Natural Language Interface for 3D Symbology: An Initial Design and Application to Utility Networks

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Abstract

The growing adoption of digital twins in geomatics sectors requires efficient 3D mapping techniques. However, the complexity and cost of producing cartographically enriched 3D scenes pose significant challenges, hindering widespread application, particularly in domains with limited mapping expertise and budgets. The proposed methodology in this paper leverages recent advances in natural language processing and artificial intelligence, particularly large language models (LLMs), to reduce the expertise required for 3D mapping and to address the high costs and complexity associated with traditional cartographic processes. It introduces a natural language interface for 3D symbology, aimed at simplifying the design and automating the creation of cartographically enriched 3D scene. By allowing cartographers converse with the mapping system, the system translates verbal descriptions into structured symbology rules in 3D digital cartographic model, which are then used to generate cartographically enriched 3D scenes. The method chains multiple ad-hoc LLM-based agents for entity linking, conversation handling, and symbology rule verification. Prompt engineering methods, such as chain-of-though and retrieval augmented generation, have been used to guide the agents' reasoning process or leverage knowledge base, respectively. Experiment and application in utility networks demonstrates the method's capability to accurately interpret and execute 3D symbology rules from natural language inputs, resulting in cartographically enriched 3D scenes that are reproducible and scalable. This work represents a pioneer study to implement a natural language interface for 3D mapping. It not only enhances the usability and accessibility of 3D mapping in digital twins but also sets a foundational method for future research in natural language-based mapping interfaces.

1. Introduction

Recent years, the adoption of digital twins is accelerating across various geomatics sectors including cadastre, urban planning, civil engineering, and more, driven by advancements in GIS (geographic information system), geomatics, AI (artificial intelligence), and cloud computing. 3D visualization has become an indispensable part in the digital twin development as it could provide intuitive presentations, 3D interactive navigation, and extra symbol design choices compared to 2D visualization (Barricelli and Fogli, 2024; Eilola et al., 2023). As 3D visualization often deals with congregated scenarios and complex physical and legal realities, fine-tuning the cartographic enrichment, saying symbology, and subsequently generate the 3D scenes are key to ensuring usable visualizing results adapted to user's need and domain regulations. However, producing cartographically enriched 3D scene for visualization is often a time-consuming task and require a high level of expertise. Consequently, this hinders the wide application of digital twin, especially in the application domain where the professional 3D cartography expert is scares and the budget is limited. How to reduce the production threshold, enhance mapping efficiency, and achieve a higher degree of intelligent automation in visualization while ensuring the regulation compliance, reproducibility, and usability of 3D maps is an urgent task in cartographic research.

Recent research in 3D cartography have developed new cartographic tools and visualization platforms (Unmüßig et al., 2023), proposed new map symbology principles, and designed algorithms for automated cartographic synthesis, labelling, and viewpoint optimization (Neuville et al., 2018). It also explores the cognitive mechanisms of human-computer interaction in 3D maps. Existing studies have produced new tools, models, designs, and algorithms, recording some 3D mapping rules and deepening understanding of the use of visual variables and user cognition principles in 3D, to some extent supporting designers' decision-making and promoting the automation of 3D mapping. However, these studies are highly specialized, often targeting specific data and needs. They focus on local optimization and control parameters, making it difficult to generalize, deduce, and reason. Therefore, these findings may still not be capable of supporting the implementation of an end-to-end automated 3D cartography solution.

