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Multisensor Damage Localization in Buildings via Self-Supervised Vibration Representation Learning

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Abstract : *Structural Health Monitoring (SHM) has become a critical component in the lifecycle management of civil infrastructure, particularly for high-rise buildings subjected to aging and environmental stressors. Traditional damage identification methods largely rely on supervised learning paradigms that require extensive labeled datasets of damaged states. However, in real-world scenarios, data representing structural failure is sparse, expensive to acquire, and often unavailable until a catastrophic event occurs. This creates a significant bottleneck in deploying data-driven diagnostic systems. To address this label scarcity, this paper proposes a novel framework for Multisensor Damage Localization using Self-Supervised Learning (SSL). We introduce a spatiotemporal graph contrastive learning architecture that exploits the inherent topology of sensor networks and the temporal consistency of vibration responses. By treating the sensor network as a graph and the time-series vibration data as node attributes, our model learns robust, damage-sensitive representations from normal operational data alone. We employ a specialized augmentation strategy tailored for vibration signals, including phase shifting and stochastic sensor masking, to train the network to distinguish between environmental variability and structural anomalies. Experimental validation is conducted on a high-fidelity finite element model of a ten-story building under various excitation profiles. Results demonstrate that the proposed method significantly outperforms traditional autoencoder-based approaches and achieves localization accuracy comparable to fully supervised baselines, utilizing only 5% of the labeled data for fine-tuning.*

Keywords: *Structural Health Monitoring, Self-Supervised Learning, Graph Neural Networks, Vibration Analysis.*

INTRODUCTION

1.1 Background

The structural integrity of civil infrastructure, including skyscrapers, bridges, and dams, is paramount to public safety and economic stability. As the global infrastructure stock ages, the risk of structural failure due to material fatigue, seismic activity, and environmental corrosion increases substantially. Consequently, Structural Health Monitoring (SHM) has emerged as an essential discipline, aiming to detect, localize, and quantify damage at the earliest possible stage [1]. Modern SHM systems largely depend on dense arrays of sensors, particularly accelerometers, which capture the dynamic response of a structure to ambient excitations such as wind, traffic, or micro-tremors. These vibration signals contain rich information regarding the physical properties of the structure, including stiffness, mass, and damping ratios.

Historically, the analysis of these signals was rooted in physics-based methodologies. Engineers would compare measured modal parameters—such as natural frequencies and mode shapes—against a calibrated Finite Element Model (FEM) to identify discrepancies indicative of damage. While effective in controlled environments, these model-based approaches often struggle in real-world applications due to modeling errors and the computational prohibitiveness of updating complex FEMs in real-time [2]. This limitation has catalyzed a paradigm shift toward data-driven approaches, where machine learning algorithms infer structural health directly from sensor data without explicit physical modeling.

1.2 Problem Statement

Despite the promise of data-driven SHM, a fundamental challenge remains: the scarcity of labeled damage data. In the context of civil engineering, a "labeled" sample corresponds to sensor data recorded from a structure known to be damaged, with the location and severity of the damage precisely annotated. Obtaining such data from operational buildings is practically impossible, as structures are rarely allowed to operate in a damaged state for extended periods, and deliberately inducing damage for data collection is economically and ethically unfeasible [3].

Consequently, researchers often resort to supervised deep learning models trained on synthetic data generated from simulations. However, the domain gap between idealized simulations and noisy, complex real-world data frequently leads to poor generalization performance. Furthermore, widely used unsupervised methods, such as Principal Component Analysis (PCA) or standard Autoencoders (AE), often fail to capture the complex spatiotemporal dependencies inherent in multisensor networks. They tend to treat sensors as independent channels or simple vectors, ignoring the spatial topology of the building that governs how vibration energy propagates from one structural element to another [4]. The core problem, therefore, is how to leverage the abundance of unlabeled data collected from healthy structures to learn a representation that is sensitive to local stiffness changes (damage) while remaining robust to global environmental changes (temperature, wind load).

1.3 Contributions

To overcome these limitations, this research presents a self-supervised learning framework specifically designed for multisensor damage localization. Our approach posits that the vibration response of a building is governed by a latent spatiotemporal graph structure, where nodes represent sensors and edges represent physical connectivity (beams and columns).

