The Framework of GeoSOT-3D Grid Modeling for Spatial Artificial Intelligence

Bing Han [1], Tengteng Qu [2]

1. Academy for Advanced Interdisciplinary Studies, Peking University, Beijing 100871, China - hanbing@stu.pku.edu.cn
2. College of Engineering, Peking University, Beijing 100871, China - tengteng.qu@pku.edu.cn

Keywords: GeoSOT-3D, Spatial AI, Grid, Neighborhood Embedding, Spatio-temporal Reasoning.

Abstract

With the development of society, spatial artificial intelligence (spatial AI) research is gradually able to play a greater role. However, spatial AI has problems such as data alignment, poor interpretability, and cross domain learning. Therefore, this paper proposes an innovative GeoSOT-3D grid modeling framework for spatial AI research, which enhances the application capabilities of spatial AI. Grid modeling will be able to run through the upstream and downstream of spatial AI research, providing encoding calculations and spatial neighborhood embedding matrices for spatial data. This paper also uses task examples to demonstrate how to effectively organize and index spatial data using GeoSOT-3D grids and conduct spatial AI research. The use of GeoSOT-3D grids for spatial AI analysis has enormous potential and broad application prospects, which will help promote the further development and application of spatial AI.

1. Introduction

In the field of spatial data analysis, methods of spatial artificial intelligence (spatial AI) are gradually emerging (Janowicz et al., 2019). Spatial AI is a branch of AI that focuses on the processing and analysis of geospatial data. Compared with traditional spatial analysis methods, spatial AI has advantages such as automation, intelligence, and high accuracy (Zhu, Gao, and Cao 2022). Spatial AI utilizes machine learning, deep learning, and other AI technologies to extract valuable information from a large amount of geospatial data to support various applications (Franch-Pardo et al., 2020). Therefore, the application scenarios of spatial AI are very extensive, such as urban planning, environmental and resource management, disaster prevention and response, logistics transportation, commercial site selection, etc (Casali, Aydin, and Comes 2022; Franch-Pardo et al., 2020). However, there are still some problems that need to be solved in the research of spatial AI, mainly including the following aspects:

- Data cleaning problem: spatial AI requires a large amount of geospatial data to support, but these data often have problems such as low quality, inaccurate labeling, and difficulty in sharing (Yuan, and Li 2021). How to obtain high-quality and large-scale standard data, as well as how to effectively share and utilize this data, are important challenges faced by spatial AI research (Wang et al., 2023).
- Interpretability and transparency issues: Many spatial AI models, especially deep learning models, are often considered "black box" models, and their decision-making processes are difficult to explain and understand (Alam, Torgo, and Bifet 2022). It is difficult for people to understand why the model makes a certain decision, reducing the credibility and acceptability of the model (Li et al., 2022).
- Lack of reasoning ability: Geospatial data has rich semantic information, but current spatial AI models often can only handle low-level spatial relationships, making it difficult to perform high-level semantic analysis and reasoning (Duckham et al., 2022; Zhu et al., 2022). For example, for a dataset of "natural disasters" in a certain region, the model may only be able to identify specific types of disasters such as earthquakes and floods, but it is hard to associate these types of disasters with broader concepts such as "natural disasters".
- Poor cross domain learning ability: Spatial AI models often only perform well in specific fields or tasks, and have weak transfer ability between different fields or tasks. This limits the application of spatial AI in a wider range of fields (Ivić 2019).

In recent research, the application of spatial grids processes of spatial AI is expected to solve some problems (Gomes, Queiroz, and Ferreira 2020). The spatial grid is a structure used to describe and organize geospatial data, dividing the geographic space into a series of discrete grid units (Sun et al., 2021). Through spatial grids, spatial AI can more effectively standardize the analysis of large-scale geospatial data (Li, and Stefanakis 2020). Meanwhile, spatial grids can also provide richer application scenarios for spatial AI. For example, in urban planning, spatial grids can be used to divide and analyze different areas within the city, thereby optimizing urban layout and resource allocation (Chen et al., 2023). The spatial grid has brought many important values and conveniences to the research of spatial AI. However, due to the limitations of existing methods, spatial grids can still only be applied upstream in spatial AI research and cannot exert greater value (Wu et al., 2022).

