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Enhancing Bridge Deterioration Prediction Using Element Adjacency Graphs by OCR-Processed Drawings: A Case Study of Girder Bridges in Japan

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Abstract: In Japan, bridge inspections are mandated every five years. The inspection database for bridges under the jurisdiction of the Ministry of Land, Infrastructure, Transport, and Tourism enables the acquisition of damage progression data for each structural element. This study develops a methodology for predicting the deterioration of girder bridges, employing a novel approach where inspection drawings are processed using Optical Character Recognition (OCR) to extract element numbers and their spatial relationships, subsequently creating a comprehensive graph of these elements. A key feature of this prediction methodology is its ability to consider the adjacency relationships between different bridge members, made possible by the detailed analysis of drawing information and a Graph Transformer model. The research examines and compares the accuracy of predictions made with and without considering adjacency relationships, highlighting the effectiveness of incorporating detailed structural information in the predictive analysis of bridge deterioration.

Key words: bridge damage prediction, optical character recognition, graph neural network

1. INTRODUCTION

In recent years, there has been a significant increase in the number of severely damaged infrastructure assets. To mitigate the risk of collapse, regular inspections have become essential. In response to a tunnel collapse in 2014, Japan's Ministry of Land, Infrastructure, Transport and Tourism (MLIT) mandated inspections of tunnels and bridges every five years. This policy has served as a key driver in promoting the comprehensive maintenance of the nation's bridges. However, the process of conducting thorough visual inspections is both time-consuming and labor-intensive. With the responsibility of overseeing more than 720,000 bridges, Japan's national and local governments face a daunting task in adhering to this prescriptive five-year inspection cycle, especially amidst a severe industry-wide labor shortage and stricter working hour regulations.

To achieve sustainable maintenance of infrastructure, there is a demand for a more flexible approach to setting inspection periods tailored to the individual bridge. For instance, bridges at a higher risk of severe deterioration within the next three to five years should be inspected annually. Conversely, it is possible to extend the inspection intervals for bridges with a slower rate of deterioration, thereby allocating resources more efficiently to severe bridges. However, making regulatory changes, though rational, requires a robust and objective basis supported by data-driven case studies and historical damage trends, namely the prediction of deterioration.

Prior research has explored two main approaches to predicting deterioration: theoretical models based on chemical and physical mechanisms and analysis of integrity transition retrieved by inspection records. For instance, studies like [1] have modeled the movement of moisture and ions within concrete to predict the onset of deterioration. The latter approach, utilizing accumulated inspection records, includes methods such as regression analysis of the temporal changes in structural integrity [2], regression analysis of factors influencing integrity [3], and the use of hazard models to determine Markov transition probabilities [4]. These inspection analyses have been conducted at the component level. However, it is empirically known that damage occurs due to interactions between components or different elements of the same component. For example, damage in girders and deck plates of steel bridges tends to be spatially biased, and corrosion progresses in areas affected by water, such as joints and drain boxes [5]. Hence, incorporating the spatial relationships between components, or even more granular subdivisions of these elements, has the potential to enhance the precision of forecasts related to their deterioration. This study aims to develop a predictive model that assesses the integrity progression at the component and element levels. This framework will distinctively incorporate the spatial interconnections among these elements, following the approach of using inspection records as the foundation for deterioration prediction.

Considering the adjacency of elements, using 3D models, including BIM, is a viable option. In [6], a method for plotting damage on 3D models was proposed. However, constructing a predictive model requires a substantial dataset of bridge 3D models reflecting damage, which is currently challenging to obtain. Nevertheless, even in situations where 3D models are unavailable, it is possible to predict deterioration while considering the spatial positioning of elements based on inspection records. This study involves the semi-automatic derivation of spatial relationships among elements from drawings. These drawings are sourced from the xROAD database, which is managed by MLIT. The process utilizes optical character recognition (OCR) and GPT-4, followed by creating a graph representation of element relationships. In this graph, every node symbolizes an element, with each element related to its respective damage assessment type. Subsequently, the study predicts the future deterioration of each element, considering the adjacency relationships represented in the graph. A Graph Transformer model is applied to the predictive model, forecasting the element-wise integrity for the time of the next inspection.

Our primary contributions can be summarized as follows:

1. We demonstrate a method to extract element adjacency information from existing records without the need for pre-constructed 3D models, employing advanced data processing techniques that combine OCR with the capabilities of GPT-4.
2. We showcase the effectiveness of predicting damage at the element level by considering the spatial coordinates of these elements, utilizing the Graph Transformer technique to enhance the accuracy of our predictions.