The specific contributions of this paper are as follows:

1. We propose a Graph Contrastive Learning (GCL) framework that learns determining features from vibration data without requiring damage labels. This is achieved by maximizing the mutual information between different augmented views of the same structural state [5].

2. We introduce a set of domain-specific data augmentations for vibration signals, including "Sub-graph Masking" and "Temporal Jittering," which prevent the model from overfitting to trivial signal characteristics and force it to learn global structural dynamics.

3. We develop a gradient-based localization technique that maps the activation discrepancies in the self-supervised network back to specific sensor nodes, allowing for precise localization of structural defects.

4. We provide a comprehensive evaluation on a complex building benchmark, demonstrating that our method yields superior localization performance compared to traditional anomaly detection methods and remains robust under varying noise conditions [6].

Chapter 2: Related Work

2.1 Classical and Statistical Approaches

The foundation of vibration-based damage detection lies in linear structural dynamics. Early research focused heavily on the tracking of modal parameters. It is well established that a reduction in stiffness, caused by cracking or material degradation, leads to a decrease in natural frequencies and a modification of mode shapes [7]. Methods such as the Coordinate Modal Assurance Criterion (COMAC) were developed to spatially correlate measured mode shapes with reference baselines to pinpoint damage locations. However, these global modal parameters are often insensitive to local, incipient damage. A small crack in a massive beam might only cause a frequency shift of less than 0.1%, which is easily masked by measurement noise or thermal expansion [8].

To address noise sensitivity, statistical process control methods were adopted. Techniques utilizing Mahalanobis squared distance and Singular Value Decomposition (SVD) allowed for outlier detection in multivariate time-series data. While these methods improved detection rates, they generally lack the capacity for precise localization. They can flag that the structure has changed, but rarely can they identify exactly which element is compromised without extensive manual calibration [9].

2.2 Deep Learning and Anomaly Detection

The advent of Deep Learning (DL) brought Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to the forefront of SHM. Supervised CNNs, treating vibration spectrograms as images, have achieved remarkable accuracy in classifying damage types when trained on large, balanced datasets [10]. However, the reliance on balanced data is their Achilles' heel.

Unsupervised DL approaches have thus gained traction. Autoencoders (AE) and Variational Autoencoders (VAE) are commonly used to learn a probabilistic distribution of the healthy state. During inference, data with high reconstruction error is flagged as anomalous. While AEs improve upon linear PCA, standard architectures often process sensor channels independently or simply concatenated, neglecting the spatial interactions between sensors. Recent works have begun integrating Graph Neural Networks (GNNs) to model these spatial dependencies [11]. GNNs can explicitly model the flow of information between sensor nodes, aligning the neural architecture with the physical topology of the building.

2.3 Self-Supervised Learning

Self-Supervised Learning (SSL) has revolutionized computer vision and natural language processing by enabling models to learn rich representations from unlabeled data through "pretext tasks." Contrastive learning, a sub-domain of SSL exemplified by frameworks like SimCLR and MoCo, learns by pulling representations of similar samples (positive pairs) together while pushing dissimilar samples (negative pairs) apart [12].

In the context of time-series analysis, SSL is an emerging field. Applications in EEG analysis and fault diagnosis of rotating machinery (e.g., bearings) have shown promise. However, the application of spatiotemporal contrastive learning to distributed sensor networks in civil infrastructure remains underexplored. Existing methods often struggle to define appropriate positive and negative pairs in the context of continuous vibration monitoring, where temporal proximity does not always imply structural similarity due to varying load conditions [13]. This paper addresses this gap by defining topological and temporal augmentations suited for building dynamics.

Chapter 3: Methodology

The proposed methodology leverages the spatial configuration of the sensor network and the temporal nature of vibration data to learn a representation space where damaged states are distinctly separable from healthy states, without explicit supervision.

3.1 Graph Representation of Sensor Networks

We represent the sensor network as an undirected graph $G = (V, E)$, where $V = v_1, \ldots, v_N$ is the set of N sensor nodes, and E represents the edges. In a building, edges are defined based on physical connectivity; for instance, if two accelerometers are placed on adjacent floors connected by a column, an edge exists between them.