In order to synthesize existing cartographic findings and rules, applying automation and intelligence in the mapping pipeline have been attracting researchers' attention since the early stage of digitalized cartography in the form of expert system and automated map generation system. It may reduce the expertise requirement for mapping and boost the productivity (Tsorlini et al. 2017). Most of these systems, sometimes refer to cartography expert systems, use direct manipulation, menu selection, or form fill-in as means of human-computer interaction (Roth, 2015). However, these solutions often provide limited pre-defined selections and failed to address the complexities of human map-making. Throughout the steps of map-making, semantic information is a key element that runs through understanding spatial data, setting map symbology, controlling mapping operations, describing mapping scenes, and integrating mapping knowledge. It is the foundation of some important cartographic models and methods, and the cornerstone of map cognition theory, reflecting the semiotic/graphic semantic origin of maps. Inspired by this, leverage semantic information and using natural language as mapping design interface have attracted the attention of map researchers but have achieved limited success due to immaturity of NLP (natural language processing) technique at that moment. Recent years as the emergence of generative AI algorithms and AI-based natural language processing, especially the large language models (LLMs), we see a rapid increase in the research of natural language-based generative map producing (Harrle et al., 2024; Oucheikh and Harrie, 2024; Juhász et al., 2023; Song et al., 2023; Tao and Xu, 2023; Feng et al., 2023). The latest work well demonstrated the feasibility, potential, and benefits of using natural language interface in 2D map producing, however, there still very few application research in 3D cartography to our knowledge. Also, current work may fall short in explainability, standardization, and reproducibility (Zhang et al., 2023). The cartographic enriched map outcomes of a same conversation or prompt in some of the existing methods may differ in each standalone session. The symbology rules are not precisely articulated, thus could not be directly reapplied to other scenes and reproduce a similar cartographic enrichment.

Addressing 3D mapping difficulties and inspired by the latest generative AI, this study takes advantage of the latest development in NLP and designed a natural language interface-based 3D mapping method for 3D symbology design to reduce the 3D mapping burden in digital twin. In such a design, the 3D cartographer can conversate with the mapping system in the form of natural language about his or her desirable symbology features and the system can automatically convert his or her description into structured symbology rule encoding, and create cartographically enriched 3D scenes accordingly.

2. Methodology

The proposed natural language-interface symbology method is centred around the 3D digital cartographic model (3D DCM), as shown in Figure 1. This method initially utilizes LLM agents to interpret users' natural language semantic inputs in human-computer dialogue and converts them into accurate semantic encoding mapping rules within 3D DCM. Subsequently, a scene construction engine follows these rules to automatically build cartographically enriched three-dimensional scenes. This innovative approach combines the intuitiveness and convenience of natural language interaction with the precision of rule-based mapping. Also, it integrates the LLM agent's robust understanding of natural language with the traditional cartographic rule-based semantic mapping models and mechanisms, offering a user-friendly human-computer interaction interface while ensuring the standardization, interpretability, predictability, and reproducibility of the mapping results.

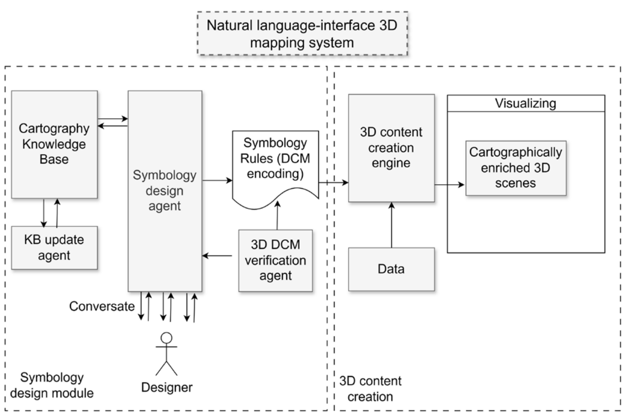

Figure 1. The general structure of the proposed natural language-interface 3D mapping system

2.1 3D digital cartographic model

Unlike direct conversion from verbal command to 3D cartography content, this paper employs a 3D DCM as the middleware between the verbal cartography command and the final 3D contents. The 3D DCM model is a structure semantic model that is encoded in XML (eXtensable Markup Language) to depict the symbology rules. It is the backbone of the solution and brings interpretability, predictability, and reproducibility to the generative 3D symbology design and mapping pipeline. This paper's 3D DCM is based on an existing model originally designed for cadastre visualization (Wang and Yu, 2021), and we re-optimize its style rules for utility networks. Additionally, we designed corresponding mapping style tags which are better align with the natural language usage habits, further optimizing the platform modelling logic. Moreover, the platform has been enhanced with features such as width grading, integration of external models, and model instantiation. Table 1 demonstrates the main tags in the proposed 3D DCM