Therefore, this paper will propose an innovative three-dimensional grid full process modeling framework for spatial AI research based on the Geographic Coordinate Subdividing Grid with One Dimension Integrated Coding on 2^n-Tree-3D (GeoSOT-3D), which can enhance the interpretability and reasoning ability of spatial AI, and reduce the efficiency of spatial data preprocessing and extraction. This framework combines the advantages of GeoSOT globally unified spatiotemporal 3D coding system with grid coding algebraic computation, aiming to solve the problems encountered in existing spatial AI analysis. By integrating key processes such as collection, processing, analysis, and visualization of spatiotemporal data. The framework can effectively organize, index, and correlate spatial data using GeoSOT-3D grids, and how to combine deep learning algorithms with grid neighborhood computing models to explore potential patterns and correlations in spatial data. This paper constructs a comprehensive and efficient spatial AI workflow. Subsequent research on spatial AI can be based on this framework, greatly reducing the difficulty of preprocessing and modeling.

2. GeoSOT-3D grid modeling

2.1 GeoSOT

The spatial grid can be two-dimensional, three-dimensional, or even contain temporal dimensions, thus forming a spatiotemporal grid. The types of spatial grids are very diverse, and can be divided into various types based on different application requirements and data characteristics (Li et al., 2020). The GeoSOT used in this paper is a Geographic Coordinate Subdividing Grid with One Dimension Integrated Coding on 2n Tree, created by three spatial extensions of the longitude and latitude range of the Earth's surface, which is shown in Figure 1 (Han, Li, and Cheng 2021). The First expansion of GeoSOT is Transforming the Earth into a plane through simple projection, expanding 180 ° x 360 ° to 512 ° x 512 °, forming a degree level grid. The second extension is to expand the 1 ° grid cells from 60 'to 64', forming a minute level grid. And third expansion of GeoSOT is to expand the 1 ° grid cells from 60 'to 64' to form a second level grid.

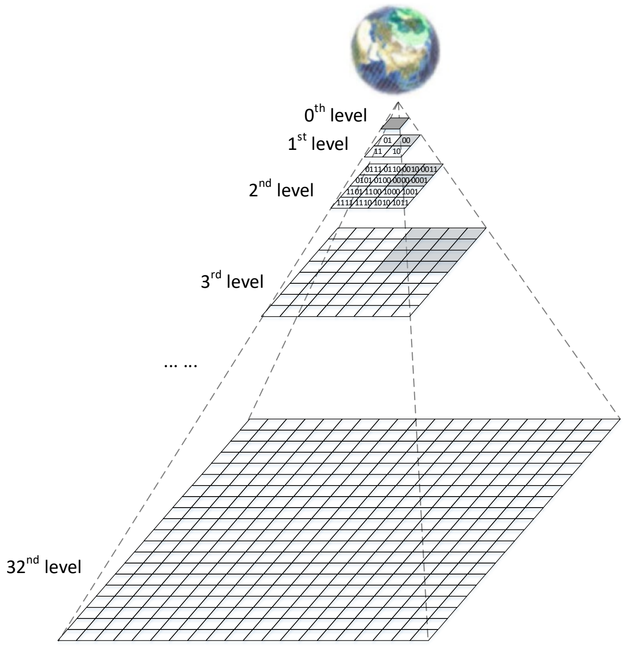

Figure 1. GeoSOT earth subdivision grid pyramid.

By constructing a multi-scale grid with 32 levels, GeoSOT has identifiability, multi-hierarchy, aggregation, and correlation compared with other spatial grids, which can achieve organic correlations between different levels and provide a foundation for spatial multi-scale expression and training embedding; by using GeoSOT as the central component, GeoSOT can be transformed into various types of existing data, which is conducive to data compatibility and cross domain spatial data integration and sharing (Qian et al., 2019).