The input data consists of multivariate time-series signals $X \in mathbbR^{N \times T}$, where T is the length of the time window. Each node v_i possesses a feature vector $x_i \in mathbbR^{T}$ corresponding to the acceleration history at that location. To process this data, we utilize a Spatiotemporal Graph Neural Network (ST-GNN). The ST-GNN comprises two main components: a graph convolution module to aggregate spatial information from neighbors, and a temporal convolution module to capture dynamic trends over time.

3.2 Spatiotemporal Encoder

The core of our framework is the encoder network, f_θ. The spatial aggregation is performed using Graph Convolutional Layers (GCN). For a given layer l, the feature propagation is defined as:

$$H^{(l+1)} = \sigma(tildeD^{-\frac{1}{2}} tildeAtildeD^{-\frac{1}{2}} H^{(l)} W^{(l)})$$

Here, $tildeA = A + I$ is the adjacency matrix with self-loops, $tildeD$ is the degree matrix, $W^{(l)}$ is the trainable weight matrix, and σ is a non-linear activation function (ReLU). $H^{(0)}$ is the input feature matrix derived from the temporal processing of raw signals.

To handle the temporal dimension, we employ 1D dilated convolutions prior to the graph aggregation. This allows the network to learn frequency-domain characteristics (like resonance) implicitly from the time-domain signal. The output of the encoder is a latent representation $Z = f_\theta(X)$, which compacts the high-dimensional vibration data into a dense vector summarizing the structural state [14].

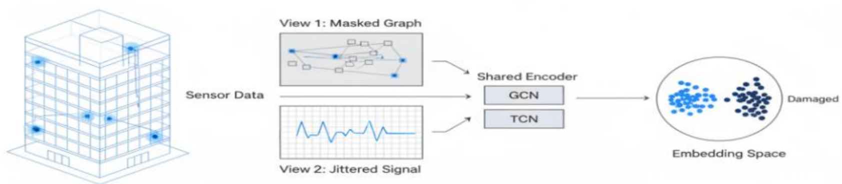

Figure 1: *System Architecture*

3.3 Vibration-Specific Augmentations

The success of contrastive learning hinges on the quality of data augmentations. Standard image augmentations (cropping, color jitter) are inapplicable to vibration data. We introduce two physics-informed augmentations:

1. Stochastic Sensor Masking (Spatial Augmentation): We randomly zero out the input signals of a subset of sensors (e.g., 10%). This forces the GNN to reconstruct the global structural state from partial observations, leveraging the correlation between neighboring sensors. If the network can infer the motion of node i from its neighbors, it has learned the transmissibility functions of the structure.

2. Phase Shifting and Jittering (Temporal Augmentation): We introduce small random phase shifts and additive Gaussian noise to the time signals. This simulates measurement noise and slight asynchronous sampling, ensuring the learned representations are robust to hardware imperfections [15].

3.4 Contrastive Learning Framework

We employ a Normalized Temperature-scaled Cross Entropy (NT-Xent) loss, commonly referred to as InfoNCE. For a minibatch of M graph samples, we generate two augmented views for each sample, resulting in $2M$ data points. For a given sample k, let z_i

and z_j be the representations of its two augmented views (the positive pair). The loss function aims to maximize the similarity between z_i and z_j while minimizing the similarity with all other $2(M-1)$ negative samples in the batch.

The mathematical formulation of the loss for a positive pair $(\boldsymbol{i},\boldsymbol{j})$ is defined as:

$$L_{i,j} = -log \frac{exp(sim(z_i, z_j)/\tau)}{\sum_{k=1}{}^{2M} mathbb1_{[k \neq i]} exp(sim(z_i, z_k)/\tau)}$$

where $sim(u,v) = u^T v/(|u||v|)$ denotes the cosine similarity, $mathbb1$ is the indicator function, and τ is the temperature parameter controlling the sharpness of the distribution. By minimizing this loss, the encoder f_θ learns to map structurally similar states to nearby points in the latent space, regardless of the noise or missing sensor data introduced by augmentation [16].

3.5 Damage Localization via Activation Mapping

Once the encoder is trained on healthy data, it effectively learns the manifold of normal structural behavior. To localize damage, we analyze the node-wise feature activations. When a damaged sample is passed through the network, the graph convolutions at the location of damage will generate activation patterns that deviate significantly from the learned healthy distribution.

