Research on Spatial Data Aggregation Based on Aggregation Degree Function

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Abstract

Restricted by the development level of hardware and software technology, computers cannot load massive data at one time, coupled with the fact that the three-dimensional linear scene is characterized by complicated lines, irregular shapes of features and a large number of features. Therefore, it is necessary to seek a three-dimensional spatial data organization and scheduling method applicable to the railroad scene to realize the display and interaction of the scene. In this paper, we propose a data organization method based on the aggregation degree function for the 3D model of features. The feature model is projected to generate an orthographic projection map, the cluster division rule is designed to divide the subsets, the feature model after clustering is aggregated using the feature model aggregation rule, and the aggregated model is displayed according to the aggregation degree function and viewpoint factor. The results of the test applied to the railroad scene show that the 3D spatial data aggregation based on the aggregation degree function can improve the loading speed of the 3D scene, and can effectively support the application of interactive visualization of the railroad 3D scene.

1. Introduction

Railroad linear scene can visually express the line entity and its surrounding topography and geomorphology, and provide support for railway-related management decisions and scientific experiments. Restricted by the development level of hardware and software technology, the computer can not load massive data at once, coupled with the railroad linear scene has the characteristics of strip and line complexity, irregular shape and large number of features, which makes the data organization of the feature model in the railroad linear scene more difficult. Therefore, it is necessary to seek a method applicable to the organization of railroad three-dimensional spatial data to achieve the display and interaction of the scene.

The current research on 3D visualization of linear scenes mainly includes visualization techniques based on point cloud data (BILJECKI, 2016), visualization techniques based on detail level models (Lausch, 2014), etc. Literature (TAO, 2014) describes the design process of linear 3D scenes. Existing research on speeding up the loading speed of visualization focuses on the use of tile pyramid and LOD techniques to solve the 3D scene loading problem and improve the scene loading speed. Literature (Liangfeng, 2018)proposes a 3D adaptive pyramid model to convert 3D terrain data into logical units of terrain data, and realizes the fast display of massive 3D terrain data in 3D GIS through multi-source heterogeneous data fusion. Literature (LI, 2018)establishes the spatial division of the feature model and the construction method of the hierarchical index based on the pyramid structure, which effectively controls the index redundancy so that a large number of 3D feature models can be displayed efficiently. Literature (ZHU, 2017)improves the loading speed of 3D scenes by studying computer caching and display strategies, which relieves the pressure of computer storage to a certain extent. Literature (Sun, 2016) solved the problem of excessive data volume caused by the requirements of different detail levels when loading 3D scenes by improving LOD technology. The above methods improve the 3D data loading speed to some extent, but the amount of stored data is large. The tile pyramid model needs to store a large number of tiles with different resolutions, and the LOD technology needs to store a large number of data at different levels of detail of the feature model, which takes up a large amount of computer cache space and affects the loading speed when loading 3D scenes. To improve the loading speed of 3D scenes, suitable indexing methods need to be applied, such as lattice grid indexing (Hu, 2014), quad-tree indexing (ZHANG and Ning, 2020), octree indexing (Zhen, 2021), R-tree indexing (Zhai, 2021) and so on.

2. Design of algorithms for aggregation of 3D scene feature models

In this paper, feature models in linear 3D scenes are aggregated by clustering. In order to reduce the amount of data of feature models in different LODs. Firstly, the feature model is projected to generate the orthographic projection map, the cluster division rule is designed to divide the subset, the feature model after clustering is aggregated by using the feature model aggregation rule, and the display of the aggregated model is carried out according to the aggregation degree function and the viewpoint factor.