2.2 GeoSOT-3D

With the expansion of research scenarios, the utilization and research of spatial data are not limited to two-dimensional scenes, and GeoSOT-3D is the three-dimensional extension of GeoSOT in high dimensions (Hou et al., 2021). GeoSOT-3D adopts octree data structure, which divides the entire Earth's space from 50000 km up to the center of the Earth into 32 levels of spatial voxels, which can carry heterogeneous spatial data from multiple sources, as shown in the Figure 2 and Figure 3 (Han et al., 2022).

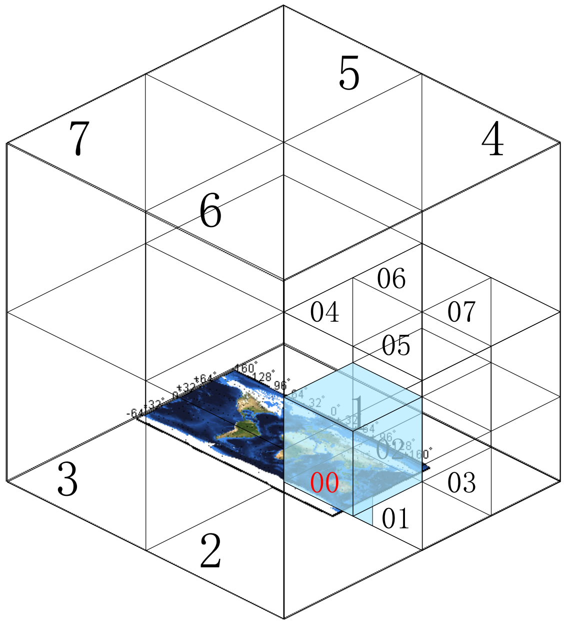

Figure 2. GeoSOT-3D octree data structure diagram.

In Figure 3, The GeoSOT-3D grid adopts a globally unified 3D gird framework, which can seamlessly cover geospatial data on a global scale. Thus, GeoSOT-3D grids have unique advantages in processing large-scale, cross regional 3D spatial data, and provides a solid foundation for building global spatial AI applications. At the same time, GeoSOT-3D mesh has the characteristics of hierarchical nesting and correlation, which can achieve efficient organization and management of three-dimensional spatial data of different scales and resolutions. This design of hierarchical nesting and correlation helps to efficiently calculate and analyze spatial data at different scales (Han et al., 2021).

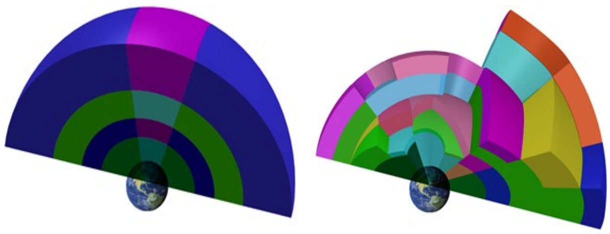

Figure 3. Actual shapes of the divided blocks of GeoSOT-3D at different levels.

More importantly, GeoSOT-3D proposed an efficient encoding algebraic model. This model can achieve rapid identification, retrieval, and association of spatial targets, providing strong support for complex spatial relationship calculation and analysis. By utilizing the encoding system of GeoSOT-3D, it is convenient to fuse and mine spatio-temporal data. Spatio- temporal data from different sensors are mapped to the same GeoSOT grid, and then spatial AI algorithm is used to discover hidden patterns and associations in the data. The advantages of GeoSOT-3D will be able to solve the problems in the current spatial AI workflow, which will be explained in detail in the next section (Han, Li, and Cheng 2021).

3. GeoSOT-3D framework for spatial AI

3.1 Framework flow

The research on spatial AI mainly includes data cleaning and feature extraction of upstream, algorithm construction and training of midstream, and task result analysis and visualization display of downstream. As shown in Figure 4, the GeoSOT-3D grid framework can play a role in various stages of research and enhance the ability of spatial AI.