Tags	Description
StyleCatalog	Style catalog node is a root node used to organize style rules for different features
FeatureTypeStyle	Feature type style node contains multiple rule nodes, it is used to organize rules for a specific feature
Rule	Rule node organizes the corresponding filtering policy and symbols for points, lines, and areas
Filter	Filter node is used to describe the filter policy in a Rule node
SolidSymbolizer	Symbol node is used to describe the style symbols of the features in the rule
ExternalRef	Model reference node contains the type and URL of external models

Table 1. Main tags in 3D DCM

2.2 Entity linking and Cartography knowledge base

Yih et al. (2016) emphasized the significance of semantic parsing in constructing knowledge bases. Following their lead, we devised an entity linking approach to associate mentions within the cartography corpus with cartography-related entities, subsequently transforming the corpus into a semi-structured cartography knowledge base. Employing a systematic mapping technique, this research initially gathers scholarly literature pertaining to two and three-dimensional cartography, forming a corpus of cartographic literature inclusive of extensive information ranging from tasks, users, and data to design and cognitive effects in mapping. Subsequently, this corpus is augmented with non-academic online articles relevant to cartography.

This study then collected cartographic entities and their semantic descriptions from 26 websites. The involved websites include but are not limited to those focusing on cartography technology and application, such as GISCafe and GISLounge; websites that provide tools and services for map making, such as Printmaps.net; repositories of GIS professional vocabulary, such as the GIS Dictionary offered by Esri; and the official websites of several universities rich in educational resources and research project information, such as the University of Alberta, University of Texas, as well as organizations focused on geospatial standards and data visualization like the Open Geospatial Consortium (OGC) and SeeingData.org. The entity database and the corpus together are used to build an entity linking test set.

We then employ chain-of-thought prompting (CoT) (Wei et al., 2019) and retrieval-augmented generation (RAG) (Lewis et al., 2020) techniques to construct a workflow for entity linking in cartography. The workflow, as presented in Figure 2, contains three consecutive stages: entity vectorization, mention-entity linking, and entity-disambiguation.

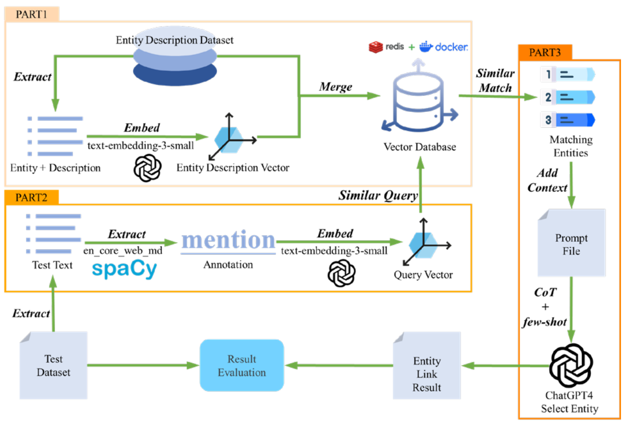

Figure 2. Cartography entity linking workflow

Firstly, this study extracted and merged "entity" and "description" fields in each item of entity database and uses OpenAI's "text-embedding-3-small" to embed each entity item into a 1536-dimensional vector, which was then combined with the original entity data and ultimately stored in a vector database. In this paper, a Redis database service was set up locally to function as the vector database. Secondly, the paper used the "en_core_web_md" model provided by the spaCy library to extract mentions from the text. Each mention was then converted into a vector using the "text-embedding-3-small" embedding model, and this vector was used to query the vector database. Multiple vectors closest to the mention's vector were matched, identifying several entities similar to the mention, which are candidate entities for the mention. Finally, the paper combined the matched candidate entities with the original text containing the annotated mentions to generate a prompt file. The "text" field in the prompt file represents the original text; the "annotations" field contains a list of annotations for each mention; and each item's "options" field includes the potential entities and their descriptions for that mention. After generating the prompt file, the paper employed chain-of-thought prompting and one-shot prompting techniques, integrating the prompt file into the prompt words as shown in Figure 3. The prompts were then submitted to OpenAI GPT-4, which used the context of the mention and the descriptions of the entities to determine the most appropriate entity, establishing the link between the mention and the entity.

