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ST-MRGAT: Multi-Relational Spatio-Temporal Graph Attention for Multi-Task Prediction of Bridge Deflection and Strain

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Abstract: *With increasing bridge service life and traffic loads, real-time structural health monitoring faces challenges from high-dimensional, non-stationary, and heterogeneous data. This paper proposes a Spatio-Temporal Multi-Relational Graph Attention Network (ST-MRGAT), which constructs spatio-temporal graphs from bridge sensor nodes and incorporates structural mechanics priors to capture complex spatial dependencies. The model employs enhanced gated temporal convolution to capture short-term dynamics and long-term evolution, and multi-relational graph attention to unify local cross-section and overall bridge responses. Experiments on real-world data show that ST-MRGAT significantly outperforms baseline models in multi-step predictions of deflection and strain, maintaining minimal error growth and demonstrating high accuracy, stability, and effective multi-task feature sharing, validating its robustness and generalizability for bridge structural health monitoring.*

Keywords: *Bridge Health Monitoring; Spatiotemporal Prediction; Multi-Relational Graph; Graph Attention Network*

1. Introduction

Bridges are critical components of transportation infrastructure, and their structural integrity directly affects public safety and economic stability. With aging structures and increasing service demands, traditional manual inspections can no longer meet the needs of real-time and precise monitoring. Sensor-based and data-driven Structural Health Monitoring (SHM) systems enable continuous observation of key responses such as deflection and strain[1].

Nevertheless, predicting structural responses remains challenging due to high-dimensional, heterogeneous, and non-stationary multi-source data. Bridge behavior exhibits strong spatiotemporal coupling, where local deformations propagate through mechanical connections, forming complex dependencies that traditional time-series models fail to capture [2, 3 4, 5].

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2. Related Works

2.1 Time Series Forecasting Methods

Time-series forecasting is central to bridge Structural Health Monitoring (SHM), aiming to predict future structural responses from historical signals. Early statistical models, such as ARIMA[6], capture linear temporal dependencies but fail under nonlinear and non-stationary conditions.

Deep learning methods have since become mainstream. Recurrent architectures (RNN, LSTM, GRU) model nonlinear temporal dependencies but suffer from sequential inefficiency and gradient decay. Temporal Convolutional Networks (tcns) improve parallelism via dilated convolutions, while

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Transformers employ self-attention to capture long-range dependencies and achieve superior accuracy.

However, these models typically treat each sensor sequence independently, ignoring the spatial topology and mechanical coupling among bridge components. This limitation motivates the integration of graph-based spatiotemporal modeling to jointly capture spatial dependencies and temporal dynamics within structural systems.

2.2 Application of Graph Neural Networks in Structural Health Monitoring

Graph Neural Networks (GNNs), such as Graph Convolutional Networks (GCNs), effectively model spatial dependencies in non-Euclidean domains through neighborhood aggregation or attention mechanisms[7]. In bridge health monitoring, they enable spatial modeling of sensor networks and local damage detection. When combined with recurrent or attention-based temporal models, spatiotemporal graph frameworks can jointly capture spatial correlations and temporal dynamics.

However, conventional GNN-based methods face limitations. A single topological graph cannot represent diverse physical interactions—such as structural connectivity, load transfer, and symmetry—nor handle cross-modal coupling between deflection and strain. Moreover, isotropic aggregation and sequential stacking of spatial–temporal modules weaken the model's capacity to capture complex structural dependencies.

To overcome these issues, this study proposes a multi-relational graph learning framework that encodes heterogeneous physical relationships—including sectional co-location, longitudinal continuity, and transverse symmetry—within a unified structure. Based on this, a physics-informed spatiotemporal attention network is developed to fuse structural priors with data-driven learning, achieving interpretable and precise modeling of both local and global bridge behaviors.

3. Proposed method

3.1 Problem Definition and Data Representation

To Bridge health monitoring aims to model the spatiotemporal evolution of structural responses unden external loads. In this study, the bridge monitoring system is represented as a spatiotemporal multirelational graph:

$$G = \{V, \mathcal{E}, A\} \tag{1}$$

Where each node $v_i \in V$ denotes a sensor, and edges E encode mechanical dependencies, including intra-sectional, Iongitudinal, and transverse relations. Node features at time t are

$$X_i = \left[x_{i,1}, x_{i,2}, \dots, x_{i,F}\right]^\top \in \mathbb{R}^F \tag{2}$$

With sensor types encoded as binary labels to unify deflection and strain measurements. The temporal input sequence preprocessed by interpolation, forward filling, and Min-Max normalization. To incorporate physical priors, a multi-relational graph with 36 nodes (0-17 deflection, 18-35 strain) is constructed. Three spatial relations are defined: intra-sectional (same cross-section), Iongitudinal (along the bridge), and transverse symmetry (across the bridge). Self-loops are added for numerical stability. This multi-relational spatiotemporal representation integrates sensor layout and bridge mechanics, providing a structured foundation for ST-MRGAT to capture local and global dynamic correlations.

