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Dynamic construction of visible knowledge graph based on 3D geographic scene for intelligent bridge management

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Abstract. Knowledge graphs are a crucial core in enhancing the intelligent management of geographic entities. Current knowledge graphs primarily focus on constructing knowledge in bridge health monitoring, often neglecting the spatial relationships of bridges as geographic entities. This oversight limits their capabilities in diagnosing, analyzing, and predicting bridge conditions. To address this, a method for dynamic construction of knowledge graphs is proposed, which is driven by semantics and data for extracting entities and relationships from geographic scene. Furthermore, a multi-level 3D knowledge graph visualization method was proposed, presenting entities and their relationships in varying levels of detail. Experiments and analyses were conducted using a geographic scene that included a building information model of a bridge. The results demonstrate that our proposed method can construct knowledge graphs both rapidly and accurately, providing a more comprehensive understanding of the relationships between bridge entities. This enhances the management of intelligent bridges.

Keywords. knowledge graph, intelligent bridge management, geographic scene, 3D visualization

1 Introduction

Bridges represent a complex field involving multidisciplinary knowledge (He et al., 2017; Zhao et al., 2021; Frangopol et al., 2021; Abdallah et al., 2022), a complexity that often hinders the rapid and sustained expansion of knowledge graphs in this domain. Current methods for constructing knowledge graphs for bridges are mainly divided into manual and automatic construction. Manual construction is a labor-intensive process that requires knowledge engineers to perform additional verification on the entities and relationships in the graph, resulting in low efficiency (Ren et al., 2019; Wu et al., 2021). Automatic construction typically extracts knowledge about bridge inspections from unstructured textual data (Liu et al., 2017; Li et al., 2021a; Siddharth et al., 2022). However, it struggles to capture the spatial structural relationships of bridges and is limited in associating this information with the bridges' geographical spaces, thereby constraining the breadth of applications for knowledge graphs.

With the advancement of BIM-GIS technology, there is an increasing trend in incorporating detailed 3D models of bridges into geographic scenes for management purposes (Ma et al., 2017; Wang et al., 2019; Zhu et al., 2021). These scenarios are used to create knowledge graphs that not only provide information about the spatial characteristics and connections of bridges at a geographic level, but also reveal their relationship with the surrounding environment. Unlike textual data, spatial structural relationships can be easily extracted from 3D scene, allowing for a more comprehensive understanding of the interaction between bridges and their surroundings. Furthermore, visualizing knowledge graphs enhances an individual's ability to comprehend, explore, and analyze information effectively (Li et al., 2021b). Compared to the commonly used 2D layout, the 3D visualization of geospatial relationships provides a clearer depiction (Wang et al., 2023).

Therefore, this paper takes a geospatial perspective and introduces an innovative method for constructing a bridge knowledge graph using 3D geographic scenes. By utilizing the spatial and attribute relationships of the 3D scene objects, a semantic and data-driven approach was proposed for extracting entities and relationships, enabling the dynamic construction of the knowledge graph. Additionally, a visualization method was proposed to represent the knowledge graph in 3D, which maps the distribution and hierarchy of nodes based on entity locations and attributes. Finally, we conducted an experimental analysis using a geographic scene that includes a detailed bridge model. The results demonstrate that our proposed method effectively utilizes the geographic scene to generate a more comprehensive and easily understandable knowledge graph.

2 Methods

2.1 Overall research framework

The process of creating a knowledge graph in a geographic scene is illustrated in Fig.1. To construct the knowledge graph, three types of objects are identified: bridges, environments, and scenes. Within the scene, various geographic entities, such as land, rivers, and buildings, are extracted. Additionally, component entities such as abutments, bearing pads, and diaphragm beams are extracted from the bridge within the scene. Finally, environmental information entities, such as temperature, wind, and stress, are also extracted from the scene. By establishing spatial relations and semantic associations, the relationships between these entities are established, resulting in the construction of the knowledge graph.



Figure 1 The overall concept of constructing a knowledge graph

2.2 Construction of knowledge graph driven by semantics and data

First, the component entities of the bridge in the scene are dynamically extracted, and the relationships between them are established. The process of extracting bridge entities can be compared to traveling throughout a bridge model, as it requires accessing and processing information from all the model's components. The main objective of this extraction is to ascertain the spatial location and semantic description of each bridge component, and then combine these components based on their spatial proximity and semantic congruity (Fig.2).



Figure 2 Process of extracting entities of bridge in the scene

The method for relationship extraction is graphically represented in Fig.3. Here, M and N represent bridge component objects. Specifically, M encompasses objects that are similar and interconnected, while N includes objects that are similar but not connected. Components of the bridge maintain a relationship characterized as 'SubClassof' with the overarching Bridge entity.