This paper uses the proposed entity link method to annotate all cartography related mentions in the cartography corpus and by this way, turning the corpus into a semi-structured knowledge base of 3D cartographic documents, which could be used as prompt input for the symbology design agents.

2.3 Chat2Map-3D LLMs framework

This paper proposes a Chat2Map-3D framework (Figure 3) which drive the collaboration of three pertained LLM agents. These three cooperative LLM agents are responsible for test conversation generation, natural language parsing and DCM generating, and evaluation of DCM results, respectively. The framework is designed to reduce training costs, improve the quality of cartography related information extraction from natural language conversation, and enhancing the quality of generated symbology rules encoded in 3D DCM. The three LLM agents are tuned using "few-shot + RAG + CoT" prompting method (figure 4). The semi-structured knowledge base previously constructed serves as one of the RAG inputs. The LLM used in test conversation generation and evaluation of results is GPT-4, and the LLM used in natural language parsing is GPT-3.5-turbo.

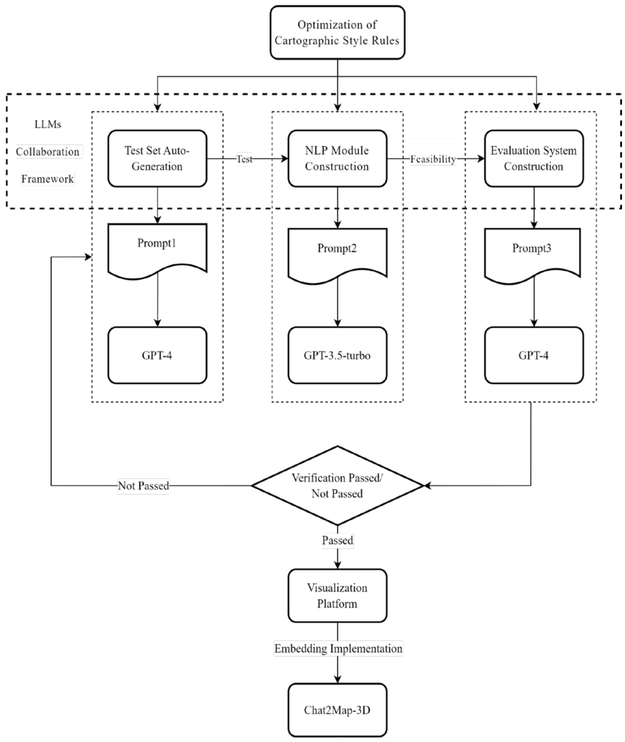

Figure 3. Chat2Map-3D LLMs framework

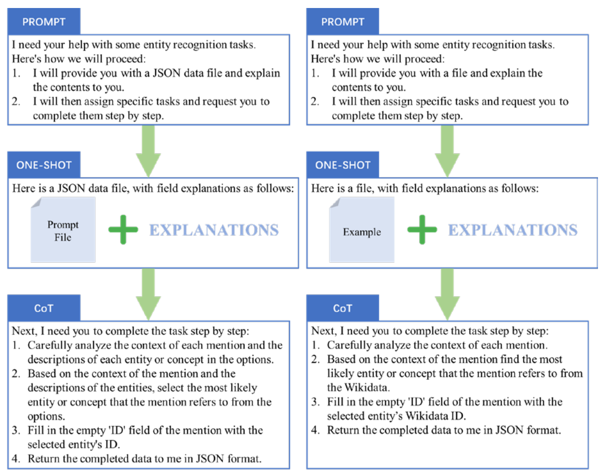

Figure 4. Prompt strategy used in entity linking process

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2.3.1 Test conversation generation agent: Considering the complexity and non-standardization of human natural language input and the difficulty of engaging a large number of participants, this paper develops a prompt strategy to guide LLMs in generating human-like natural language conversations that mimic potential human flaws. This strategy identifies five types of flaws: (1) weakened descriptions, (2) synonym substitution, (3) potential ambiguity, (4) jargon, and (5) spelling errors. Initially, we manually create a substantial number of pre-designed symbology rules encoded in 3D DCM files as ground truth, which we input into the test conversation generation LLM agent as prompt (Figure 5). The LLM then generates multiple natural language conversations with random flaws covering the aforementioned five types. The objective is to ensure that the test set encompasses a wide variety of conversation inputs. This diversity will enable the assessment of the methodology's robustness and the prototype system's comprehension capabilities.

