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Hierarchical visualization of geographical areal data with spatial attribute association

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ABSTRACT

Geographical areal data usually presents hierarchical structures, and its characteristics vary at different scales. At the higher scales, the visualization of geographical areal data is abstract and the detailed features are easily missed. As a difference, more detailed information is presented at the lower scales while the visual perception of global features is easily disturbed due to the overdrawing of visual elements. As the geographical areal data is visualized at a single scale at the same time, it seems impossible to balance the visual perception of both the global features and detailed characteristics. In this paper, we propose a multi-scale geographical areal data visualization method based on spatial attribute association to enhance the visual perception of both the global features and detailed characteristics. Firstly, the geographical areal data is aggregated into hierarchical clusters based on the spatial similarity. Then, the coefficient of variation is applied to estimate the attribute distribution of each cluster in the hierarchy, and a novel geographical areal data visualization scheme is proposed to adaptively present the multi-scale clusters with lower variation coefficients at the same time. In addition, a rich set of visual interfaces and user-friendly interactions are provided enabling users to specify those clusters of interest at different scales and compare multi-scale visualizations with different hierarchies. Finally, we implement a geographical areal data visualization framework, allowing users to visually explore the global features and detailed characteristics at the same time and get deeper insights into the potential features in the geographical areal data. Case studies and quantitative comparisons based on real-world datasets have been conducted to demonstrate the effectiveness of the proposed multi-scale visualization method for in-depth visual exploration of geographical areal data.

1. Introduction

With the rapid development of information technology, geographical areal datasets are widely collected, including geographical features such as positions and attribute information such as population, income and other statistics. Choropleth map and Voronoi diagram are always used to visualize the geographical areal dataset, with the geographical features presented with polygonal boundaries and the attribute information mapped with different visual cues, such as colors and textures (Polczynski and Polczynski, 2014; Pinho et al., 2006). They are really helpful for users to understand the characteristics of areas and further make decisions for local economics and social development.

In general, geographical areal datasets usually present typical hierarchical characteristics. For example, administrative boundaries are divided layer by layer (Zhang et al., 2016), British census datasets are counted at different scales (Manley et al., 2006), and the road features are presented level of detail (Wang and Liu, 2010). The stratification of administrative boundaries is of great significance for the collection, management and analysis of the large-scale and wide-ranging geographical datasets.

Facing a geographical areal dataset with a typical hierarchical structure, visualization methods are usually carried out allowing users to conduct geospatial analysis at a single scale. However,

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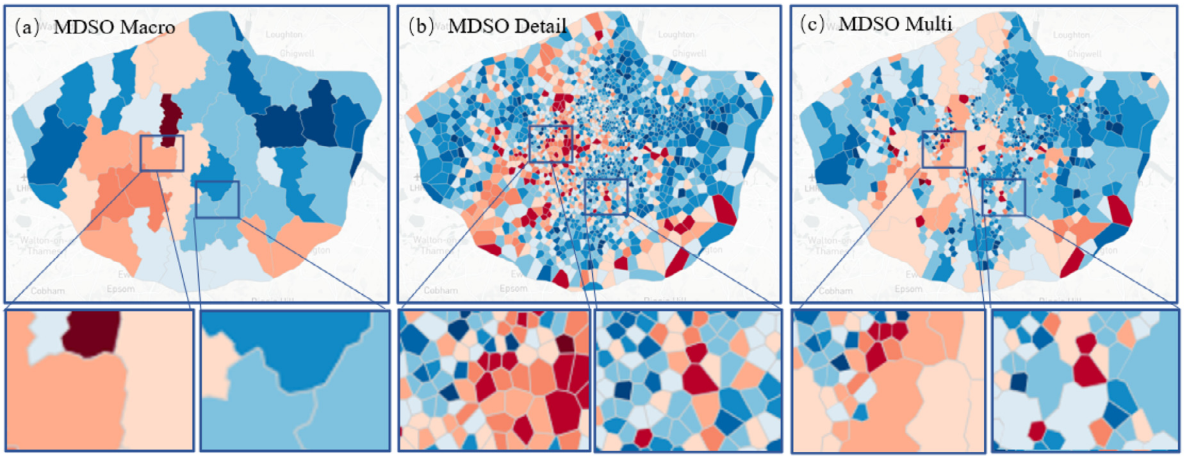

Fig. 1. A case study for the visual analytics of the UK census occupation proportion dataset. (a), (b) and (c) present the Voronoi diagrams generated from the geographical areal data at the macro scale, detailed scale, and multi-scale. (a) presents the global characteristics of the area but lacks detailed information. (b) presents the attribute characteristics of original geographical areal data in detail but lacks general characteristics. We can observe both general features and detailed features at the same time in (c). The geographical attribute characteristics can be observed more comprehensively with our multi-scale visualization, which is of great significance for the in-depth exploration of geographical data.

single-scale visualization usually brings the following problems: **P1.** The overall distribution characteristics of attributes can be observed at the higher scales, but the detailed features are easily missed because of the high abstraction of geographical areal data (as shown in Fig. 1a). **P2.** Although more detailed attribute distribution features can be described at the lower scales, global features are not easily perceived due to the overdrawing of visual elements (as shown in Fig. 1b). It can be seen that single-scale visualization is the cause of the problems which makes it a difficult task to explore the global features and detailed characteristics simultaneously. It would be an effective way to realize collaborative visualization at different scales for a joint geospatial analysis based on the global features and detailed characteristics.