Figure 3 Relationship extraction based on incidence matrix

For other geographic entities in the scene, the coordinates of their centroids are obtained and classified into three types: line, face, and body. The line and face types record the coordinates of each vertex. The body type records the bounding box. These are used to determine the spatial relationship between other entities in the scene and the bridge. Fig.4 illustrates the judgment of the relationship between land and the bridge.



Figure 4 Determining entity relationships based on spatial location

In terms of the environment, data on wind, temperature, and stress are dynamically monitored. The relationships between these factors and the bridge are determined through semantic judgments. Wind causes vibrations in the main beams, bridge deck, and cables. Temperature changes lead to expansion and contraction in the steel structure of the bridge. The stress endured by different components of the bridge at various locations is consistent.

2.3 Visualization of knowledge graph

A 3D visualization of the knowledge graph can be created, utilizing the spatial locations of the bridge and its geographical surroundings. This visualization is broken down into three core components: nodes, connecting lines, and text.

The textual elements primarily serve to semantically annotate the nodes and relationships. Each node is labelled with its unique identifier and type, with the text positioned centrally within the node.

Nodes and lines are partitioned into three levels to represent entities and relationships across different scales. On the first level, the "SubClassof" relationship is only displayed for node B in the pair <A, SubClassof, B>. Thus the bridge is represented solely as a single node, exhibiting its connections with the nodes of the geographical scene. The second level presents an approximate illustration of the relationships between the components of the bridge. Here, all entities sharing the "SameType" relationship are represented by a single node. On the third level, all nodes are displayed, and the relationships between all bridge components are detailed meticulously, including the relationship between bridge components and the surrounding geographical scene. The sequence of the rendering process is depicted in Fig.5.



Figure 5 Rendering process of visual knowledge graph

2.4 Data and software availability

The datasets and codes for visualizing entities and relationships in this study are openly available (https://github.com/kamikaku/kgnode). The datasets of bridge scene involve actual engineering, which is not exposed.

3 Experiment

3.1 Study area

The data presented in this paper includes a meticulously detailed model of a canyon suspension bridge, complete with its location information and associated geographic elements. The data for the geographic scene in which it is located encompasses Digital Elevation Models (DEM), Digital Orthophoto Maps (DOM), and geographic elements like temporary buildings, rivers, and houses, as depicted in Fig.6.



Figure 6 3D geographic scene

3.2 Results

The knowledge graph extracted in the scene is shown in Fig.7, which demonstrates the multi-level visualization of the knowledge graph.





Figure 7 Visualization of knowledge graph

A detailed breakdown of the types and quantities of relationships in the knowledge graph is presented in Fig.8.

In addition, this paper aims to compare the perception of a three-dimensional knowledge graph with that of a twodimensional knowledge graph. Thirty participants were selected to complete three tasks involving finding objects within a knowledge graph. The tasks are described below:

Figure 9 Completion of the task time

4 Conclusion

This paper thoroughly considers the spatial relationships of bridges and the impact of the geographic environment from the perspective of geospatial analysis. Driven by semantics and data, a more comprehensive bridge knowledge graph with extensive entity relationships was constructed. This method aids in the rapid and accurate



■ SubClassof Sar сТур

Figure 8 Information of relations

- Task1: Find the node where the pile foundation is located:
- Task2: Find the node where the pile foundation, stiffener beam and tower column are located;
- Task3: Find the nodes where the pile foundation, stiffened beams, tower columns, land and houses are located.
- Appendix: supplementary material can be • provided in an appendix at the very end of the paper (after references).

Fig.9 depicts the reaction times taken by the two groups to complete the tasks. From the results, it is evident that the 3D group completed the tasks approximately 1.5 times faster than the 2D group. The accelerated visual search speed signifies a more prompt and precise understanding of the meanings conveyed by the nodes in the graph.

expansion of knowledge graphs in the field of bridge management, thereby enhancing the overall analytical capabilities in bridge management.

However, the method presented in this paper still has limitations, as the entities and relationships heavily depend on the data quality of the 3D geographical scene. Additionally, the internal spatial relationships within bridges have not been extensively detailed. Relationships in the time dimension have also not been considered. In the future, it will be necessary to further refine the structural relationships of bridges for a more precise description. Moreover, by considering the time dimension, extracting, and storing the entity relationships throughout the entire lifecycle of a bridge, a more comprehensive knowledge graph can be established. Finally, the experimentation in the article is limited to one region due to the openness constraints of the fine bridge model. This limitation affects the generalizability of the methodology. This will further enhance the effectiveness of intelligent management practices and look for more bridge projects to carry out the practice.