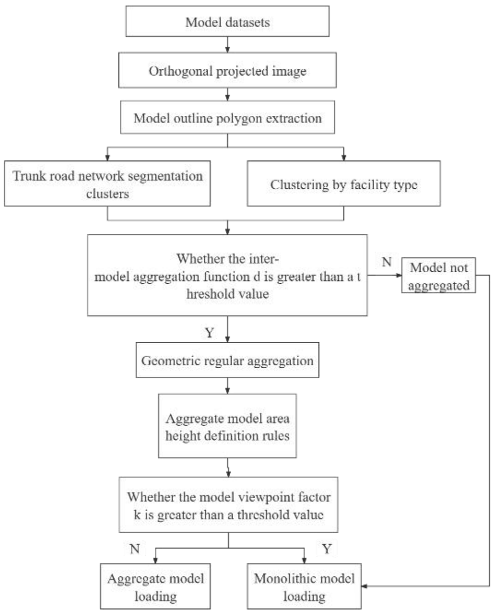


Figure 1. Technical flow chart

2.1 Three-dimensional feature model projections and clusters

To speed up the loading of the 3D scene, the amount of data for loading the model is reduced by aggregating the feature models in the linear scene of the linear railroad. By appropriately organizing the degree of model aggregation under each abstraction level, the presentation of the 3D scene can be accelerated without causing distortion of the 3D scene's feature models.

2.1.1 Projection of three-dimensional feature models. The model in the 3D scene is represented by I={op, name, height, area, type}, where op denotes the orthographic projection of the model, name denotes the name of the model, height denotes the height of the model, the highest point of the feature model before projection is taken as the height of the model, area denotes the area of the model, and the projected area is taken as the height of the model.Orthographic projection map of the model, name denotes the name of the model, height denotes the height of the model, taking the highest point of the feature model before projection as the height of the model, area denotes the footprint of the model, the polygon area after projection is taken as the area of the feature model, and type denotes the type of the model. In order to facilitate the model aggregation later, the model in the 3D scene is projected to get the orthographic projection of the feature model.

The projection rules are as follows: in order to facilitate the large-scale scene calculation, the paper adopts the block processing of 3D model data, and divides the scene into a number of local regions; by giving a minimum elevation plane, a parallel virtual "horizontal cutting plane" can be formed. In the cutting projection, the triangular surface of the model is projected to the elevation plane and rasterized to obtain a binarized raster orthographic projection image.

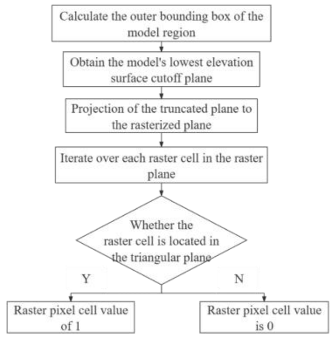
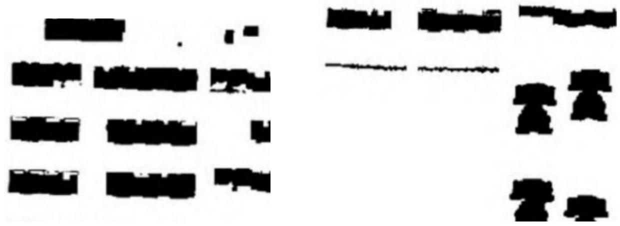
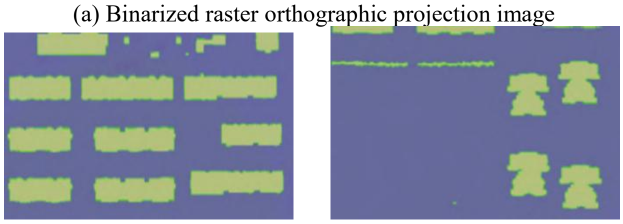


Figure 2. Orthographic map acquisition process

In order to obtain the building outline vector data, it is necessary to extract the edges of the building from the raster data, which is a typical raster data to vector data algorithm. At present, the algorithm of providing the contour edges from raster data is more mature. Considering that the binarized raster data processed in the paper has simple information, large image range, and the vector objects to be generated are polygons, we choose to use the method based on image edge detection and boundary tracking for the contour polygon extraction of binarized images.