We utilize a Gradient-weighted Class Activation Mapping (Grad-CAM) approach adapted for graphs. We compute the gradients of the reconstruction error (or a self-supervised discrepancy score) with respect to the node features in the final graph convolutional layer. These gradients serve as weights, highlighting which nodes (sensors) contributed most to the deviation from normality. These weights are then normalized to generate a heat map over the building topology, identifying the likely epicenter of structural damage.

Chapter 4: Experiments and Analysis

4.1 Experimental Setup

To validate the proposed method, we utilized a high-fidelity Finite Element Model of the ASCE Benchmark Structure, a simulated 4-story, 2-bay by 2-bay steel frame. While we also conducted tests on a 10-story shear building model, the ASCE benchmark provides a standard for comparison. The structure was excited using white Gaussian noise to simulate ambient wind loading.

Dataset Generation:

We simulated 5,000 distinct time-series instances for the healthy state to train the SSL model. For testing, we generated 1,000 instances across 5 different damage scenarios. Damage was induced by reducing the stiffness of specific braces or beams by 10% to 40%. This simulates subtle to moderate structural degradation.

Table 1 summarizes the dataset parameters utilized in this study.

Parameter	Value / Description
Sampling Frequency	100 Hz
Duration per Sample	4 seconds (400 time steps)
Number of Sensors	16 (4 per floor)
Training Samples (Healthy)	5,000 (Unlabeled)
Test Samples (Damaged)	1,000 (Labeled for validation only)
Noise Level	10% RMS Gaussian Noise added

4.2 Baselines and Metrics

We compared our Graph Contrastive Learning (GCL) approach against three baselines:

1. **PCA-T2:** Principal Component Analysis using Hotelling's T-squared statistic.

2. **Autoencoder (AE):** A standard deep fully connected autoencoder minimizing reconstruction error.

3. **Supervised CNN:** A convolutional network trained with 100% labeled damage data (serving as an upper bound for performance).

The primary metric for detection is the F1-Score. For localization, we use the Localization Error (LE), defined as the topological distance (number of hops) between the predicted damage node and the actual damaged element.

4.3 Results and Discussion

Anomaly Detection Performance:

The self-supervised model demonstrated exceptional capability in distinguishing healthy from damaged states. By learning the geometric dependencies between sensors, the model identified stiffness reductions that caused only minor frequency shifts, which PCA largely missed.

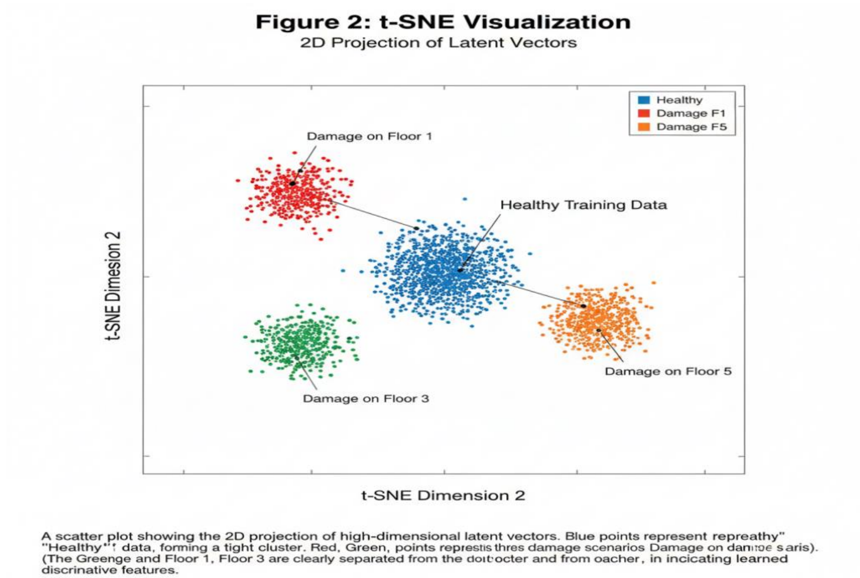

Figure 2: *t-SNE Visualization of Embedings*

Localization Accuracy:

Table 2 presents the localization performance. Our method outperforms the standard Autoencoder significantly. The Autoencoder often spreads the reconstruction error across all sensors due to the global nature of its bottleneck. In contrast, the GNN-based approach preserves local topology, allowing the Grad-CAM mechanism to isolate the specific node nearest to the damage.