However, there are several challenges for the design of multi-scale collaborative visualization: **C1.** How to estimate the relationships between local areas and construct an attribute-based hierarchy rather than original administrative hierarchy or distance-based hierarchy? **C2.** How to design a collaborative multi-scale visualization allowing users to synchronously perceive both the global features and detailed characteristics in a single map? **C3.** How to evaluate the effectiveness of multi-scale visualization in gaining insights into the hierarchical features and relationships between local areas in geographical areal data?

To cope with the above challenges, we propose a novel multi-scale geographical areal data visualization method based on the spatial attribute association, enabling users to explore the global features and detailed characteristics at the same time and get deeper insights into the potential features in the geographical areal data (as shown in Fig. 1c). We first utilize the coefficient of variation to estimate the attribute distribution of each cluster in the hierarchy, and construct a multi-scale hierarchy by selecting those clusters with smaller coefficients of variation (C1). Then, a multi-scale Voronoi diagram is designed to visually present the leaf clusters in the hierarchy, in which those clusters with the smaller coefficients of variation are visualized as polygons on behalf of those child clusters (C2). Thus, the account of polygons is reduced while the visual perception of global features and detailed characteristics are both enhanced in the Voronoi diagram. Furthermore, a rich set of visual cues and interactions are provided enabling users to evaluate the effectiveness of multi-scale geographical areal data visualization, and the practicability of the proposed method and system is verified through case studies based on real-world datasets (C3). To sum up, the main contributions of this paper are as follows:

- A common metric widely used in the field of geospatial analysis, coefficient of variation, is employed to estimate the attribute similarity between pairs of local areas, enabling users to further construct an informative hierarchy.
- A multi-scale Voronoi diagram is designed based on a hierarchy constructed according to coefficients of variation, to enhance the visual perception of geographical areal data, especially with the global features and detailed characteristics highlighted at the same time.
- A rich set of visual interfaces and interactions are designed, enabling users to explore the potential features in the geographical areal data and visually compare results obtained through different methods.
- Case studies and quantitative comparisons based on real-world datasets are further conducted to demonstrate the effectiveness of our hierarchical visualization of the geographical areal data.

The rest of this paper is organized as follows. Section 2 reviews the related work. Section 3 presents the analytical requirements and system overview. The algorithms are depicted in Section 4. Section 5 presents the visual designs and interactions in our system. In Section 6, quantitative comparisons, case studies, and expert interviews are discussed. Section 7 draws the conclusions.

2. Related work

Three relevant topics are covered in this section, including geographical data visualization, hierarchical data visualization and attribute-based geographical analysis.

2.1. Geographical data visualization

Visual analytics has been widely applied in many applications (Xia et al., 2020b,a; Zhou et al., 2019), ranging from sports analytics (Wang et al., 2021; Chen et al., 2016), and urban computing (Ye et al., 2020), to network analysis (Chen et al., 2018a; Zhao et al., 2021, 2020) and machine learning (Yuan et al., 2021; Liu et al., 2016a). For example, Liu et al. (2014) presented a comprehensive survey for gaining insights into information visualization. Zhao et al. (2019) introduced a visual analytics system for electromagnetic situation awareness to help radio supervisors perceive and understand the electromagnetic situations. Zhou et al. (2020a) designed a graph sampling method to preserve the contextual structures of networks. Weng et al. (2020) proposed a visual analytics solution for the performance analysis of complex bus networks. Zhou et al. (2021) proposed a context-aware visual sampling method for the exploration of crowded parallel coordinates, enabling users to easily capture the contextual features. In the field of geographical data visualization, geographical data visualization can be categorized into three classes.

(1) point-based visualization. For example, Zhou et al. (2020b) visualized data items as dots with their positions decided according to geo-tags, enabling users to intuitively perceive the distribution of original and sampled datasets. Wang et al. (2014) proposed a visual analytics system to explore sparse traffic trajectory data, in which points are applied to encode the geographical coordinates of traffic monitoring cells. SmartAdP (Liu et al., 2016b) preserved the relative geographical positions among different objects by using a circle to present a selected billboard location.

(2) line-based visualization. Lambert et al. (2010) used a 3D line visualization method to bundle thousands of initial aircraft routes for a global air traffic network. A radial timeline chart (Chen et al., 2018b) was generated and placed on the location in the map view for each location visited by the target. Wang et al. (2017) employed a streamline method to show population mobility patterns on a map, where lines denoted population movement among stations. Zhou et al. (2018a) proposed a visual abstraction system for massive OD flow graphs, in which the OD flows were visualized by means of straight lines.

(3) area-based visualization. There are many manifestations of geographical data area-based visualization, such as the Choropleth map, Voronoi diagram, which are applied in many fields. For example, Huang et al. (2019) studied the influence of attribute uncertainty on choropleth visualization. Polczynski and Polczynski (2014) used k-means to classify geographical data with multiple feature attributes on a Choropleth map. Pinho et al. (2006) introduced an exploration tool, Voromap, which was based on Voronoi diagrams of the projected data. Feng et al. (2020) proposed Topology Density Map, yielding a weighted Voronoi diagram-like effect of space division, to obtain an accurate and intuitive density map under the background of an urban environment.