(a) Binarized raster orthographic projection image



(b) Contour Polygon Extraction

Figure 3. Model Contour Vector Data Acquisition

2.1.2 Clustering of three-dimensional feature models. In the three-dimensional side station scene before the aggregation, the need for three-dimensional model of the railroad feature model cluster division, so that is located in the same side of the railroad trunk road and belongs to the same type of feature model can be aggregated. The type of railroad 3D feature model is divided into engineering, power supply, etc., of which the engineering model includes houses, structures, houses include general production plant, management office, non-production rooms, structures include plate culvert, moment culvert, etc., power supply model includes substation equipment, power supply system, communication equipment and so on.

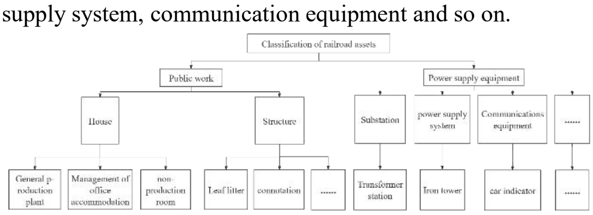


Figure 4. Classification of railroad assets

The clusters are divided as follows: (1) Division based on the main road network. Since the aggregation of the feature models located on both sides of the railroad trunk road will affect the overall appearance of the three-dimensional scene, a subset of the feature models is formed by the area formed by the intersection of the trunk road network in the first scene. (2) Further division based on facility types. It is stipulated that different categories of 3D models of railroad infrastructure cannot be aggregated, and the subset of feature models obtained from the initial division is further divided according to the type of facility, and finally the subset I of feature model clustering is obtained.

2.2 Aggregation algorithm for feature model aggregation based on aggregation degree function

The above pre-processing of the feature model by projection and clustering is performed, and in order to reduce the complexity of the feature model data, the feature model is aggregated based on an aggregation degree function. degree function.

2.2.1 Rules for aggregation of feature models. The geomodel aggregation rules include geometric aggregation rules and post-aggregation height definition rules.

(1) Geometric rules when aggregating orthographic projections. The geometric rules for the aggregation process contain three general cases.

Case 1 Iterate over all the edges of the orthographic projection of a feature 3D model, and find the two edges that are closest to each other in the two orthographic projections, e.g., a1b1 in Fig. Connect the vertices of the two edges that are closest to each other, and yes connect the two edges that are connected to the smallest sum, to form a convex bag; and then extend the two edges of the closest edges, and keep them if the extension line intersects with the projected graphs, and delete them otherwise.

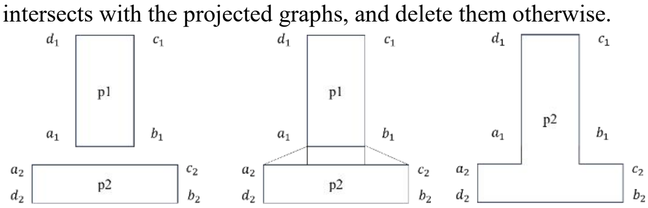


Figure 5. Feature model aggregation process

Case 2 When the orthographic projection includes circles and polygons, make a vertical line from the center of the circle to the edge of the polygon, choose the shortest vertical line, get the diameter perpendicular to the vertical line, and use the diameter as the edge of the circle to polymerize in the above method.

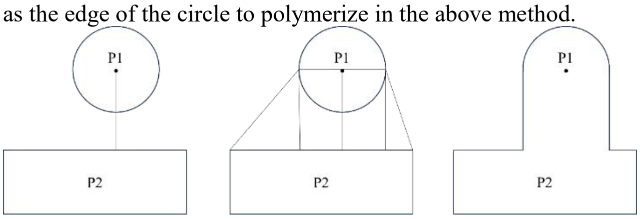


Figure 6. Aggregation process when the projection map of the feature model is circular

Case 3 If both edges in the orthographic projection are at the shortest distance from the edge of the other orthographic projection, one of them is selected. As shown in Fig. 6, when both a_1 a_2 and a_2 a_3 edges have the shortest distance from the polytope Ps_2, the a_1 a_2 edge is selected for aggregation.