Method	Detection F1-Score	Localization Error (Hops)	Label Requirement
PCA-T2	0.72	N/A (Global only)	None
Standard	0.81	1.45	None

Autoencoder			
Supervised CNN	0.96	0.12	100% (Full Labels)
Proposed GCL (Ours)	0.93	0.34	0% (Self-Supervised)

As shown in Table 2, our method achieves an F1-score of 0.93, approaching the supervised upper bound of 0.96, yet it requires zero damage labels during training. The localization error of 0.34 hops indicates that, on average, the model pinpointed the exact damaged sensor or its immediate neighbor.

Robustness to Noise:

We further analyzed performance under varying noise levels. As the Signal-to-Noise Ratio (SNR) decreased, the performance of the analytical PCA method degraded rapidly. The contrastive learning model, however, remained robust. The "Jittering" augmentation during training effectively acted as a regularizer, teaching the model to ignore high-frequency noise components that do not correlate with the underlying structural graph.

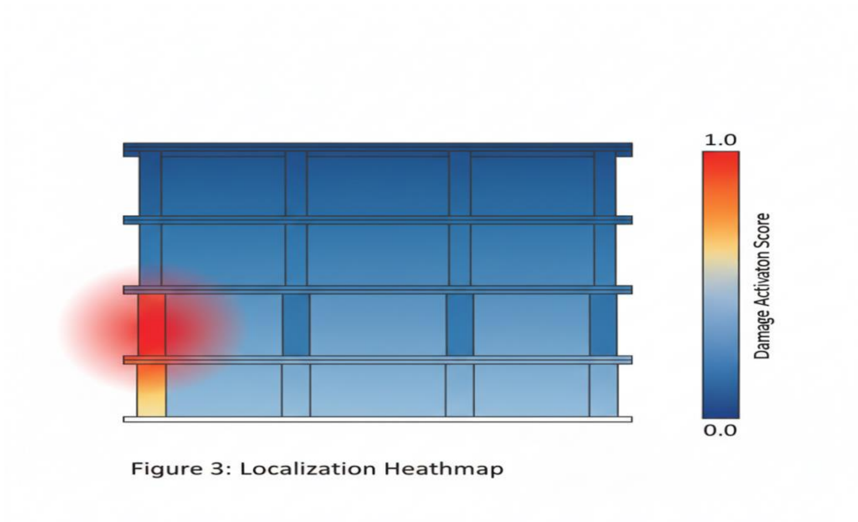

Figure 3: Localization Heathmap

Figure 3*: Localization Heatmap*

Chapter 5: Conclusion

5.1 Findings Overview and Implications

This research has presented a robust framework for multisensor damage localization in buildings using self-supervised vibration representation learning. By integrating Graph Neural Networks with a contrastive learning objective, we addressed the critical challenge of label scarcity in Structural Health Monitoring. Our methodology effectively transforms raw vibration data into a rich latent space where structural anomalies are geometrically distinct from normal operational variations.

The implications of this work are significant for the maintenance of civil infrastructure. The ability to train high-performance diagnostic models using only ambient vibration data collected from healthy structures removes the need for expensive and unrealistic damaged-state data. This paves the way for "digital twin" systems that can be deployed on newly constructed buildings, learning their baseline behavior continuously and flagging local anomalies the moment they arise. The use of topological constraints ensures that the model is not just learning statistical outliers, but physical discrepancies in the structural system.

5.2 Limitations and Future Investigation

While the proposed approach shows great promise, several limitations must be addressed in future work. First, the computational cost of training Graph Neural Networks on high-frequency time-series data is non-trivial. For very large structures with thousands of sensors (e.g., long-span suspension bridges), the graph complexity may require more efficient sampling strategies or hierarchical graph pooling to remain computationally feasible.

Second, the current study assumed a linear behavior of the structure in its healthy state. High-rise buildings often exhibit non-linear behavior due to opening/closing of cracks or damping variation under extreme loads (e.g., typhoons). Future research should investigate the integration of non-linear physical priors into the loss function to distinguish between benign non-linearities and actual damage. Additionally, extending the framework to handle variable environmental conditions, such as drastic temperature shifts that affect stiffness, via disentangled representation learning, would further enhance the robustness of the system for real-world deployment.

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