2.2. Hierarchical data visualization

A couple of visualization methods are usually applied to visually explore the hierarchical relationships, such as the node-link diagram (Robertson et al., 1991; Burch et al., 2011, 2013) and the treemap (Kong et al., 2010; Wood and Dykes, 2008). For a node-link diagram, nodes represent data objects and the connecting lines between nodes represent the hierarchical relationships. Its layout can be roughly divided into three types: orthogonal layout (Munzner et al., 2003; van der Ploeg, 2014), and radial layout (Arce-Orozco et al., 2017; Lott et al., 2015). For the area-based method, treemap, the hierarchy is encoded by inclusion and the values are visualized by areas. The sum of values from child nodes defines the values of their parent in the hierarchy (Feng et al., 2019). In addition, many methods of combination node-link tree and treemap were presented to visualize hierarchical data. For example, Zhao et al. (2005) explored combinations of node-link and treemap forms to combine the space-efficiency of treemaps with the structural clarity of node-link diagrams.

Geographical data usually exists hierarchical structure characteristics. There are many visualization methods to depict geographical hierarchical data (Biswas et al., 2016; Stolte et al., 2003). To intuitively analyze and display the distribution characteristics of geospatial data at different scales, Goodwin et al. (2015) designed a hierarchical color map and used color components to describe the differences of multi-scale geospatial data. Packer et al. (2013) provided a comprehensive solution to hierarchical spatial clustering, in which color was used to encode individual clusters along with the different hierarchy levels. TopoGroups (Zhang et al., 2017) conveyed the hierarchical information of the geographical aggregates at different scales by exploring multiple visual encoding strategies including color, transparency, shading, and shapes. Delort (2010) used Voronoi polygons as aggregation symbols to represent clusters, which retained hierarchical relationships between data items at different scales.

2.3. Attribute-based geographical analysis

In the field of spatial statistics, attribute distribution is commonly used for many attribute-oriented tasks, such as spatial autocorrelation, spatial interpolation and spatial regression. Dormann et al. (2007) inferred correlates of species distributions, while accounting for spatial autocorrelation in model residuals. Le Rest et al. (2013) integrated residual spatial autocorrelation into a generalized linear model framework for estimating species distribution and its population size. Ninyerola et al. (2007) took into account geographical information to interpolate the climate data for developing an objective climatic cartography of precipitation. Thom et al. (2015) detected public safety events through the anomalous distribution of Twitter data.

The attribute distribution is significant for geographical visualization, and many visualization approaches have been proposed to describe attribute information of geographical datasets (Turkay et al., 2014). For example, Tiede (2014) used object hierarchy to hold GIS layers representing classifications of different time stamps for performing change comparison analyses. He et al. (2011) combined traditional thematic maps with information maps to greatly enrich the visual representation of geospatial data. Zhou et al. (2020b) preserved the attribute characteristics of the original geographical points to simplify the disorganization of large-scale geographical data points. Biswas et al. (2016) visually presented the multi-dimensional sensitivity attribute differences under multi-resolution at different time steps with MDS. Zhou et al. (2018b) explored the urban functions based on designing a set of visual encodings to visualize spatio-temporal attributes of taxi OD data. Simmons et al. (2015) increased the number of attributes that could be displayed on graph edges to ensure that the traffic network operated efficiently. Liu et al. (2019) fully visualized the multiple attributes of trajectory data to facilitate users to explore movement patterns.

3. Requirement analysis and system overview

In this section, a series of analytical tasks are summarized after in-depth discussions with domain experts. Then the overview of our multi-scale geographical visualization system is illustrated.

3.1. Requirement analysis

Our research focus is gained by in-depth discussions with three collaborative experts (E_1, E_2 and E_3) who are engaged in geographical analytics and visual analysis regarding their needs in exploring geographical visualization. E_1 majors in the geographical data analysis field for more than five years and is still active in visualization development. E_2 has seven-year experiences of geographical visualization working in a research institute. E_3 is a senior engineer in a large company with extensive experience in visualization. At present, he is focusing on the research of visualization algorithms and visualization trends.

During the preparation period, we had numerous profound discussions with the three experts about their ongoing projects, such as geographical data exploration and spatial visualization, and asked them for the issues in the process of project implementation. E_1 claimed that spatial clustering analysis has been widely used in various fields. However, it is difficult to intuitively perceive the spatial clustering relationships, because of the large volume and complexity of spatial data. E_2 pointed that traditional area-based spatial data visualization methods usually present too detailed information at the lower scales which ignore the visual perception of global features. Therefore, it is still a significant issue how to design multi-scale visualizations allowing users to synchronously perceive both global features and detailed characteristics. E_3 claimed that it was a necessary task to provide visual cues and quality metrics to evaluate different spatial visualization methods, facilitating the selection of a suitable geographic spatial visualization strategy. They all agreed that it was helpful to implement geographical visualization at multiple scales, providing comprehensive information of attribute features for the whole geographical space.

After in-depth discussions with three experts and our experiments, we preliminarily confirmed the possibility of multi-scale visualization of geographical areal data and decided to design a visualization system for multi-scale visualization of geographical areal data. To sum up, we present four requirements as follows:

R1. Constructing an attribute-based hierarchy based on the attribute similarity across local areas. It is a vital task to define an appropriate attribute-related spatial analysis metric to estimate the attribute similarity between pairs of local areas, enabling users to further construct an informative hierarchy.