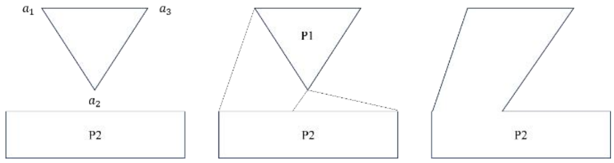


Figure 7. Aggregation process for minimizing the distance between multiple edges in an orthographic projection graph

(2) Rules for defining the area and height of the model after aggregation

Aggregating 2 feature models with large differences in heights in a linear scene may cause large differences in the display of feature models when switching between different LOD levels, resulting in model mutations and jumps. Therefore, it is necessary to design appropriate aggregation rules so that the relationship between area and height before and after the aggregation of feature models is not seriously distorted.

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$$area = area_1 + area_2 \tag{1}$$

$$height = \frac{area_1 + height_1 + area_2 + height_2}{area} \tag{2}$$

Where $area_1$, $area_2$ =area of 2 feature models
$area$ = model area after aggregation
$height_1$, $height_2$=height of feature model
$height$ = height of feature model after aggregation

2.2.2 Geomodel Aggregation Process. Based on a subset Ii of the clustered feature models, the feature models with large differences in area are weighted by the relative area parameter d as shown in Equation (3):

$$d = d_e \times \frac{A_{min}}{A_{max}} \tag{3}$$

Where d = relative area parameter
d_e = Euclidean distance between the centers of the orthographic projections of the 2 models
A_{min} = smaller value of area
A_{max} = larger value of area

Where d_e denotes the Euclidean distance between the centers of the 2 model orthographic projections, A_min and A_max are the smaller and larger values of the area of the 2 model orthographic projections in the subset, respectively. If d is smaller than the threshold value, the model projection map with smaller area is deleted, and the area of the larger model orthographic projection map is extended to the sum of the 2 model areas; if d is larger than the threshold value, it is judged whether to aggregate based on the aggregation degree function equation (4). By setting the threshold value, the aggregation status of feature models under different LOD levels is realized:

$$D = \sqrt{d_e^2 + \ weight(height_i - \ height_j)} \tag{4}$$

Where d_e = Euclidean distance between the centers of the orthographic projections of the 2 models
$weight$ = value of weights
$height_i$, $height_j$ = height of feature model
D = set threshold value

Where d_e denotes the Euclidean distance between the centers of the orthographic projection maps of the 2 models, $height_i$ and $height_j$ are the heights of the 2 feature models in the subset that satisfy the above conditions, and $weight$ denotes the weights that the heights occupy in the aggregation function, and the appropriate weights are set so that the models are displayed without serious distortion.

Based on the aggregation degree function the subsets after cluster division are aggregated, and the binary tree is generated bottom-up until all the feature models are aggregated. The process of binary tree generation is shown in Figure 8. At the beginning, the set of feature models is I = { 1, 2, 3, 4, 5}, and according to the value of the aggregation degree, 1 and 2 are merged into d, and the set becomes { d, 3, 4, 5}; then according to the value of the aggregation degree, 4 and 5 are merged into b, and the set becomes { d, 3, b }; and according to the value of the current minimum aggregation degree, d and 3 are merged into c, and the set becomes { c, b}; and finally c and b are merged to form the final aggregated binary tree. Finally, c and b are merged to form the final aggregated feature model set G_i = { a}.