2. Related Work

In the statistical analysis of inspection results for deterioration prediction, several distinct approaches have been undertaken. These involve studies analyzing the time variation of soundness [2], analyzing and selecting indicators that could affect soundness [3, 7, 8], and calculating transition probabilities between specific time intervals [4, 9]. In a method introduced by [2], inspection records were filtered by construction years using piecewise linear regression analysis to develop a pure degradation progression model excluding the restoration of soundness through repairs. It is crucial to consider the impact of repairs when developing regression models for soundness transition over elapsed years since construction. In practice, whether repairs have been made in the past is determined using outliers in the transition of soundness. By introducing piecewise linear regression analysis, it was shown that using inspection data up to about 40 years after construction can exclude the effects of repairs and result in predictions that are on the conservative side of safety, except for components that are frequently updated, like expansion joints. A mixed Markov degradation model was created using the filtered data, but the impact of using it on the model was smaller than on the regression model. Also, the prediction of severe degradation transitions by the Markov model was more towards the risky side compared to the regression model, indicating that scrutiny of prediction models remains unresolved. Study [3] involved creating a regression model by selecting appropriate explanatory variables from records through ordinal regression analysis, demonstrating the statistically significant impact of multiple variables such as bridge age, traffic volume, and deck area size. In [4], an exponential hazard model was developed to obtain a damage transition probability matrix. Regression methods for determining hazard model parameters incorporated parameters like traffic volume and deck area for deterioration prediction. Study [9] examined the appropriateness of the assumption that inspection records accumulate at fixed intervals for calculating the transition probability matrix of soundness. It showed that the decision to apply Bayesian principles to consider variations in inspection intervals results in a 22% error in estimating service life.

In addition to the studies using classical statistical analysis methods, there are also strategies that use deep neural networks for degradation prediction. Study [7] predicted the degradation of deck slabs using features of bridges selected by Boruta feature selection as inputs for k-nearest neighbor and multi-layer perceptron (MLP) models. Study [8] analyzed the soundness of 3k bridges using long short-term memory (LSTM) on the analysis of cumulative factors like traffic, chloride, and temperature. The LSTM method showed higher predictive performance compared to MLP.

The above methods predict the condition of a specific member, or the entire bridge based on macroscopic features or degradation factors regarding the entire bridge, without explicitly considering the interrelation of damage between members. There is a prior study focusing on the interrelation of damage between different members. In Japan, regular inspections are mandated every five years. However, it is desirable to detect abnormalities that may occur in shorter periods than this five-year span. Study [10] examined a decision tree method to estimate the degradation of hard-to-inspect elements like deck plates, bearings, and piers from routine inspections of easily observable members. Interpretations of the rules represented by the decision tree were made and it suggested correlations between asphalt damage and deck slab cracking and between road width, which reflects traffic capacity, and concrete pier damage. However, issues such as low classification accuracy and the necessity for rule validation were raised. Note that it estimates the degradation degree at a point in time from information of other members, rather than the progression of degradation caused by interactions between elements.

Regarding the graph analysis method, study [11] is an example of introducing graph neural network to consider the relationships between assets. It predicted degradation of each pavement section using GraphSAGE [12] and demonstrated that considering relationships among adjacent sections improves prediction accuracy, as they are likely to have similar traffic volumes and environmental conditions.

In terms of analyzing inspection reports, study [13] used ontology-based, semi-supervised conditional random fields to perform class classification to retrieve items like damage reasons from the text of reports. On the other hand, our research indicates a lack of significant studies focusing on identifying member and element positions through drawing interpretation.

3. Problem Formulation

This study targets girder bridges in Tokyo that are managed by MLIT, representing a subset of the nationwide bridges under their jurisdiction. Although the method developed in this research can be applied to other regions due to the uniformity of the nationwide bridge database, we initially aim to construct the methodology using data from Tokyo.