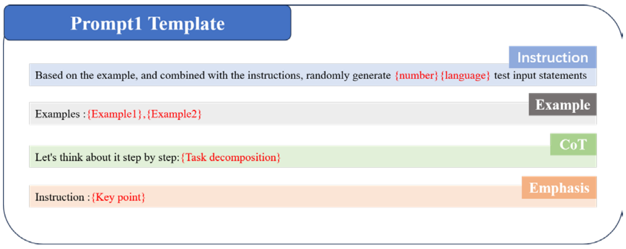

Figure 5. Prompt strategy 1 for test conversation generation

2.3.2 Natural language conversation parsing and DCM generation agent: We develop an LLM agent to interpret natural language conversations and generate DCM files of symbology rules. Akin to a Text2Text type task, the focus of this agent is on extracting content entities from natural language conversation and accurately generating these entities within the predefined DCM tag structure, guided by cartographic style rules. Figure 7 demonstrates the correspondence between natural language conversation and DCM fragments. Given that the 3D DCM structure relies on pre-designed tags, it offers a degree of predictability and stability, which facilitates few-shot prompting based on the contextual relevance of the input. Considering this, we integrate chain of thought, few-shot learning (Figure 6) with crafted conversation examples, and the cartographic knowledge base to guide the LLM in the agent for parsing natural language and generating DCM files. The LLM utilized is the pre-trained GPT-3.5-turbo model, known for its effectiveness in inference and entity recognition tasks as well as its cost efficiency. The proposed approach could significantly minimize hallucination and improve the accuracy of the final outputs.

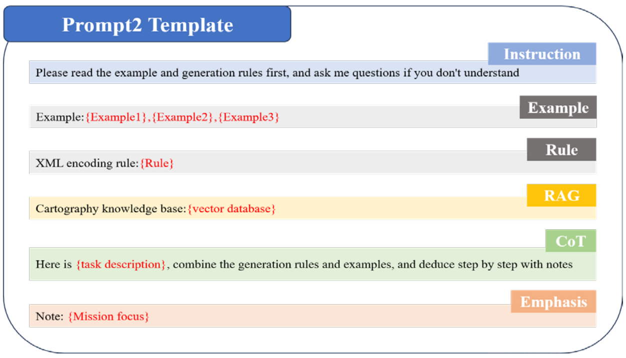

Figure 6. Prompt strategy 2 for conversation parsing and DCM generation

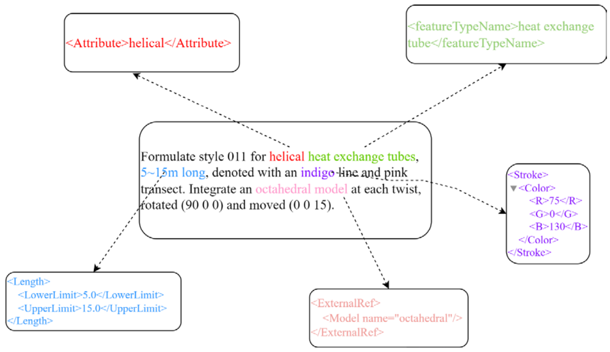

Figure 7. Demonstration of conversation parsing and DCM generation

2.3.3 DCM verification agent: Inspired by Liu et al. (2023)'s research, we developed an evaluation agent tailored specifically for assessing the quality of 3D DCM files generated by the preceding agent. This evaluation agent produces reports based on predefined metrics, as delineated in Table 2. The evaluation process resembles a Text2Text task, with conversations and DCM files serving as inputs, and evaluation reports as outputs. To guide the ChatGPT-4 based agent in this task, we provide it with ground truth conversation-3D DCM examples and predefined metric definitions as prompts, structured in a question-and-answer format (see Figure 8). Additionally, a quantitative DCM quality index, ranging from 0 to 1, is provided. This methodology requires considering both accurately and inaccurately extracted entities to ensure a comprehensive evaluation. The verification agent continually assesses and refines the DCM outputs, with the evaluation reports automatically fed back to the preceding agent for performance enhancement and refinement of the generated DCM files until a stable version is achieved.