R2. Designing a collaborative multi-scale geographical areal data visualization. It is a significant task to enhance the visual perception of geographical areal data at multiple scales, allowing users to synchronously perceive both the global features and detailed characteristics in a single view.

R3. Evaluating the multi-scale Voronoi diagrams from various perspectives. In practical geographical applications, real-time evaluation of geospatial visualization is very significant for the efficiency of geospatial analysis, enabling users to quickly identify the spatial areal features to support further spatial analysis and gain insights into the spatial relationships. Thus, it is necessary to carry out a quantitative evaluation, case studies and visual evaluation on the multi-scale visualization effect of geospatial data.

R4. Developing system tools for the multi-scale visualization of geographical areal data. Domain experts also claim that system tools are required enabling users to generate semantic optimized Voronoi diagrams with the algorithmic models and visual interfaces integrated for multi-scale geographical areal data visualization and exploration.

3.2. System overview

Motivated by the identified requirements, a novel variable-scale geographical visualization method is proposed to present attribute features more comprehensively and carefully.

The system pipeline is presented in Fig. 2. Firstly, a geographical areal dataset is loaded into the visualization system, and two steps of data preprocessing are conducted in advance, including the statistics of attribute values and hierarchical construction based on the spatial similarity. Then, a novel multi-scale geographical areal data visualization model is conducted to estimate the attribute distribution of each cluster in the hierarchy by the coefficient of variation, for adaptively presenting the multi-scale clusters with lower variation coefficients at the same time. Furthermore, a rich set of visual interfaces and user-friendly interactions are provided for users to specify those clusters of interest at different scales, compare multi-scale visualization with different scales and explore the multiple features at the same time. We also conduct quantitative comparisons and case studies based on real-world datasets to exactly assess the quality of the proposed multi-scale visualization method for in-depth visual exploration of geographical areal data.

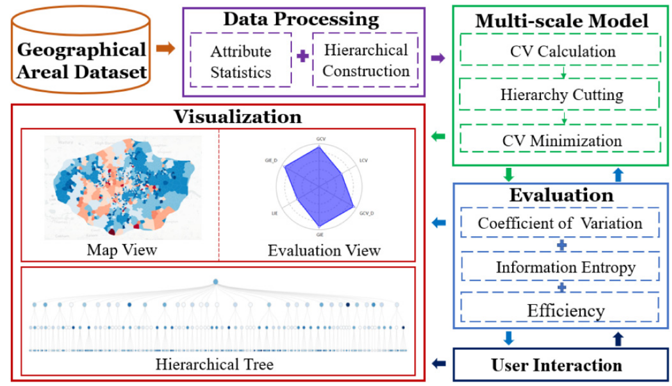

Fig. 2. The overview of our visual system for hierarchical geographical areal data via spatial attribute association.

4. Algorithm

4.1. Hierarchical construction

Geographical areal datasets usually present typical hierarchical characteristics which are generally determined by a prior of the regional boundaries. Since spatial areal datasets often exhibit different distribution patterns at multiple scales, the stratification of administrative boundaries cannot effectively express and reflect hierarchical relationships. In this section, the geographical areal data is aggregated into a hierarchical clustering tree based on spatial similarity measures. Four steps are included as follows:

Step1: Input geographical dataset as samples;

Step2: Utilize k-means to generate clusters for each areal data item;

Step3: Recalculate the centroids of all generated clusters as input samples;

Step4: Repeat step 2 and step 3 until all areal data items in highest layer are aggregated into one cluster, where the height of the hierarchical tree is determined by the number of clusters in each layer.

An adaptive k-means clustering algorithm is developed for hierarchical tree construction by optimizing the sum of the squared errors (SSE). The SSE is expressed as the formula (4.1).

$$SSE = \sum_{i=1}^{K} \sum_{p \in C_i} |p - m_i|^2 \tag{4.1}$$

where C_i is the i_{th} cluster, p is the point of C_i and m_i is the barycenter of C_i.

Finally, the constructed multi-scale clusters are represented as a tree structure that naturally depicts the hierarchical relationships of clusters at different scales. In this hierarchy, nodes represent individual spatial clusters, while the edges represent parent–child relationships of clusters at adjacent spatial scales, as shown in Fig. 3a.

4.2. Attribute feature definition

In probability theory and statistics, the coefficient of variation is the statistics to measure the variation degree of each observation value (Xing, 2018). The coefficient of variation of the expression is the ratio of σ and μ. As formula (4.2) below:

$$CV = \sigma/\mu \tag{4.2}$$

where σ is the standard deviation of the attribute, μ is the mean value of the attribute.

$$\mu = \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{4.3}$$

$$\sigma = s = \sqrt{s^2} = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 \tag{4.4}$$

where datasets $D = \{x_1, \ldots, x_n\}$ are real numbers that are not all zero, $x_i(i=1,2,\ldots,n)$, and we express them as $X = (x_1, x_2, \ldots, x_n)^{\mathrm{T}}$ in one-dimensional array. $\bar{x}$ is the mean, s is the standard deviation and s^2 is the variance.