3.2 ST-MRGAT Model Design

To achieve accurate modeling and prediction of bridge structural health, we propose the ST-MRGAT model, which jointly captures the temporal evolution of structural responses and multi-relational spatial dependencies among sensor nodes. This unified spatio-temporal framework enables multi-task prediction of deflection and strain.

The model employs a modular spatio-temporal stacked structure. Input features are first projected to a high-dimensional space, then processed through multiple sequential Spatio-Temporal Blocks (ST-Blocks). Residual and skip connections facilitate multi-scale feature fusion and stabilize deep network training. The output layer aggregates skip connections along the temporal dimension and applies a terminal convolution to generate multi-step predictions. The overall architecture is illustrated

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in Figure 1.

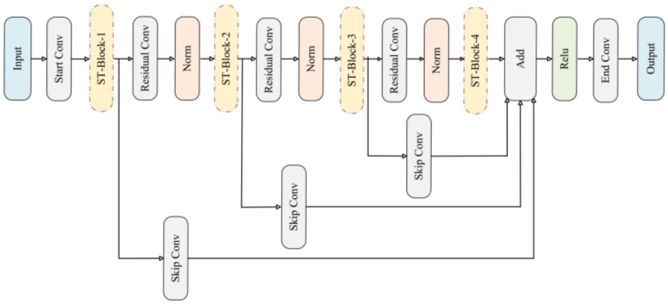

Figure 1 Structure of ST-MRGAT.

To clarify the internal mechanism and spatio-temporal fusion, the core unit of ST-MRGAT, the Spatio-Temporal Block (ST-Block), is introduced, as shown in Figure 2. Each ST-Block consists of a temporal layer and a spatial layer, capturing temporal dynamics and spatial dependencies, respectively. Their outputs are combined via a residual fusion mechanism, enhancing spatio-temporal interaction, stabilizing deep network training, and improving representation expressiveness.

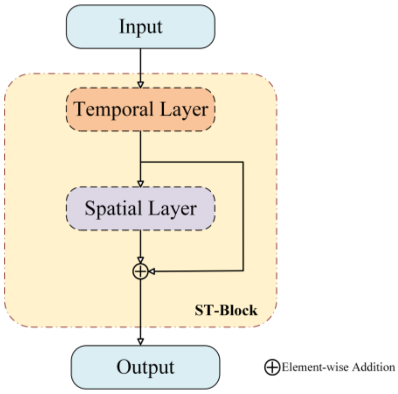

Figure 2 Structure of ST-Block.

In the temporal layer, ST-MRGAT utilizes an Enhanced Gated Temporal Convolution to capture both short-term dynamics and long-term trends of bridge responses. As shown in Figure 3, this mechanism extends the conventional Gated Linear Unit (GLU) with a residual channel, ensuring stable feature propagation and smooth gradients. The temporal block comprises three parallel 1D convolutions:W_1 and W_2 ,form the gating mechanism to generate feature transformations and gate signals, form the gating mechanism, while W_3 provides a residual path preserving the original temporal information. Formally, the computation is:

$$H = \mathrm{ReLU}\big((X * W_1) \odot \sigma(X * W_2) + (X * W_3)\big) \tag{3}$$

Here * denotes the 1D convolution operation,$\odot$ represents the element-wise multiplication, $\sigma(\cdot)$ is the Sigmoid activation function. This design enables adaptive temporal feature selection through the gating mechanism, while the residual connection preserves critical information from the original time series, thereby enhancing the robustness and stability of dynamic response modeling in bridge structures.

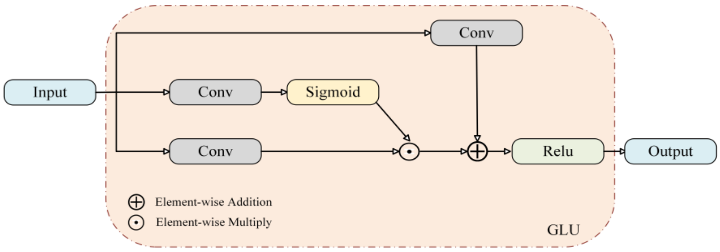

Figure 3 Structure of the temporal convolution block.

In the spatial modeling layer, a Multi-Relational Graph Attention (MR-GAT) mechanism is employed to capture the structural dependencies and heterogeneous spatial interactions among bridge

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components. As illustrated in Figure 4, let the feature representation of node i under relation r be denoted as $h_i^r = W_r h_i$, The attention coefficient between node pair (i, j) is then computed as:

$$\alpha_{ij}^r = \frac{\exp\left(\mathrm{LeakyReLU}\left(a_r^\top\left[h_i^r \| h_j^r\right]\right)\right)}{\sum_{k\in\mathcal{N}_i^r}\exp\left(\mathrm{LeakyReLU}\left(a_r^\top\left[h_i^r \| h_k^r\right]\right)\right)} \tag{4}$$

Neighboring node features are aggregated using attention weights to obtain the node representation under relation r .

$$m_i^r = \sum_{j\in \mathrm{N}_i^r} \alpha_{ij}^r \, \mathrm{h}_j^r, \tag{5}$$

The final spatial feature of each node is obtained by averaging across all relations, followed by a residual connection and an activation function. This design enables the model to balance different structural dependency patterns within a multi-relational framework, thereby efficiently capturing the spatial coupling characteristics of bridge components.