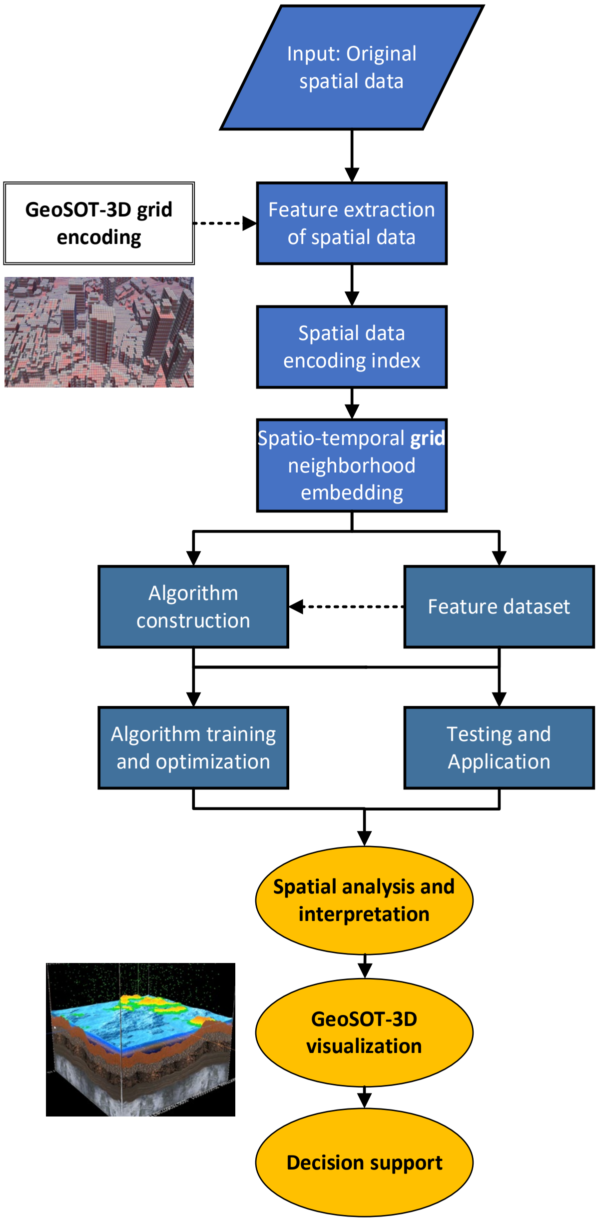

Figure 4. The Framework flow schema of GeoSOT-3D modeling service for spatial AI.

3.2 Spatial data processing by GeoSOT-3D

Using GeoSOT-3D grids to process spatial data can greatly reduce the difficulty of cleaning and aligning spatial data, as shown in Figure 4. In the specific research process:

1. Input original spatial data: Collect original data related to spatial AI analysis, including geospatial data (satellite images, map data), flow data (meteorological observation data, traffic flow data), and multi-media data (text, videos, and images with spatial information), and import them into the GeoSOT-3D grid database.

2. GeoSOT-3D grid encoding: Based on the GeoSOT-3D grid system, the collected raw data is preprocessed, and each spatial data is encoded at 32 levels. Various complex spatio-temporal coordinates are cleaned and unified at multiple scales, and each grid unit is assigned a unique encoding. According to the requirements of subsequent tasks, the corresponding grid level can be accurately selected to quickly organize and index the data.

3. Feature extraction of spatial data: Based on the spatial range of the GeoSOT-3D grid, extract relevant spatial and time series features within each grid unit, such as terrain and landforms, land use types, population density, traffic flow, etc. Based on the grid as the basic unit, these features will serve as inputs for subsequent AI analysis.