The coefficient of variation is a dimensionless quantity that can be used to measure samples with a large mean difference or different units (Fisz, 1999). The higher the value of the coefficient of variation, the greater the degree of dispersion. In this paper, the coefficient of variation is utilized to estimate the attribute distribution of each cluster in the hierarchy. Furthermore, due to the influence of scale on geographical data, the corresponding coefficient of variation of geographical data will be distinct at different scales, so that it can be used to judge the degree of areal separability

4.3. Multi-scale specification

Based on the hierarchical clusters of the geographical areal data, we construct a multi-scale hierarchy by selecting the desired nodes in the hierarchical clustering tree with the smaller coefficient of variation. Given the hierarchical clustering tree, we introduce a threshold of the coefficient of variation (TCV) representing the variation degree of attributes in each cluster. The node selection algorithm does a bottom-up search from the first layer of clusters until the nodes with the coefficient of variation greater than TCV are searched, and it returns the previous nodes, as shown in Fig. 3b. It is important to note that the attribute and the TCV are defined by users according to their needs before constructing the hierarchical clustering tree.

A set of nodes returned by this algorithm are the desired nodes whose children should be cut in the hierarchical clustering tree. Fig. 3a, 3b illustrate the single-scale and multi-scale cuts for the hierarchy of aggregations.

To generate the visual representations of leaf nodes in the hierarchical clustering tree, we use Voronoi polygons to render geographical areal data items on the map, as shown in Fig. 3e. Considering that dense and compact clusters covering small areas will be smaller and less visible than sparse clusters covering larger areas, which may mislead the users, the size of Voronoi polygons can be adjusted by controlling the space between clusters, which reasonably avoids the cluster coverage.

5. Visualization

5.1. Hierarchical tree visualization

The tree view is designed to visualize the hierarchy of aggregations, in which a node-link tree diagram is presented and the color of nodes is mapped according to the coefficient of variation about the attribute, as shown in Fig. 3a. After the selection of the optimal scale, the selected nodes are represented as the leaf nodes in the hierarchical clustering tree, enabling users to intuitively perceive the hierarchical structure.

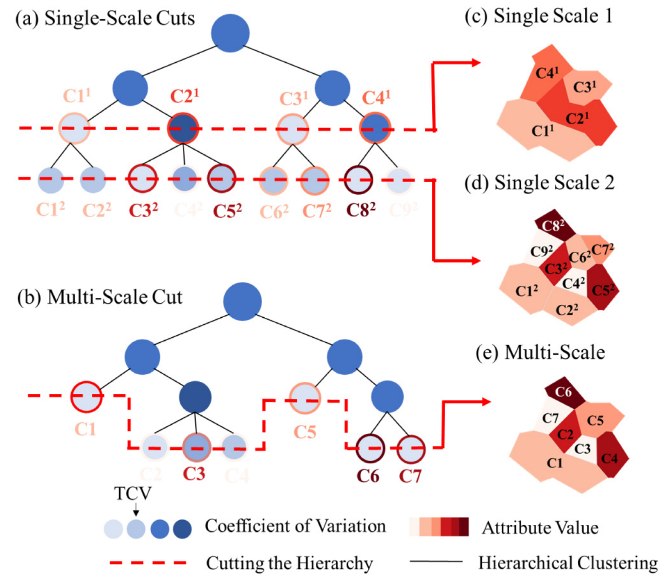

Fig. 3. The Voronoi diagrams are generated with different scales. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5.2. Multi-scale geographical visualization

To facilitate the effective visual perception of the global features and detailed characteristics of the geographical areal dataset, a multi-scale Voronoi diagram generated on the map view is designed to visually present the leaf nodes in the cut hierarchical tree, in which those clusters with the smaller coefficient of variation are visualized as polygons on behalf of those child clusters, as shown in Fig. 3e. In addition, the location and color of patches represent the geographical information and attribute information of the original data respectively.

Due to the multi-scale geographical areal data visualization which can significantly affect the subsequent analysis of geographical data, a series of quality metrics are introduced to evaluate the effectiveness of multi-scale visualization from various perspectives, as detailed in Table 1. Furthermore, in order to evaluate the effectiveness of multi-scale visualization in gaining insights into the hierarchical features and relationships between local areas in geographical areal data, the radial coordinate diagram presented in the evaluation view is utilized to display the evaluation results of our multi-scale visualization results of each metric compared with others, as shown in Fig. 5g.

5.3. Interaction

Our multi-scale geographical visualization framework consists of a rich set of visual and interactive dialogs. These dialogs are coordinated and seamlessly integrated into the process of exploration.

The control panel provides several configurable parameters for users to specify clusters of interest at different scales, including attribution, the number of clusters in the lowest scale, the number of iterations of clustering, and the TCV. Furthermore, in order to make visualization more interpretable for users, several visual design-related elements of Voronoi polygons can also be defined interactively, such as the opacity which can build a correspondence between geolocations and Voronoi diagrams, and the color gamut that encodes the attribute value. The tree view is coordinated with the map view by selecting the nodes with a single scale or multiple scales. When performing single-scale

Table 1
Evaluation Metrics.

Coefficient of variation(CV)	Global coefficient of variation(GCV)	GCV is calculated by the attribute value of the CV of all nodes at selected scale.
	Local coefficient of variation(LCV)	LCV is the mean value of the CV of all nodes at the specified scale.
	GCV_D	*GCV_D* is calculated to measure the difference between global variation of the specified scale and original global coefficient of variation.
Information entropy(IE)	Global information entropy(GIE)	GIE is calculated by the attribute value of all nodes at selected scale.
	local information entropy(LIE)	LIE is the mean value of the IE of all nodes at the specified scale.
	GIE_D	*GIE_D* is the differential value between the global information entropy of the scale and the original global information entropy.