References

- Abdallah, A. M., Atadero, R. A., & Ozbek, M. E. A state-of-the-art review of bridge inspection planning: Current situation and future needs. Journal of Bridge Engineering, 27(2), 03121001. https://doi.org/10.1061/(ASCE)BE.1943-5592.00018. 2022.
- Frangopol, D. M., Dong, Y., & Sabatino, S. Bridge lifecycle performance and cost: analysis, prediction, optimisation and decision-making. In Structures and Infrastructure Systems (pp. 66-84). Routledge. https://doi.org/10.1080/15732479.2016.1267772. 2019.
- He, X., Wu, T., Zou, Y., Chen, Y. F., Guo, H., & Yu, Z. Recent developments of high-speed railway bridges in China. Structure and Infrastructure Engineering, 13(12),1584-1595.

https://doi.org/10.1080/15732479.2017.1304429.2017.

- Li, R., Mo, T., Yang, J., Li, D., Jiang, S., & Wang, D. Bridge inspection named entity recognition via BERT and lexicon augmented machine reading comprehension neural model. Advanced Engineering Informatics, 50, 101416. https://doi.org/10.1016/j.aei.2021.101416. 2021a.
- Li, H., Wang, Y., Zhang, S., Song, Y., & Qu, H. KG4Vis: A knowledge graph-based approach for visualization recommendation. IEEE Transactions on Visualization and Computer Graphics, 28(1), 195-205. 10.1109/TVCG.2021.3114863. 2021b.
- Liu, K., & El-Gohary, N. Ontology-based semisupervised conditional random fields for automated information extraction from bridge inspection reports. Automation in construction, 81, 313-327. https://doi.org/10.1016/j.autcon.2017.02.003. 2017.
- Ma, Z., & Ren, Y. Integrated application of BIM and GIS: an overview. Procedia Engineering, 196, 1072-1079. https://doi.org/10.1016/j.proeng.2017.08.064. 2017.
- Ren, G., Ding, R., & Li, H. Building an ontological knowledgebase for bridge maintenance. Advances in Engineering Software, 130, 24-40. https://doi.org/10.1016/j.advengsoft.2019.02.001. 2019.
- Siddharth, L., Lucienne TM Blessing, Kristin L. Wood, and Jianxi Luo. Engineering knowledge graph from

patent database. Journal of Computing and Information Science in Engineering 22, no. 2: 021008. https://doi.org/10.1115/1.4052293 .2022.

- Wang, S., Li, W., & Gu, Z. GeoGraphViz: Geographically constrained 3D force-directed graph for knowledge graph visualization. Transactions in GIS, 27(4):931-948. https://doi.org/10.1111/tgis.13053. 2023.
- Wang, Hao, Yisha Pan, & Xiaochun Luo. Integration of BIM and GIS in sustainable built environment: A review and bibliometric analysis. Automation in construction 103, 41-52. https://doi.org/10.1016/j.autcon.2019.03.005. 2019.
- Wu, C., Wu, P., Wang, J., Jiang, R., Chen, M., & Wang, X. Ontological knowledge base for concrete bridge rehabilitation project management. Automation in construction, 121, 103428. https://doi.org/10.1016/j.autcon.2020.103428. 2021.
- Yang, Jianxi, Fangyue Xiang, Ren Li, Luyi Zhang, Xiaoxia Yang, Shixin Jiang, Hongyi Zhang, Di Wang, & Xinlong Liu. Intelligent bridge management via big data knowledge engineering. Automation in Construction 135: 104118. https://doi.org/10.1016/j.autcon.2021.104118 .2022.
- Zhao, R., Zheng, K., Wei, X., Jia, H., Liao, H., Li, X., ... & Yu, C. State-of-the-art and annual progress of bridge engineering in 2020. Advances in Bridge Engineering, 2, 1-105. https://doi.org/10.1186/s43251-021-00050-x. 2021.
- Zhu, J., Tan, Y., Wang, X., & Wu, P. BIM/GIS integration for web GIS-based bridge management. Annals of GIS, 27(1), 99-109. https://doi.org/10.1080/19475683.2020.1743355. 2021.
- Zou, Yang, Arto Kiviniemi, & Stephen W. Jones. A review of risk management through BIM and BIM-related technologies. Safety science 97: 88-98. https://doi.org/10.1016/j.ssci.2015.12.027. 2017.