4. Spatio-temporal grid neighborhood embedding: Through the inherent encoding algebra theory of GeoSOT-3D, it is possible to quickly calculate the first-order and second-order spatiotemporal neighborhoods of each spatial data through grid encoding, and intelligently generate embedding matrices. Compared with traditional semantic training, this can greatly improve the interpretability and reasoning ability of spatial AI models

3.3 Spatial AI analysis using GeoSOT-3D

After completing the processing and encoding of spatial data, spatial AI tasks can also be further analyzed and displayed in conjunction with GeoSOT-3D:

1. Algorithm construction: Based on specific analysis tasks and data characteristics, select appropriate AI algorithms and models. It is best to combine learning algorithms with spatiotemporal embedding matrices in the process effectively to improve the training effect of the model, such as machine learning algorithms (decision trees, or support vector machines), deep learning algorithms (convolutional neural networks, or graph neural networks) And spatiotemporal analysis algorithms (spatio-temporal autocorrelation analysis, or spatio-temporal clustering analysis).

2. Algorithm training and optimization: Using extracted spatial features and corresponding label data, train and optimize the selected algorithm to obtain an AI model suitable for spatial analysis. During the training process, techniques such as cross validation, regularization, and hyperparameter tuning can be used to improve the performance of the model. Meanwhile, different levels of spatial grids in GeoSOT-3D can be added to the model's training to try to improve accuracy.

3. Spatial analysis and interpretation: By GeoSOT-3D grid, diverse 3D testing scenarios can be constructed, and the trained model can be applied to test data to obtain spatial analysis results.

4. GeoSOT-3D visualization: Based on GeoSOT-3D's fast and accurate 3D reconstruction ability, it can visualize the analysis results of spatial AI in a dynamic grid graph, making it easier for decision-makers to analyze and use the training and testing results better.

5. Decision support: By analyzing and interpreting the results, discover patterns and trends in spatial data, and provide support for decision-making.

3.4 Discussions

Through the framework flow of GeoSOT-3D modeling service for spatial AI mentioned above, this paper integrates the grid generation and neighborhood concept of GeoSOT-3D into the entire process. In response to the current problems in spatial AI, the framework of GeoSOT-3D grid modeling can first standardize and quickly encode and clean multi-source heterogeneous spatial data through unified spatial encoding; The encoding algebra of the grid and the inherent connotation of its own encoding can help spatial AI construct its spatio-temporal embedding matrix, which has better interpretability and spatio-temporal reasoning ability compared with traditional text image training; At the same time, the grid can associate various semantic and spatio-temporal data, achieving cross domain and multimodal learning. Through grid-based improvements, spatial AI will be able to play a greater role. This paper will demonstrate the advantages of the current GeoSOT-3D framework in spatial AI in the next section.

4. Grid task experiments of spatial AI

4.1 Intelligent driving

In Spatial AI, GeoSOT-3D can be used not only for organizing and analyzing static spatial data, but also for simulating and predicting dynamic spatio-temporal processes (Jiang et al., 2022). By combining spatio-temporal data models and dynamic simulation algorithms, complex spatiotemporal processes such as urban traffic flow can be modeled and predicted, thereby achieving intelligent driving.

As shown in Figure 5, in intelligent driving, GeoSOT-3D can improve Spatial AI by quantifying the various driving environments and surrounding obstacles encountered by autonomous vehicles during the driving process according to the grid, and expressing them directly in red, green, and blue colors. Through neighborhood calculation and reinforcement learning of grid coding, inheritance based local dynamic updates can be achieved, thereby constructing a grid driving map for autonomous vehicles. Compared with traditional polar coordinate models, the speed of environmental data transfer, efficiency of situation update, and efficiency of driving decision calculation have all been significantly improved (Yu et al., 2021).

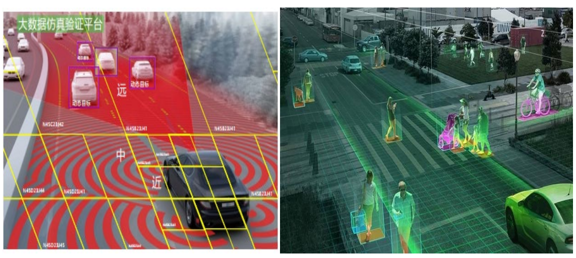

Figure 5. GeoSOT-3D Intelligent driving.