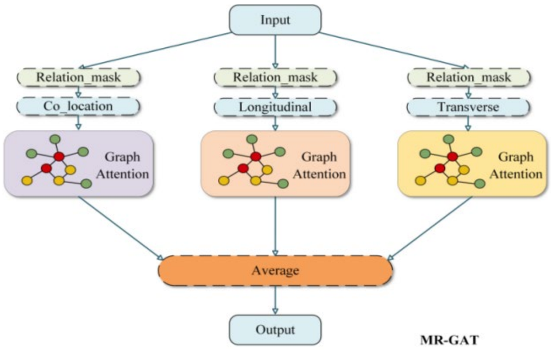

Figure 4 Structure of the spatio module.

In the output layer, the prediction of bridge health involves the joint forecasting of deflection and strain. ST-MRGAT employs a multi-task learning framework to enable collaborative modeling across tasks. The model extracts unified feature representations through a shared spatio-temporal encoding module and generates joint features for all tasks via a terminal convolution module (comprising two convolutional layers). These joint features are then split along the predefined channel dimension to produce separate prediction sequences for deflection and strain. Specifically, the model's final output corresponds to task-specific predictions:

$$\{\mathbf{Y}_{\mathrm{deflection}}, \mathbf{Y}_{\mathrm{strain}}\} = f_\theta(\mathbf{X}, \mathcal{A}) \tag{6}$$

Here, $f_\theta(\cdot)$ denotes the parameterized ST-MRGAT function, and AAA represents the set of multi-relational adjacency matrices. To predict structural responses over multiple future time steps, the model employs a rolling prediction scheme, which recursively generates subsequent predictions based on an autoregressive approach:

$$\hat{\mathbf{Y}}_{t+h} = f_\theta\left(\left[\mathbf{X}_{t-L+1:t}, \hat{\mathbf{Y}}_{t+1:t+h-1}\right], \mathcal{A}\right), \quad h = 1,2,\ldots,H \tag{7}$$

This scheme dynamically updates the input window while keeping its length constant, enabling multi-step temporal inference and facilitating continuous monitoring and early warning of bridge structural health.

4. Experimental Analysis

4.1 Dataset

Experiments were conducted on a real-world bridge health monitoring dataset comprising deflection and strain measurements from 36 deck sensors. Data were sampled every 10 minutes over seven consecutive days, capturing structural responses under varying traffic and environmental conditions. Each input sequence of 12 time steps was used to predict the next 3 steps.

4.2 Evaluation Metrics and Experimental Setup

Model performance was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error

(RMSE), providing complementary measures of accuracy and stability. The implementation was based on PyTorch 2.1.1, optimized with Adamand trained for 100 epochs with a batch size of 64. The best model was selected according to validation performance.

4.3 Multi-Task Prediction Results and Baseline Comparison

Multi-step forecasting experiments for deflection and strain show that ST-MRGAT consistently outperforms all baseline models. As summarized in Table 1, for a 3-step prediction task across eight baselines—including temporal models (LSTM, GRU, TCN, Transformer) and classical spatio-temporal models (DCRNN, STGCN, Graph wavenet, ASTGCN)—ST-MRGAT achieves relative MAE improvements of ~2.96% for both deflection and strain, and RMSE reductions of 2.5%–2.6% compared to the strongest baseline ASTGCN. The comparable prediction errors for deflection and strain indicate that the shared spatio-temporal representation effectively captures their coupled dynamics. Minimal error growth over successive steps further demonstrates the robustness and stability of ST-MRGAT for continuous bridge health monitoring and early warning.

Table 1 Comparison of Multi-Step Prediction Performance of Deflection and Strain across Baseline Models and ST-MRGAT.

Method	Deflection MAE	Deflection RMSE	Strain MAE	Strain RMSE
LSTM[2]	0.284	0.374	0.283	0.372
GRU[3]	0.282	0.371	0.281	0.369
TCN[4]	0.279	0.368	0.278	0.366
Transformer[5]	0.277	0.366	0.276	0.364
DCRNN[8]	0.273	0.362	0.272	0.360
STGCN[9]	0.272	0.361	0.271	0.359
Graph WaveNet[10]	0.271	0.360	0.270	0.358
ASTGCN[11]	0.270	0.359	0.269	0.357
ST-MRGAT	**0.260**	**0.350**	**0.261**	**0.348**

5. Conclusions

The proposed ST-MRGAT integrates spatio-temporal dependencies with structural priors for accurate prediction of bridge sensor data. Experiments show improved accuracy and stability in deflection and strain forecasts, demonstrating the effectiveness of multi-relational spatio-temporal graph modeling for structural health monitoring. Incorporating physical priors enables unified modeling of dynamic bridge evolution, supporting multi-task prediction. Future work may extend to multi-scale graphs and dynamic topology learning for enhanced long-term predictions.

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