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DISPLAY SPACE AND DISTRIBUTION VISUALIZATION OF INTELLIGENT ALGORITHMS AND 3D INTERACTIVE IMAGING TECHNOLOGY

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Abstract. The traditional two-dimensional data visualization method is difficult to accurately express and display the three-dimensional information of the data, while the 3D interactive image technology can visually display the data in the three-dimensional space. At the same time, it can also operate and edit the data through interactive methods to help people better understand and use the data. Intelligent algorithms are an important supplement to 3D interactive imaging technology, which can improve visualization and analysis accuracy through calculations, model building, and other methods, achieving more accurate data display and analysis. This article aimed to explore the application of intelligent algorithms and 3D interactive imaging technology in the field of spatial visualization. Intelligent algorithms can help analyze data features and relationships, extract data attributes, and optimize data display effects. 3D interactive imaging technology can present processed data in a virtual three-dimensional space, enhancing the interaction and visualization effect between users and data. The combination of the two can achieve better data analysis and presentation results. This article conducted simulation experiments on spatial visualization based on intelligent algorithms and 3D interactive imaging technology, and scored some experimental indicators using a scoring sys-

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tem. The experimental results of this article indicate that the intelligent algorithm had a time efficiency of 46.5 seconds and an accuracy of 95 % in displaying spatial and distribution visualization. The usability score was 75. The interactivity score of 3D interactive imaging technology in displaying spatial and distribution visualization was 96. The visual effect score was 96, and the usability score was 65. The combination of the two in terms of displaying spatial and distribution visualization had a time efficiency of 50.8 seconds, interactivity of 86 minutes, and accuracy of 98 %. It shows that different data visualization technologies have their own characteristics in display space and distribution visualization, and suitable technologies can be selected according to actual needs and application scenarios.

Keywords: Space and distribution visualization, 3D interaction, intelligent algorithms, imaging technology

1 INTRODUCTION

With the rapid development of digital and information technology, the rapid growth of spatial data volume has become an inevitable trend. With the application of more powerful computer and sensor technologies, people can collect more geospatial data, such as environmental data, agricultural data, and urban data. However, the storage, management and processing of these data is a complex task, especially because the data exists in 3D space, so it is difficult to intuitively present the characteristics and relationships of the data. In order to solve this problem, the visualization technology of display space and distribution has gradually become a field of much attention. Display space and distribution visualization technology is a data visualization technology that maps spatial data and related data to two-dimensional or three-dimensional space, and is presented in the form of graphs and graphs. It can help people to intuitively understand the distribution patterns, spatial relations, and characteristics of the data. Intelligent algorithms can process and optimize the data for better display results. The combination of intelligent algorithms and 3D interactive imaging technology can achieve more powerful data analysis and visualization capabilities, enabling users to explore the internal laws and structure of data more deeply. By visualizing the distribution and association of data in three-dimensional space, users can understand the data more intuitively, discover the patterns and trends, and conduct more in-depth data mining and decision support, which can also provide more scientific and accurate suggestions for urban planning and land use.

From the perspective of data exploration and analysis, many works that focus on spatiotemporal simulation data often share similar exploration techniques, such as exploration schemes and their combinations designed in simulation space, parameter space, and feature space. However, it lacks a survey to systematically outline the basic commonalities shared by these works. Chen et al. adopted a novel multi spatial perspective and categorizes the most advanced works into three categories. Specifically, these works are characterized by the use of similar technologies, such as visual design in simulation space, parametric spatial analysis and data processing in feature space [1]. Zhu et al. introduced a general process visualization method that uses parameters to visualize real-time process information and correlations between variables on a 2D (Two Dimensional) map. As a unsupervised learning method, it learns mapping by using a deep neural network to minimize the Kullback Leibler bifurcation between the original high-dimensional space and the potential space [2]. In addition to the standard representation of search centric and grid based interfaces, various methods have recently been adopted to achieve visual access to cultural collections and explore them as complex and comprehensive information spaces through interactive visualization. Windhager et al. reviewed the information visualization method of digital cultural heritage collection, and reflected on the status quo of technology and design choices [3]. In order to expand the data processing of hyperspectral datasets, Pouyet et al. proposed an innovative method for data reduction and visualization. It uses a statistical embedding method called t-distributed random neighbor embedding to provide a nonlinear representation of spectral characteristics in lower 2D space [4]. However, these scholars lack certain technical arguments for exploring spatial and distribution visualization. Through research, it has been found that 3D interaction technology is more helpful for spatial and distribution visualization. The relevant literature on 3D interaction technology has been consulted.