In our approach, data preprocessing involves creating a dataset by combining element-wise damage assessments with graphs representing the spatial relationships of elements, using diagrams that indicate element numbers. These drawings include the names of the component type and their respective element numbers. The layout of the drawings reflects the shape of the bridge in a grid form. For instance, the drawing of a girder is created from a perspective looking upwards from below, and reflects the number of girders, with each edge representing a girder element. This grid is typically rectangular but can curve to reflect bending road. For more complex structures like substructures, the drawings are schematically adapted to clearly represent the parts corresponding to the element numbers. Our study primarily focuses on creating adjacency graphs for the main superstructure. This includes main girder, cross girder, and deck slab, while excluding substructures. This exclusion is due to the complexity and labor-intensive process of graphing them, and the obscurity of inferring connection between substructures and superstructures from these drawings. The drawings, though divided by component, share common grid shapes. For example, the girder and deck slab drawings use almost identical grid shapes, with distinctions in edge thickness to emphasize which edge corresponds to element number. Damage assessment for each element is conducted according to the type of component and damage, with a grading system ranging from 'a' to 'e', where 'a' represents the healthiest condition and 'e' indicates the most damaged. However, according to the guidelines, damage is sometimes recorded in fewer than five categories. For example, cracks are recorded using a three-level system: 'a'→'c'→'e'.

The constructed graph is undirected, with nodes representing elements and edges representing the adjacency relationships between elements. Nodes store the type of component and integrity assessments for multiple damages. Regarding the edge connections, while there is flexibility in how to represent adjacency in graph form, our study bases its edge connections on the assumption that the main girder extends laterally in the drawings and the deck slab is sandwiched between the girders. Based on the constructed graph, we predict the damage of each element at the next inspection. The flow of our study is depicted in Figure 1. Previous studies [4, 9] have highlighted the need to consider the timing of damage progression and inspection intervals. However, our study focuses on predicting the assessment of the next inspection, assuming a general inspection interval of approximately five years. It aims to examine the accuracy of predictions, with or without the introduction of a method reflecting inter-element damage.

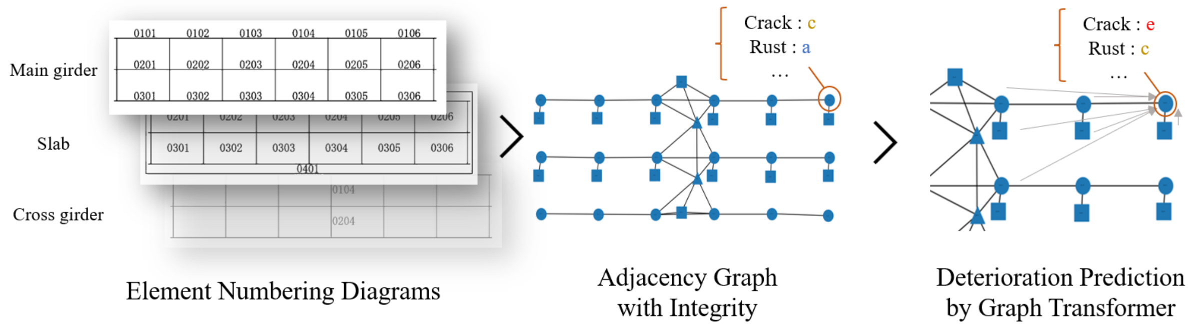

Figure 1. Workflow of the deterioration prediction

4. Method

In this study, we developed a method for constructing adjacency graphs using damage records and element number figures obtained from the xROAD database. Our approach involves node-level graph predictions to estimate the damage level of each element using a Graph Transformer. However, actual on-site assessment data for structural integrity often contains uncertainties, including variations in inspector recordings. To address this, we created a synthetic dataset to investigate the applicability of the Graph Transformer in an ideal scenario. Our results demonstrate the Graph Transformer's capability to make predictions considering adjacency relationships, highlighting its potential for practical implementation in structural health predictions.

4.1. Graph Dataset Creation from Diagrams

In this research, we combine OCR and GPT-4 to extract element numbers from multiple element number diagrams and use their spatial relationships to create adjacency graphs. Google Cloud Vision API is utilized for OCR. While OCR is generally successful in extracting element numbers, we encountered specific errors, necessitating a cleansing process using GPT-4 to refine the extracted strings into appropriate element number sets. One notable issue is the OCR's misidentification of diagram lines as characters, such as interpreting grid lines as the character '/'. Another issue involves the occasional occurrence of missing characters in the extracted text. An additional issue involves the OCR process capturing text in chunks, which sometimes results in errors where a single chunk contains either multiple element numbers or only partial numbers. To address these errors, we leveraged the standard format of element symbols. This format comprises two alphabet characters representing the name of member, followed by a four or five-digit number indicating its relative position. Thus, by considering adjacent strings on the diagram, we can correctly infer and adjust element numbers. By instructing GPT-4 to output both the original strings and inferred element numbers, we maintain the positional context of these numbers on the diagrams, thereby ensuring accurate identifications. This process enables the matching of graph nodes with damage data. However, considering that a fully automated system may not always yield correct element numbers, we implemented a semi-automated system that also allows for manual corrections. This approach significantly enhances efficiency compared to manual processing. It can automatically acquire approximate element numbers and overlay separated diagram information into a single graph by capturing the textual strings' positions on the diagrams.