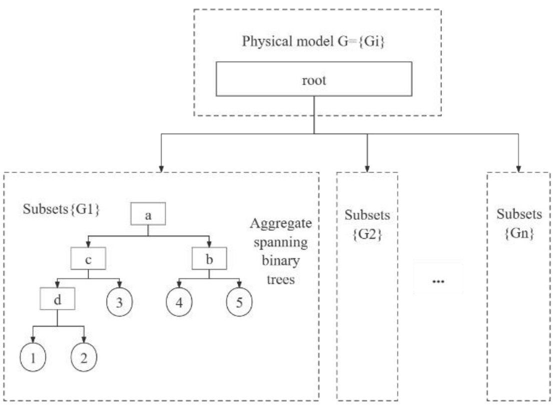

Figure 8. The process of aggregation of feature model ensembles

The aggregation process of the feature models actually refers to the aggregation process of the feature model nodes they index. define the node node={op, type, height, area, father, lchild, rchild} of the hybrid structure of the multinomial tree, where op, height, area, and type are the ortho-projection, type, and height and area of the ortho-projection, respectively, of the feature model represented by that node. projection map, type and the height and area of the orthographic projection map, respectively, father points to the parent node in the binary tree, and lchild and rchild point to the left and right child nodes.

2.2.3 Viewpoint-based 3D scene display. The 3D visualization of a linear scene is related to the viewpoint at which the user views the 3D scene and the area of the feature model, defining the viewpoint factor k as the ratio of the area of the orthographic projection and the square of the distance to the viewpoint. Starting from the root node, if the viewpoint factor k value of the root node is less than the threshold, the whole scene area is displayed; if the viewpoint factor k value is greater than the threshold, the child nodes are tested. During the 3D interaction process, the nodes of the multinomial tree hybrid structure are dynamically selected according to the movement of the viewpoint, and the scene tree is generated in real time for visualization. The specific rules are as follows.

(1) Test the root node of the tree, calculate the area of the orthographic projection map of the feature model indexed by the root node and the distance d_{vp} from the center of the orthographic projection map to the viewpoint, and calculate the viewpoint factor according to equation (5):

$$k = \frac{area}{\mathrm{d}_{vp}^2} \tag{5}$$

Where k = viewpoint factor
$area$ = area of an orthographic projection
d_{vp} = distance from the center of the orthographic projection to the point of view

(2)If the viewpoint factor k is less than the set threshold, the node is displayed in the 3D scene; otherwise, calculate the k values of the two children of the node and determine whether it is displayed in the 3D scene.

(3) If the current node has no children, the current node will be displayed directly and the children will not be counted.

With the above rules, the viewpoint factor k of the hybrid structure nodes can be dynamically tested in real time according to different viewpoints to form the 3D scene of the railroad. Based on the viewpoints, the 3D scene is displayed, models farther away from the viewpoints are loaded with aggregated models, and models closer to the viewpoints are loaded with separated refined feature models, which reduces the amount of feature models loaded and the cache overhead of the computer.

3. Application of Spatial Data Aggregation Based onAggregation Degree Function in Shuo Huang Railway Asset Management Project

3.1 Models and Data Applied in the Baigou Digital Pipeline System

In order to verify the validity of the method of this paper, the linear 3D scene of Shuo Huang Railway is rendered using the Cesium 3D engine using railroad data, tectonic data, etc. The multi-source data stored in the scene is shown in Table 3-1.The spatial data aggregation algorithm based on the aggregation degree function established in this paper is utilized as a rule for the call of the front-end visualization platform in the form of 3DTile.json data format. In the 3D linear scene, the core idea of event simulation is to decompose the complex event into multiple independent parts and realize the construction of each part of the scene by calling and loading them separately. Based on the visualization and display strategy of Cesium 3D engine for Shuo Huang Railway images, topographic data, tilt data and 3DMAX data, experiments are conducted to establish the dynamic visualization visualization of each railroad asset aggregation model.

Date Type	Data Volume
Image Data	49.2GB 97.6GB
Oblique Image Data Topographic Data	32.0GB
3DMax Data	5.2GB

Table 1. Data type

3.2 Comparison test between this paper's algorithm and LOD model of railroad 3D scene

(1) Comparison test of loading frame rate.The loading time of the railroad 3D scene is recorded by Chrome Dev tools, and the loading frame rate is recorded for the 3D substation scene roaming process using the algorithm in the paper and the LOD technology respectively, and the results are shown in Fig. 13. The loading frame rate of the 3D scene realized by using the aggregation algorithm is higher than that realized by using the LOD model, which basically stays at about 38 frame/s, so that the 3D scene realized by using the aggregation algorithm has improved the loading speed.