Some scholars also have some research on 3D interaction technology. Deng et al. analyzed the urban waterlogging emergency management system based on cloud computing platform and 3D visualization. He collected data through street surveillance and drones, reanalyzed the collected images, and screened cities prone to waterlogging. Researchers can rely on the high-performance computing power of the system and a visual integrated environment to achieve online monitoring, early warning, and three-dimensional visualization display of waterlogging [5]. Karatzas et al. introduced Arena3Dweb, the first fully interactive and dependency free web application that allows for the visualization of multiple layers of graphs in 3D space. He uses Arena3Dweb, where users can integrate multiple networks and their intra and inter layer connections in one view. In order to obtain a clearer and more informative view, users can choose between too many layout algorithms and apply them individually or in combination to a set of selected layers. Users can align the network and highlight node topology features, while each layer and the entire scene can be translated, rotated, and scaled in 3D space [6]. However, these scholars have not conducted research on the visualization of display space and distribution based on intelligent algorithms and 3D interactive imaging technology, only exploring it from a shallow perspective.

In order to solve the problem which cannot be met by traditional methods, mainly the needs of large-scale data visualization, this paper analyzes the application of intelligent algorithms and 3D interactive image technology in the field of spatial visualization. They can be used together in cluster analysis, spatial analysis, data visualization, data analysis, feature extraction and configuration operations to achieve better data display effect and user interaction. In the 3D city model, intelligent algorithms are used to predict traffic congestion in different regions and present them in the model. Users can then explore and edit in real time through 3D interactive imaging technology. This would provide more intuitive, efficient, and scientific data support for urban planning and management.

2 INTELLIGENT ALGORITHMS AND 3D INTERACTIVE IMAGING TECHNOLOGY

2.1 Application of Intelligent Algorithms in Visualization of Display Space and Distribution

Intelligent algorithms, as a part of artificial intelligence, can autonomously learn data patterns and patterns, and perform operations such as data classification, clustering, and prediction. Therefore, it plays an important role in displaying spatial and distribution visualization [7, 8].

1. **Cluster analysis.** Cluster analysis refers to the process of dividing a group of unlabeled and unclassified data samples into several categories or clusters. Cluster analysis is a very common operation in visualization of presentation space and distribution. Cluster analysis is an unsupervised learning method for dividing a set of data objects into multiple categories or groupings with similar characteristics. The basic principle is to classify similar objects into the same category by evaluating the similarity or distance between data objects, thus realizing the classification and aggregation of data. By aggregating certain similar data together, the distribution and relationships of the data can be better reflected. Clustering algorithms can gather similar data together to display data in a simpler and more compact manner during the visualization process [9, 10].

   Given a dataset $X = \{x_1, x_2, \ldots, x_n\}$ containing n data points, it can be divided into k disjoint subsets, namely cluster $C = \{c_1, c_2, \ldots, c_n\}$, where each cluster C_i contains a set of related or similar data points.

   Common clustering algorithms include K-Means, hierarchical clustering, density clustering, mean drift, etc. Among them, K-Means is a distance-based clustering algorithm. It divides the data into K disjoint clusters and assigns each data point to the nearest cluster, with the goal of minimizing the difference in data within clusters; the degree clustering algorithm clusters the data points according to their density. The goal of clustering algorithms is to minimize the average similarity of data points within all clusters and the average difference between adjacent clusters, namely:

$$\min \sum_{i=1}^{k} W(C_i) + \sum_{i \neq j} V(C_i, C_j). \tag{1}$$

Among them, $W(C_i)$ represents the average similarity of data points within cluster C_i, and $V(C_i, C_j)$ represents the average difference between cluster C_i and C_j.