4.2 spatio-temporal reasoning

Spatio-temporal reasoning refers to the ability to calculate or predict unknown spatio-temporal information in complex geographical environments, which requires spatial AI models to have strong interpretability. Therefore, based on the GeoSOT-3D model, we propose a grid-augmented geographic knowledge graph (AugGKG), which establishes a geo-hidden layer by setting the grid as a node in the graph (Han et al., 2023). AugGKG enables the knowledge graph to support efficient expression and spatio-temporal reasoning of multi-source heterogeneous data from geographic spatial nodes, and provides spatio-temporal object retrieval, inference, calculation, and management capabilities.

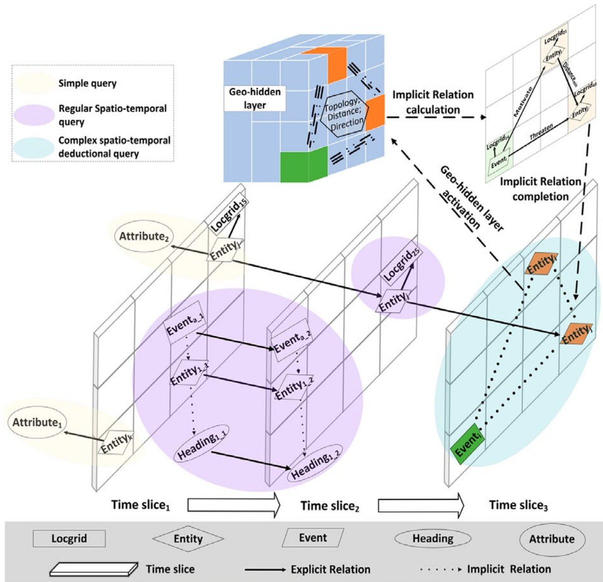

Figure 6. The framework schema of AugGKG (Han et al., 2023).

4.3 Disaster monitoring

Disaster monitoring analysis is a hot topic in the field of geospatial information, and in many cases, it is necessary to comprehensively utilize various types of data for analysis. The integration and analysis of multiple types of geospatial information poses challenges for existing spatial data organization models and deep learning analysis models (Han et al., 2021). For multi type geospatial data, the GeOSOT-3D model proposes a spatial AI model for disaster warning, and fuses features of multi type geospatial data based on standard grids, establishing a 3D convolutional neural network model based on grouped convolution, which is shown in Figure 7.

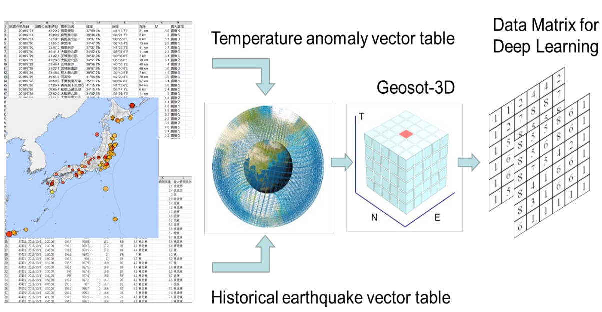

Figure 7. GeoSOT-3D disaster monitoring grid model

5. Conclusions

Spatial AI has broad application prospects, which can help us better understand and utilize geographic data, improve decision making efficiency and accuracy. However, there are still some issues to be solved in spatial AI. Compared with other 3D grids, GeoSOT-3D has a globally unified 3D grid framework, hierarchical nesting and correlation, and efficient encoding algebraic models. Thus, this paper proposes the GeoSOT-3D grid model to solve the problems of data cleaning, poor interpretability, insufficient spatial reasoning ability, and cross domain analysis in current spatial AI research through GeoSOT-3D grid model, spatial AI can more effectively process and analyze large-scale geospatial data, and perform more in-depth spatio-temporal analysis and inference tasks. GeoSOT-3D would provide a method for the standardization research of spatial AI.

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