4.2. Damage Level Prediction by Graph Transformer

In this study, we introduce the Graph Transformer as a method for predicting element-wise integrity. We expect it to be capable of implicitly reflecting trends in damage transitions caused by adjacency relationships. Predicting soundness considering only first-order adjacency (i.e., immediate neighboring nodes) can be feasibly achieved through explicitly calculated transition matrices due to the limited number of combinations involved. However, for predictions that account for the broader impact of damage, including second-order adjacencies and beyond, a model like the Graph Transformer is essential. For our Graph Transformer, we adapted the implementation of Graphormer [14]. Graphormer, originally designed for graph prediction tasks, enhances the standard Transformer model [15] with graph-specific modules such as centrality encoding, spatial encoding, edge encoding, and special nodes. These additions have proven effective in classifying and regressing the overall meaning represented by a graph. For node-level prediction, we modified the implementation, omitting centrality encoding and edge encoding. Centrality encoding is typically used to highlight nodes of significance in graphs, such as social media networks. However, it was deemed unnecessary for our data, where all structural elements should be treated symmetrically regardless of their centrality degree. Similarly, edge encoding, useful for graphs with multiple edge types, was not required as all edges in our dataset uniformly represent adjacency relations.

To evaluate the performance of predictions made by the Graph Transformer, we compared its accuracy with a baseline model that utilizes the percentage prediction method [16]. The baseline employs a transition probability matrix aggregated from transition summaries for each node and damage type, represented by a 5x5 matrix. In the baseline model, surrounding nodes do not influence predictions. Predictions exclude cases where structural integrity has been restored through repairs or other interventions.

4.3. Validation of Graph Transformer by Synthetic Dataset

This study introduces the Graph Transformer to predict damage propagation, which is based on implicit rules governed by adjacency relationships. To ascertain its capability, we prepared a controlled synthetic dataset for validation. This ensures an ideal scenario with sufficient data for the Graph Transformer to effectively learn the degradation process. For comparison, the baseline mentioned in section 4.2 is utilized.

In the synthetic dataset, the graph comprises 16 nodes arranged in a 4x4 grid, each node connected to its immediate neighbors. Nodes represent structural elements, with one of three types of elements randomly assigned to each node. Each node is assigned two types of damage, Dam1 and Dam2, simulating real-world inspection records where multiple damage types are observed per element. The integrity of each node is graded on a scale from 'a' to 'e', similar to real data, with 'a' indicating the highest integrity. Initial damage values are randomly assigned.

Three distinct datasets were created, each following the initial value settings and different damage progression rules, varying in the extent of adjacency influence and whether transitions are deterministic or probabilistic.

Dataset 1 allows damage progression influenced only by first-order adjacent nodes. For nodes of element type 1 (EType1), Dam2 degrades by one stage if the Dam2 of any first-order adjacent node is at level 'b' or worse. Dam1 follows the same value as Dam2, but if the initial value of Dam1 is more severe than Dam2, it will follow the progression of Dam2. For nodes of element type 2 (EType2), Dam1 and Dam2 assume the healthiest value among the damages of adjacent nodes. Element type 3 (EType3) nodes do not undergo temporal damage changes.

Dataset 2, building upon Dataset 1, includes the influence of second-order adjacent nodes. The transition rule for Dam2 remains the same as in Dataset 1, but Dam1's rule is modified for EType1 nodes. Consider a node N of EType1 that is adjacent to all three types of elements. If any adjacent EType1 or EType2 nodes have a damage level at or below 'b', then the Dam1 of node N worsens by one stage. Transition rules for other element types remain as in Dataset 1.