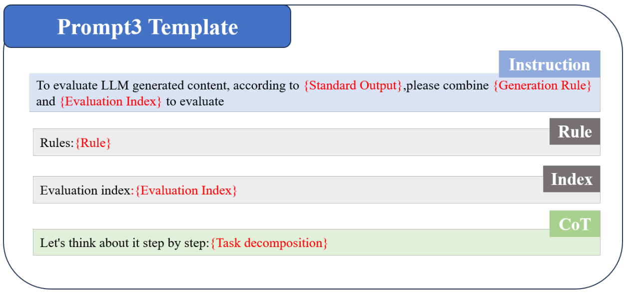

Figure 8. Prompt strategy 3 for DCM verification

2.4 3D content creation module

We combined Cesium and Three.js to craft a 3D content creation module capable of processing symbology rules encoded in 3D DCM files. This module enhances geospatial data by incorporating these rules into detailed 3D scenes and tiles, thereby establishing a rule-based, automated, and scalable workflow for 3D cartography. This process transforms raw utility network data into cartographically enriched outputs suitable for 3D visualization. Furthermore, we devised an initial framework enabling DCM generation agents to manipulate the 3D content creation module and generate cartographic content within a sample scene, allowing symbology designers to receive real-time feedback during their conversations with the agent. However, at this nascent stage of development, this framework primarily serves as a workflow control mechanism rather than directly AI agents manipulating.

Metric	Description	Proportion (%)
Completeness	Necessary for the presence of labels	10
Correctness	XML structures are correctly organized by rules	10
Format consistency	The format accuracy of all data points	20
Content accuracy	How well the content matches the expected or referenced data	40
Identify differences	Identify differences and calculate the proportion of inconsistent content	20

Table 2. DCM evaluation metrics

3. Implementation and Evaluation

3.1 Implementation

This study leverages the spaCy library, OpenAI library, and Redis to support the operations of LLM agents within a collaborative framework. Utilizing these technologies, we have developed a prototype 3D symbology design platform featuring a natural language interface. Employing a Browser/Server Architecture (B/S Architecture), this platform enables users to connect via a web browser, access 3D scenes on the Cesium virtual globe, and engage with a specially designed API. The prototype facilitates user conversations, extraction of 3D DCM, and real-time rendering and visualization of cartographically enriched 3D scenes. The system layout, illustrated in Figure 9, comprises a functional area on the left where users can load models in 3D Tiles or glTF formats, and a natural language interaction area on the right where users can input statements to generate symbology style rules and save automatically generated 3D DCM files. Following model loading, users can interact with it by querying attributes or utilizing functional buttons on the left to toggle dynamic water surfaces and apply 3D DCM files. Figure 10 delineates a mapping pipeline within the prototype system.

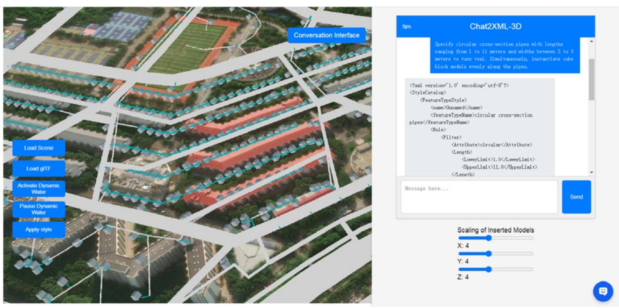

Figure 9. The layout of the prototype system

3.2 Evaluation

We firstly evaluated the entity linking agent's performance on two subsets of the testbed, utilizing precision, recall, and F1 score as evaluation metrics. Additionally, the study investigates the impact of the framework on the ChatGPT-4 model's performance in general entity linking tasks. To conduct this evaluation, we utilized the DWIE (Deutsche Welle corpus for Information Extraction) dataset (Zaporojets et al., 2021) and the Wikidata-Disamb dataset (Cetolie et al., 2018). The test results are presented in Tables 3 and 4.