Table 2
Quantitative comparison.

Dataset	attribute	GCV			LCV			GCV_D			GIE			LIE			GIE_D		
		sig1	sig2	our	sig1	sig2	our	sig1	sig2	our	sig1	sig2	our	sig1	sig2	our	sig1	sig2	our
D1	APTO	0.25	0.28	**0.42**	**0.12**	0.27	0.19	0.15	0.11	**0.03**	0.56	0.58	**0.72**	**0.29**	0.62	0.56	0.09	0.08	**0.07**
	STO	0.27	0.33	**0.59**	**0.15**	0.37	0.23	0.23	0.18	**0.08**	0.83	0.87	**0.95**	**0.32**	0.63	0.52	0.16	0.11	**0.04**
	MDSO	0.25	0.28	**0.46**	**0.12**	0.31	0.24	0.18	0.15	**0.02**	0.75	0.80	**0.95**	**0.31**	0.65	0.58	0.17	0.12	**0.02**
D2	NP	0.04	0.05	**0.18**	**0.02**	0.03	0.07	0.11	0.09	**0.02**	0.44	0.50	**0.98**	**0.07**	0.12	0.19	0.50	0.44	**0.04**
	OP	0.08	0.11	**0.61**	0.07	**0.06**	0.21	0.32	0.29	**0.21**	0.36	0.47	**0.91**	0.16	**0.15**	0.22	0.56	0.45	**0.01**
	TOMP	0.21	0.24	**0.86**	**0.10**	0.14	0.37	0.47	0.43	**0.19**	0.58	0.62	**0.89**	**0.07**	0.09	0.17	0.36	0.33	**0.06**
D3	SIG	0.12	0.16	**0.29**	0.07	**0.05**	0.10	0.11	0.07	**0.05**	0.67	0.72	**0.95**	**0.06**	0.07	0.11	0.29	0.24	**0.01**
	MAR	0.14	0.17	**0.38**	0.07	**0.06**	0.13	0.21	0.17	**0.03**	0.54	0.75	**0.95**	0.09	**0.06**	0.11	0.43	0.21	**0.01**
	SPT	0.15	0.25	**0.65**	**0.13**	**0.13**	0.25	0.44	0.34	**0.05**	0.43	0.59	**0.92**	0.08	**0.07**	0.14	0.48	0.33	**0.01**

visualization, users can make manual scale selections to obtain a better result based on their judgment by observing the color of nodes of the hierarchical node-link tree. For the multi-scale visualization, there are two interactive functions for the selection of the optimal scale. Users can subjectively select cut nodes in the tree or the cut nodes can be automatically selected by setting the TCV. As users navigate on the map, the effectiveness of multi-scale clustering is presented as the radial coordinate diagram in the evaluation view.

6. Evaluation

In this section, three geographical areal datasets (D_1, D_2, D_3) are used to evaluate the effectiveness of our multi-scale visualization. D_1 records the UK census occupation proportion, D_2 and D_3 respectively depict the household situation and the marital status in England and Wales. We first conduct quantitative comparisons to demonstrate the advantages of our multi-scale visualization. Case studies are then conducted and the effectiveness of visual analytics for hierarchical geographical areal data is further evaluated by experts. The validity of our multi-scale visualization algorithm is further discussed.

6.1. Quantitative comparison

To further evaluate the effectiveness of our multi-scale visualization of geographical areal data, we have conducted a set of experiments to compare multi-scale visualization results with single-scale visualization results from perspectives of the coefficient of variation and the information entropy.

The coefficient of variation (CV) of attributes is used to evaluate the attribute associations of Voronoi diagrams. The information entropy (IE) is used to describe the uncertainty of information sources. The attribute values are divided into different groups by the Jenks Natural Breaks classification method, and then the IE is calculated due to the groups. The greater the information entropy of the node, the more details the node contains. The attribute dispersion can be well measured by IE and CV, so these metrics are utilized to measure the multi-scale results. The specific metrics are listed in Table 1.

We compare the results of different scales at three attributes in three datasets respectively, i.e., Associate professional and technical occupations(APTO), skilled trades occupations(STO) and Managers, directors and senior officials(MDSO) in D_1; no people in the household with a long-term health problem or disability (NP), one person in the household with a long-term health problem or disability(OP) and two or more people in the household with a long-term health problem or disability(TOMP) in D_2; single(SIG), married(MAR) and separated(SPT) in D_3, using the above six metrics. Single-scale and multi-scale geographical areal data visualization results are marked as sig1, sig2 and ours respectively. The obtained results are listed in Table 2.

Table 2 presents six metrics obtained by visualizing different attributes of different network datasets at different scales. Obviously, it can be seen that the global coefficient of variation and the global information entropy of the multi-scale visualization results obtained by our method are the largest, and GCV_D and GIE_D by our method are the smallest at all attributes. Therefore, our multi-scale method performs better than single-scale methods for D_1 on GCV, GCV_D, GIE and GIE_D. For D_2 and D_3, our method achieves similar results. However, single-scale methods perform better on the metric of LCV and LIE, but our multi-scale method performs a little inferior on the two metrics. Instead, the LCV and LIE metrics obtained by our method are the second smallest. Above all, the results demonstrate that our method almost retains the original data features distribution and reduces visual confusion and our method gains a more balanced representation of desired characteristics and more information.