Dataset 3 extends Dataset 2 by introducing probabilistic transitions for Dam1. In Dataset 2, if a node of EType1 meets the condition considering up to second-order adjacencies, Dam1 would degrade with a 100% probability. On the other hand, in Dataset 3, we set this transition probability to 75%. Dam2 continues to undergo the same deterministic transitions as Dataset 1 and 2.

5. Experiment and Discussion

5.1. Damage Prediction of Real Dataset

In this study, we acquired graphs for 33 bridges encompassing 119 spans by interpreting diagrams from inspection reports. The xROAD database provides inspection records dating back to 2004, allowing us to obtain four or five sets of element integrity assessments for each bridge. A total of 379 transitions were collected for this study. We allocated 90% of this data for training and 10% for testing to train the Graph Transformer and predict integrity transitions. The Graph Transformer was configured with an embedding dimension of 128 and eight transformer blocks. The embedding was done at the node level, representing each node's structural element type and 22 types of damage, with each damage type assigned an integrity assessment ranging from 'a' to 'e'. A learning rate scheduling was implemented, setting the maximum learning rate at 5e-5, and the model was trained over 600 epochs.

We evaluated the model's performance on the test data using the node and damage-wise accuracy metric, assessing whether the predicted integrity values for each node and type of damage matched the ground truth. The baseline model achieved an accuracy of 0.9614, while the Graph Transformer reached 0.9877, indicating that predictions using the Graph Transformer are more accurate. This suggests that considering the influence of surrounding elements can enhance the accuracy of integrity predictions. It is noteworthy that the damage-wise accuracy was also high for the baseline; this is primarily because many transitions do not result in degradation but rather maintain the current integrity level, making it predictable based on the current state of the focused node alone. However, for multi-step predictions, it is crucial to enhance accuracy to prevent the accumulation of errors, and in this regard, the methodology of this study proves to be valuable.

5.2. Damage Prediction of Synthetic Dataset

For the three types of synthetic datasets, the Graph Transformer was trained with a maximum learning rate of 1e-4 over 200 epochs, similarly to section 5.1. Table 1 presents the test accuracy for models trained on each dataset. In addition to node and damage-wise accuracy, stepwise accuracy was also calculated, assessing whether all damages across all nodes match in a single step transition. Given that the datasets were created based on rules outlined in 4.3, predictions referencing the damage of surrounding nodes are advantageous. The Graph Transformer, by considering the state of surrounding nodes, demonstrates improved performance over the baseline. For deterministic transitions, as in Dataset 1 and 2, accurate prediction of transitions is achievable with sufficient data. Furthermore, the results suggest that even in scenarios where damage influences a broader range, the performance degradation is potentially suppressed.

Analyzing the node and damage-wise accuracy of the Graph Transformer on Dataset 3, we find that deterministic transitions of Dam2 are predicted correctly in all cases, while probabilistic transitions of Dam1 achieved an accuracy of 0.9823. The Graph Transformer framework, utilizing information about various types of damage in the vicinity, can account for cross-type damage influences. For example, in

Table 1. Evaluation accuracy for three synthetic datasets

	Synthetic Dataset	1	2	3
	Data generation method	Deterministically		+Stochastically
		1st-order neighbor	+2nd-order neighbor	
Baseline	Node & damage-wise	0.9392	0.9298	0.9255
	Stepwise	0.2759	0.2057	0.1698
Graph Transformer	Node & damage-wise	0.9995	0.9999	0.9912
	Stepwise	0.9851	0.9977	0.7806

Dataset 1, Dam1 transitions due to the influence of Dam2. Conversely, for damages that do not influence each other, as in Dataset 3, the model successfully disentangles and learns their transitions independently. Thus, even in cases where damages with different transition rules coexist, the Graph Transformer is capable of appropriately learning these variations.

6. Conclusion

This research aimed to predict the degradation of structural elements at an individual level, employing a combination of OCR and GPT-4 for diagram interpretation and the creation of a predictive model using the Graph Transformer. While not fully automated, the diagram interpretation significantly reduced effort compared to manual adjacency graph creation. Predictions of integrity transitions using the graphs demonstrated higher accuracy compared to a baseline model that did not consider adjacency relations. Additionally, we examined the feasibility of applying the Graph Transformer for integrity prediction using synthetic datasets. The study showed that, with a sufficient amount of training data, the Graph Transformer could enhance prediction accuracy for data where damage is influenced by adjacent nodes. The results highlight the need for further refinement of the graph data creation methodology and call for extensive studies using large-scale real inspection data.

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