Dataset	Precision	Recall	F1Score
Non-academic articles	0.800	0.984	0.883
Academic articles	0.890	0.992	0.938

Table 3. The performance of entity linking

Dataset	Precision (original)	Precision (carto-specific framework)
DWIE	0.728	0.737
Wikidata-Disamb	0.813	0.811

Table 4. The entity linking performance on non-cartography dataset

In general, the entity linking framework demonstrated robust performance across two distinct cartography test sets, notably excelling in the professional paper test set where it attained very high accuracy, recall, and F1 scores. This suggests the framework's efficacy in handling texts characterized by elevated levels of professionalism and standardized terminology. Despite a slightly lower accuracy observed for semi-professional articles, both recall and F1 scores remained strong, underscoring the framework's ability to adeptly process such texts. Furthermore, while the framework proves successful in the realm of cartographic entity linking, it does not detrimentally affect the performance of general entity linking tasks.

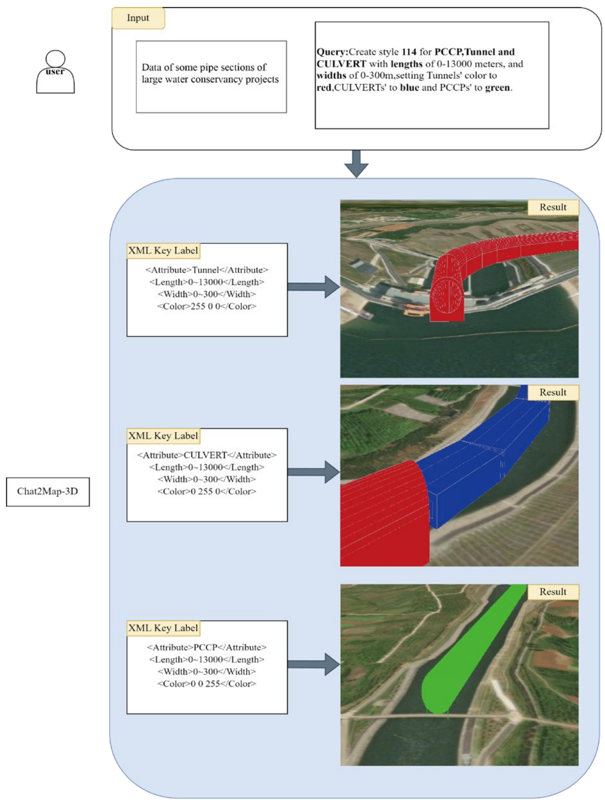

Figure 10. An example of mapping pipeline from conversation to 3D content

To verify the validity of the DCM content creation and the capability of the evaluation agent, a series of classic metrics are employed to assess the encoding quality of generated 3D DCM compared with the ground truth. These metrics include precision, recall, F1 score, Jaccard Index, and Tree Edit Distance. In the encoding content comparison task, the definitions of precision and recall are slightly modified from those in classification tasks. Precision is defined as the proportion of correct nodes (tags and attributes) in the generated DCM, where the total number of nodes in the generated DCM is termed PN (Predict Nodes) and the number of correct nodes is termed CN (Correct Nodes). Recall is defined as the proportion of nodes in the reference DCM that are correctly generated, with the total number of nodes in the reference DCM termed RN (Reference Nodes). The formulas of precision and recall are:

$$Precision = \frac{CN}{PN}, \tag{1}$$

$$Recall = \frac{CN}{RN}, \tag{2}$$

Since the 3D DCM is encoded in XML format, we incorporate the Jaccard Index and Tree Edit Distance into our evaluations. The Jaccard Index, which represents the similarity between two sets using, has been applied in XML similarity comparisons (Wen et al., 2008). The formula is:

$$Jaccard\ Index(A, B) = \frac{count(A \cap B)}{count(A \cup B)}, \tag{3}$$

The *A* and *B* represent two texts in comparison, here representing the parsed subsequence string sets from constructed DCM and the ground truth DCM respectively. Jaccard Index ranges from 0 to 1. The higher the index, the more similar *A* and *B*. Considering that the DCM is encoded hierarchically in XML file and can be represented as trees (Wang et al., 2003), Tree Edit Distance is an appropriate measure for assessing the similarity between two DCM files. Scores closer to 0 indicate greater similarity between two DCM files. The test results are presented in Table 5, accompanied by scores from our DCM evaluation agent.

Metric	Value
Precision	0.929
Recall	0.949
F1	0.939
Tree Edit Distance	2.333
Jaccard Index	0.899
LLM evaluation	0.927

Table 5. Constructed 3D DCM evaluation

As indicated in the table, both traditional evaluation metrics and LLM agent evaluation scores are consistently high. These outcomes validate the feasibility of this cartography symbology natural language parsing framework. Furthermore, the close alignment between traditional metric scores and LLM evaluation scores confirms the validity of this agent-based automatic evaluation system.

The prototype system has been experimentally integrated into several digital twin projects for utility networks to gather feedback from designers. Snapshots from these experimental implementations are illustrated in both Figure 9 and Figure 10. Even in this early developmental phase, participating designers have demonstrated interest in and confirmed the usability and value of such a natural-language interface for 3D symbology design and content creation. The generated symbology rules are interpretable and modifiable by designers, thus providing excellent explainability of 3D symbology. These rules can be effortlessly and effectively applied to various utility network scenarios, offering reproducibility and scalability. Additionally, user interactions with the system at this developmental stage have contributed valuable training and testing data for further refinement of the agent.

3.3 Discussion

The method introduced in this study leverages multiple LLM agents to construct cartography knowledge base, parse designer's natural language design conversation, encode DCM symbology rules, and finally generate cartographically enriched 3D scene. This methodology enables the realization of a natural language interface for 3D symbology, empowering cartographers to effortlessly communicate and produce cartographically enriched 3D scenes accordingly. Tests conducted on various components of the method demonstrate good performance in cartography entity linking, conversation parsing, DCM generation, and DCM evaluation. The prototype system has already been experimentally deployed in the utility network domain and has gained positive user feedback.

Despite its success, the development of the proposed method remains in its early stages. Firstly, the current cartography knowledge base is semi-structured, comprising a corpus with entity annotations. The establishment of a formal cartography knowledge graph has the potential to enhance the agents' comprehension of cartography-related terms. Secondly, the data utilized in the current implementation consists of predefined utility network data types with fixed structures. It would be valuable for the methods to autonomously interpret various data types in the future. Thirdly, the evaluation of symbology rule generation primarily focuses on validity and integrity of the DCM files rather than the suitability of the design and the usability of the visualization results. Assessing the visual outcomes of the cartographically enriched 3D scenes and offering design suggestions to designers during conversations could prove to be a valuable feature in future research. Finally, the current mapping workflow is triggered by DCM files with limited self-control and design optimization loops. In the future, constructing a human-in-the-loop style cartography design process, integrating humans and AI agents deeply, and constantly refining symbology designs according to human designers' requirements and cartography knowledge base would be valuable.

4. Conclusion

This paper introduces a novel natural language interface methodology for 3D symbology design and content creation within digital twins, utilizing a 3D DCM as middleware to translate verbal commands into the automatic generation of 3D scenes. Our case studies, focused on utility network mapping, demonstrate the methodology's usability, explainability, reproducibility, and scalability. This innovation not only pioneers a new interaction paradigm for cartographers in the realm of digital twin 3D mapping but also significantly reduces the mapping burden, thereby having broad practical implications. As an early effort in natural language interface research for 3D mapping, our work sets a new methodological paradigm and lays the groundwork for future expansions throughout the entire mapping pipeline. We plan to extend the natural language interface to other aspects of the mapping process, including data preprocessing, level of detail generation, 3D scene browsing, dynamic content design, and comprehensive mapping process management.

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