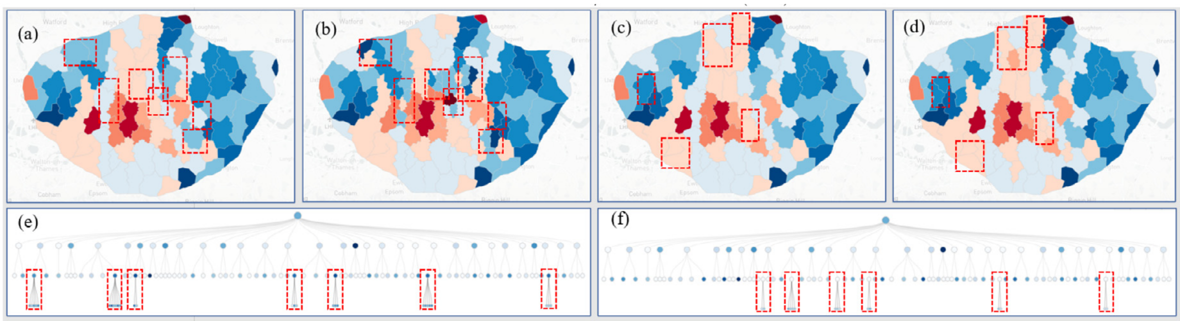

Fig. 4. Comparison of Voronoi diagrams before and after manual scale division of the nodes with different values of the coefficient of variation. There are apparent differences in Voronoi diagrams before and after manual dividing the nodes with high coefficient of variation and there are no apparent differences in Voronoi diagrams before and after manual dividing the nodes with low coefficient of variation. (a) and (c) are the Voronoi diagrams before manual division. (b) and (d) are Voronoi diagrams generated by manually dividing nodes with high coefficient of variation and nodes with low coefficient of variation. (e) and (f) are the hierarchical trees generated by manual division. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

6.2. Case study

Case1. Multi-scale visualization exploration.

In our experiments, we used multiple scales to conduct visualization with the attribute specified as MDSO for D_1. As shown in Fig. 1a, the overall distribution characteristics of attributes of geographical areal data could be observed in the Voronoi diagram, but the detailed features were easily missed because of the high abstraction of geographical areal data, and it was not conducive to observe detailed geographical features, making it impossible to measure the differences in particular areas. However, as shown in Fig. 1b, detailed attribute distribution features were presented at a detailed scale while global features were not easily perceived due to the overdrawing of visual elements, which was not conducive to the comprehensive exploration of geographical areal data.

After multi-scale visualization, our multi-scale result performed better as shown in Fig. 1c. The global features and detailed characteristics could be explored visually at the same time and users could get deeper insights into the potential features in the geographical areal data and the visual perception of both the global features and detailed characteristics was enhanced. Therefore, the experimental results prove that our system can help users observe a lot of hidden information and facilitate data exploration compared with single-scale visualization, and our multi-scale visual analytics is of great significance for geographical areal data analysis and exploration.

Case2. Interactive exploration based on Voronoi diagram.

In our system, we also can perform multi-scale visualization by manual scale division to make the result better on Voronoi diagram. Users can manually divide the scale of points with the large coefficient of variation for multi-scale visualization until getting the desired Voronoi diagram effect. Fig. 4 presents the comparison of Voronoi diagrams before and after manual scale division of the nodes with different values of the coefficient of variation for D_2.

After clicking on a layer of the hierarchical node-link tree for geographical areal data single-scale visualization, it could be seen that there were many nodes with larger values of the coefficient of variation of this layer of the node-link tree and the visualization effect on the Voronoi diagram was not as expected. Then we further used the cut tool to divide the scale of these nodes manually for multi-scale visualization. The colors of the sub-regions after cutting differed significantly from before, as shown in Fig. 4(a, b and e). In addition, the nodes with smaller values of the coefficient of variation were cut for manual scale division as well. The colors of the sub-regions after cutting were similar as before, as shown in Fig. 4(c, d and f). To sum up, the scale division of nodes with large coefficient of variation is beneficial to further multi-scale visual analysis.

Case3. Scale selection with reference to evaluation metrics.

Evaluation view can help users evaluate the visualization effects, and users can adjust the operation through the evaluation view to realize better visualization results. After single-scale visualization by selecting one layer in the hierarchical node-link tree based on MAR attribute for D_3, it could be seen that the evaluation metrics performed a little inferior at the radial coordinate diagram as shown in Fig. 5a, and there were some nodes at this level that had higher values of the coefficient of variation in the hierarchical node-link tree. Then we interactively clicked on another layer of the hierarchical node-link tree for single-scale visualization, it could be seen that the metrics in the evaluation view were also less than satisfactory as shown in Fig. 5b. Finally, we used the system to perform multi-scale visualization operations. After multi-scale visualization, through observing the evaluation view as shown in Fig. 5c, it could be seen that the metrics were better than the metrics obtained by single-scale visualization, and the global features and detailed characteristics could be observed simultaneously on Voronoi diagram. Of course, compared with single-scale visualization, our visualization method has a better evaluation effect and visual effect through the evaluation view, enabling users to perform multi-scale geographical areal data analysis and exploration.

6.3. Expert interview

We invited the domain experts to conduct in-depth interviews and invited them to evaluate the feasibility and effectiveness of our system.

