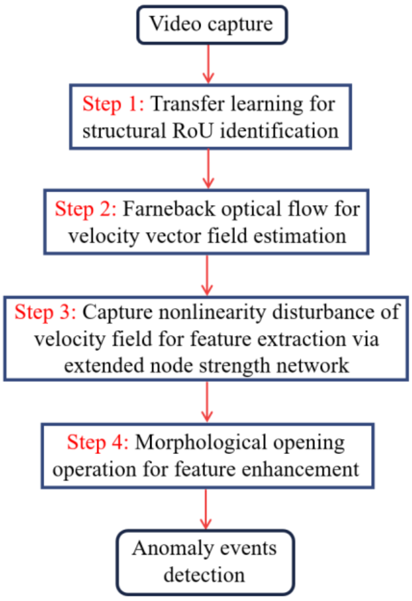

Figure 1. Flowchart of the proposed method

2.1 *Transfer learning for RoU identification*

Recently, Transformer-based models have gained attention for image recognition as alternatives to Convolutional Neural Networks (CNN). Transformers excel at capturing long-distance dependencies, which partly accounts for their superior performance compared to CNN. However, Transformers generally require large amounts of training data. TL addresses this issue by allowing models trained on extensive datasets to perform effectively on specific tasks with smaller datasets. Consequently, BEiT [7], a transformer-based model, was employed, leveraging TL to segment the RoU components. BEiT utilizes the BERT approach [8], a widely used transformer-based model in natural language processing, for image recognition. BEiT treats images as sequences of words and learns to extract features through a masked part-prediction task.

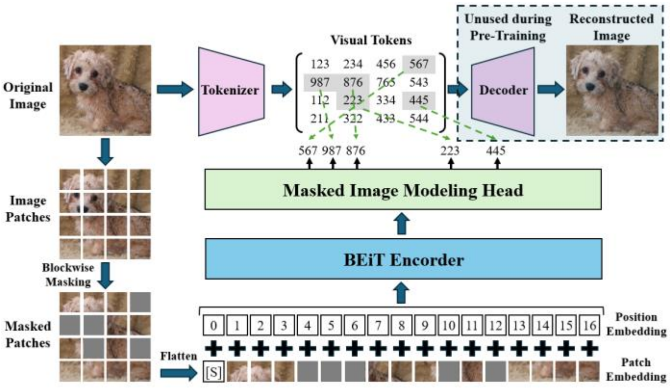

Figure 2. The overview of pre-training BEiT

After pre-training BEiT using Masked Image Modeling (MIM) as shown in Figure 2, the BEiT+UPerNet model, pre-trained for semantic segmentation, was further trained to segment the RoU, specifically targeting windows and doors. An example of RoU recognition for removing the window parts of a building using NIED video data is shown in Figure 3. These images depict the frames before and after RoUs recognition. In the detected area, pixel values are set to zero, allowing for the removal of these pixels in the subsequent anomaly event detection process. By successfully identifying the structural RoUs, video data that exclusively contains structural component information is utilized, thus improving the computational efficiency of the feature extraction process.


(a) (b)

Figure 3. An Example for structural RoUs identification based on TL (a) original frame (b) processed frame

2.2 *Anomaly events detection by proposed extended node strength network*

The anomaly event detection method for video data, as detailed in [6] is summarized here and shown in Figure 4. The method comprises three main steps: (1) estimating the velocity field using Farneback optical flow, (2) extracting anomaly features with the extended node strength network, and (3) enhancing features through a morphological opening operation. This approach allows for the visualization of the timing and location of anomalous events, which result from local disturbances in the vector field caused by nonlinear structural vibrations.

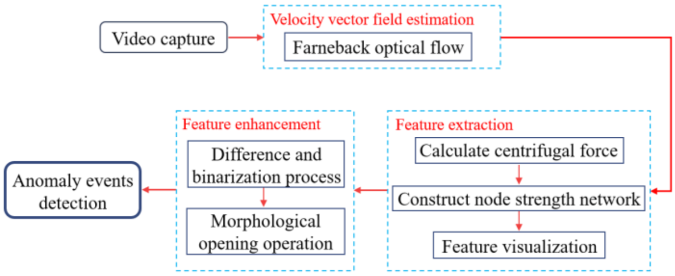

Figure 4. Flowchart of the anomaly events detection method

3 ANOMALY EVENT DETECTION FOR 3D SCALED SHAKING TABLE TEST

In this section, the proposed method is validated using two cases from a full-scale shaking table test conducted by the National Research Institute for Earthquake Science and Disaster Resilience (NIED) in Hyogo, Japan. The test included a 1/3 scale model of a six-story Reinforced Concrete (RC) building and a three-story full-scale wooden house. The example frames for the two cases are shown in Figure 5.


(a) (b)

Figure 5. Example frames for (a) RC building (b) wooden house

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TL is first applied to identify the RoUs and the results are represented in the black area of Figure 6. Then, Farneback optical flow is employed to estimate the velocity field, the results for the damage frame of the two cases are shown in Figure 6. The length of the arrows represents the instantaneous velocity of the pixel points, while the direction of the arrows indicates the velocity direction. In Figure 6(a), It is observed that the occurrence of shear cracks caused a distinct nonlinear change in velocity within the affected area. However, Figure 6(b) reveals that only short arrows are present in the area of the tiny crack, making it difficult to identify the crack solely by evaluating the velocity field. This limitation is due to the fact that changes in velocity cannot uniquely identify anomalous events, as other regions, such as window edges and areas around wires and bolts, also show velocity variations.

(a) (b)

Figure 6. Results of velocity field estimation: (a) RC building (b) wooden house

To represent the anomaly event and enhance its features, an extended node strength network, and a morphological opening operation are utilized. After feature enhancement, as illustrated in Figure 7, nearly all noise areas are effectively removed and only the highlighted area near the crack is retained. The results demonstrate the occurrence of anomalous events and indicate improved detection effectiveness.

(a) (b)

Figure 7. Results of anomaly detection: (a) RC building (b) wooden house

4 DISCUSSION FOR COMPUTATIONAL EFFICIENCY

In this study, a key advantage of combining TL is the improvement in computational efficiency. Early identification and removal of RoUs reduce the number of input pixels needed for subsequent node strength network construction. Table 1 compares computational efficiency before and after employing TL for structural RoU identification. Additionally, we expanded our dataset for comparison by incorporating data from the 4-story steel structure shaking-table test mentioned in Figure 3. Table 1 illustrates a positive correlation between improvements in computational efficiency and the proportion of structural RoUs. The selected test cases demonstrate an average efficiency improvement of approximately 10%. In practical applications, analyzing cases with a larger proportion of structural RoUs results in greater efficiency gains.

Table 1. Comparison of computational efficiency after using TL.

Case	Computing time sec/frame		Improve-ment ratio	RoU proportion
	Before	After		
Four-story steel building	64	59	7.81%	8.59%
Six-story RC frame building	159	144	9.43%	9.66%
Three-story wooden house	249	224	10.04%	10.21%

5 CONCLUSIONS

This study proposed a novel anomaly detection algorithm that focused on nonlinearity occurrence by combining deep learning techniques with an optical flow-based extended node strength network. The approach stems from the observation that such events cause nonlinear disturbances in the velocity vector field, which can be estimated from video data. Additionally, structural RoUs, such as doors and windows, are often not the primary focus of structural health monitoring. Pre-identifying these areas before initiating damage detection can significantly enhance the efficiency of the process.

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