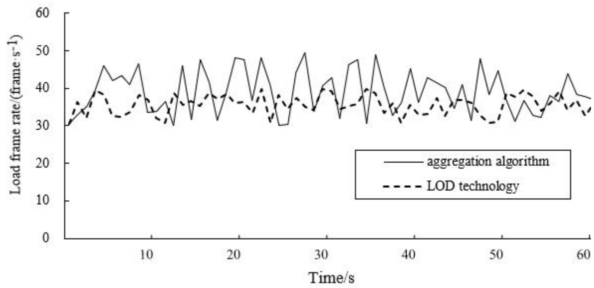

Figure 9. Railroad 3D scene roaming frame rate comparison test

(2) Comparative testing of 3D visualization effects.Figure 10 compares the visualization effect of the two groups, the left mage is the 3D scene map realized by LOD technique, and the right image is the 3D scene map realized by using the algorithm of this paper, the left image is a refined feature model near the viewpoint, and the viewpoint is far away from the rough single feature model, the single loading of the long-distance feature model doesn't provide too much contribution to the visual effect, and it increases the memory overhead of the computer. The image on the right is a single refined model close to the viewpoint by judging the k-value, and the substation feature model far away from the viewpoint is in the aggregated state, which shows the complete outline of the feature model, and the use of the aggregation algorithm achieves the effect of maintaining the overall display of the 3D scene without the need of loading multiple single feature models.

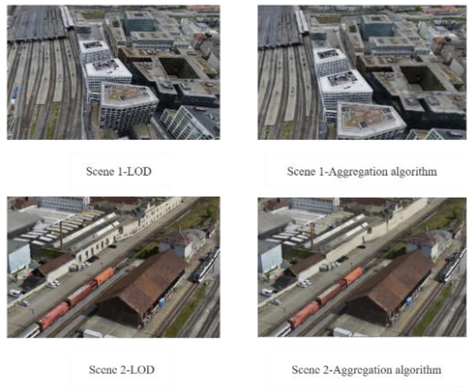

Figure 10. Railroad 3D scene test results

Figure 11 compares the number of models to be loaded and the loading time of the 3D scenes realized by the two methods in the process of gradually approaching the viewpoints from the global scene and finally arriving at the original scene, of which the loading time of the global scene refers to the time required to load the whole global scene when the 3D scene is started, and it can be seen in Figure 11 that the number of models to be loaded is less and the loading time is faster than that of the 3D scene realized by LOD technology.

From Figure 11, it can be seen that the 3D scene realized by this paper's algorithm requires less model loading and the loading time is faster than that of the 3D scene realized by LOD technology, and this paper's algorithm improves the loading speed of the railroad's 3D scene without causing distortion of the 3D scene.

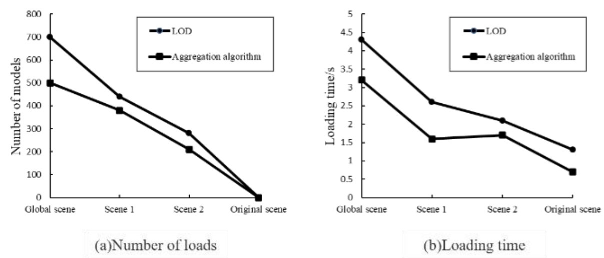

Figure 11. Railroad 3D scene model loading quantity and loading time

Concluding remarks

Aiming at the problem of slow loading speed of linear 3D scene of railroad, this paper proposes a data organization method of feature model cluster aggregation. The feature models in the substation are projected, and the feature clusters are divided according to the main road lines and the types of feature models in the railroad scene. The models are aggregated based on the aggregation degree function. A dynamic visualization scene based on viewpoints is formed by determining whether the value of viewpoint factor k is greater than a threshold value. This method can effectively improve the loading speed of the railroad 3D scene, and can provide support for the interactive visualization of the 3D scene of railroad engineering.

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