System usability and improvement. All three experts said that our system can observe the characteristics of geographical data from different scales, which is of great significance for the analysis and exploration of geographical data. E_2 claimed that "Geographical areal data lacking hierarchical relationships can be aggregated into hierarchical clusters based on the spatial similarity measured by this system." E_1 emphasized that "Geographical areal data usually has a hierarchical structure at present, and its characteristics will have different performances at different levels. The system can observe the characteristics from different scales, which is conducive to further analysis of geographical space." E_3 indicated that "He can observe detailed features of data in the overall features through multi-scale visualization, which is superior to other single-scale visual methods."

Visual design and interaction. The three experts studied the visual and interactive interface of our system and found that the interface was intuitive and easy to operate. E_1 commented that

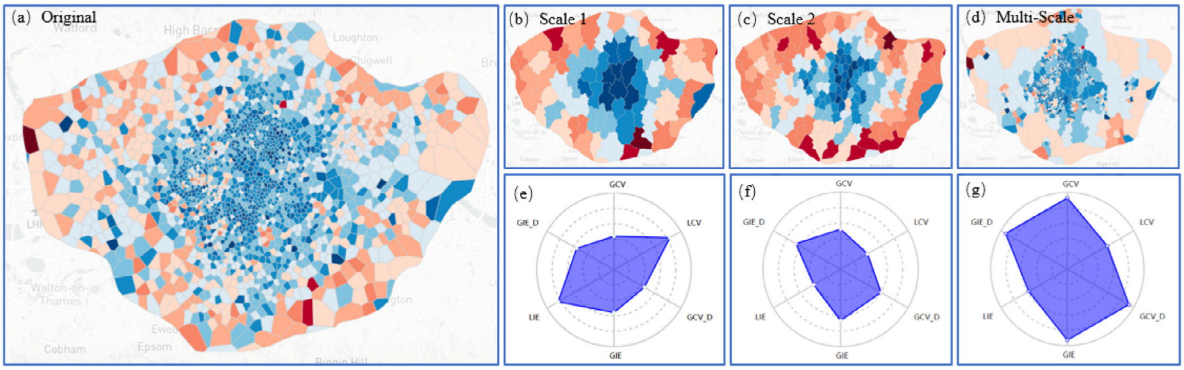

Fig. 5. Comparison of the evaluation metrics and Voronoi diagrams of single-scale visualization and multi-scale visualization. (a) is the Voronoi diagram obtained by original geographical data. (b) and (c) are the results of single-scale visualization. (d) is the result of multi-scale visualization. (e) and (f) are the evaluation views obtained by single-scale visualization. (g) presents the multi-scale visualization evaluation metrics result.

"Voronoi diagram can intuitively reflect the relationship between geographical areal data." E_3 said that "Interactive design of the system is easy for users to understand and operate." E_2 thought that "By means of the visualization of the hierarchical tree, users cannot only see the hierarchical relationship of geographical data, but also observe the optimal scale selection of hierarchical node-link tree. This would make it more beneficial for users to conduct data analysis."

6.4. Discussion

Compared with single-scale visual methods, the proposed multi-scale visualization method performs better on visual perception and enhances the visual perception of global features and detail features. The main advantage is that we use the coefficient of variation to estimate the attribute distributions between areas for multi-scale visualization. However, there are still some unsolved issues in this paper, which would be further investigated in future work. (1) In this paper, the coefficient of variation and the information entropy are used for the evaluation of the effectiveness of multi-scale visualization. In future work, we will look for authoritative metrics to further verify the effectiveness of our multi-scale visualization. (2) In this paper, we provide a hierarchical node-link tree to show the hierarchical structure of geographical areal data. The scales are divided and selected based on the hierarchical node-link tree, so as to better carry out multi-scale visualization. However, there are many limitations in the visualization of node-link trees in extensibility especially when there are many hierarchical structures, for example, all nodes of the tree cannot be fully displayed. In future work, we will look for a more suitable way to fully visualize the structure of the node-link tree. (3) Although a rich set of interfaces have been designed to meet user requirements. However, the multi-scale visualization obtained by our system will not exactly meet user expectations since the hierarchical tree is constructed only considering the metric of distance and the leaf nodes are specified with the coefficient of variation. In the future work, we will further integrate artificial intelligence models to learn user requirements and provide an adaptive multi-scale visualization work to exactly meet user requirements.

7. Conclusion

In this paper, we have presented a multi-scale geographical areal data visualization method based on the spatial attribute association. In order to explore the global features and detailed characteristics at the same time and get in-depth insights into the potential features, we aggregate the geographical areal data into hierarchical clusters based on the spatial similarity measured by distance. In particular, a novel geographical areal data visualization scheme is proposed to present the multi-scale clusters with lower coefficients of variation adaptively. In addition, we also provide a set of visual interfaces, allowing users to visually explore the potential features by the Voronoi diagram and the hierarchical tree. Quantitative comparisons and case studies based on real-world datasets have proved the effectiveness of our system in multi-scale visualization of geographical data.

CRediT authorship contribution statement

Haoxuan Wang: Conceptualization, Writing – original draft. **Yuna Ni:** Conceptualization, Writing – original draft. **Ling Sun:** Supervision, Writing – review & editing. **Yuanyuan Chen:** Investigation. **Ting Xu:** Validation. **Xiaohui Chen:** Validation. **Weihua Su:** Resources. **Zhiguang Zhou:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Ethical approval

The study does not involve human subjects. All data used in the study are taken from public databases that were published in the past.

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