Some points can be marked on the map, and machine learning algorithms can help with clustering analysis to find the spatial distribution patterns of these points. On this basis, 3D interactive imaging technology can be used to present these points and display different features of the data through changes in attributes such as color, size, and shape. In this way, it can intuitively understand the distribution of these points and the connections between them.

2. Spatial analysis. Intelligent algorithms can also be used for spatial analysis to help better understand the distribution and relationship of data. Spatial analysis is a GIS technology, which converts geospatial data into visual form, and performs statistics, model analysis, pattern recognition and other operations in space. In a city, demographic data from different residential areas can be analyzed. Through cluster analysis, the population distribution can be divided into several different groups. Then, 3D interactive imaging technology can be used to display this data and present it in a virtual 3D city. Users can explore information such as population density and changing trends in different regions through operations such as rotation and scaling, and also learn about policy or planning issues.

The common spatial analysis method is local spatial autocorrelation analysis based on kernel density estimation. Firstly, the distance $d(i,j)$ from all points in the neighborhood around each data point to $K(d)$ can be calculated, and a kernel function $K(d)$ can be constructed within this distance range. Then, for each point i, the weight $w_j = K(d(i,j))$ of all points in its neighborhood can be calculated, and its local autocorrelation coefficient can be calculated:

$$I_i = \frac{\sum_{j=1}^{n} w_j(y_j - \overline{y})(y_i - \overline{y})}{\sqrt{\sum_{j=1}^{n} w_j(y_j - \overline{y})^2}\sqrt{(y_i - \overline{y})^2}}. \tag{2}$$

The common spatial visualization method is based on virtual reality technology for urban 3D models [11, 12]. Firstly, ground feature points (X_i, Y_i, Z_i) and camera pose (R_i, T_i) are extracted from satellite remote sensing images using photogrammetry technology. Then, these point cloud data are concatenated using a 3D reconstruction algorithm and processed with texture maps to obtain a complete 3D model of the city. The model can be imported into the virtual reality software, and the following formula can be used to achieve interactive operation:

$$P_{carn} = P_{world}R_{carn} + T_{carn}, \tag{3}$$

$$P_{screen} = P_{proj}P_{carn}. \tag{4}$$

P_{world} is the point cloud coordinate in the world coordinate system, R_{carn} and T_{carn} are the rotation matrix and translation vector of the camera, respectively, and P_{proj} is the projection matrix. P_{carn} is the point cloud coordinate under the camera coordinate system, and P_{screen} is the point coordinate under the screen coordinate system, which can be used to realize interactive operations.

3. Data visualization. Intelligent algorithms can also help better reflect the characteristics and relationships of data in the process of data visualization [13, 14]. Data visualization refers to the process of transforming abstract data into charts, statistical graphs or other forms of graphical expression. It can display the road system of a city in a 3D map, use machine learning algorithms to analyze data such as road traffic flow, speed, and congestion, and present them on the map. Machine learning algorithms can be used to predict traffic congestion in different regions. First by collecting traffic data, including road network, road topology, traffic flow, speed and time, etc., and then according to the data characteristics and requirements, extract meaningful features, and data preprocessing, including data cleaning, missing value processing, feature normalization, etc., to ensure the accuracy and consistency of the data.

For the analysis and visualization of road traffic data, first, convert the traffic data into a vector $x = (x_1, x_2, \ldots, x_n)$, where n represents the number of features. The definition of different features can be considered from aspects such as vehicle speed, congestion level, and daily time changes. Then, construct a model $f(x;\theta)$, where θ represents the parameters of the model. This model can map the input vector x to the corresponding predicted traffic flow value y:

$$y = f(x;\theta) \tag{5}$$

During the training process, optimization algorithms such as random gradient descent can be used to adjust the model parameter θ by minimizing the error between the predicted value and the true value.

Finally, the trained neural network model can be applied to urban road system data to obtain traffic flow prediction values for each road segment. Then, the data can be presented on a 3D map using the following formula:

$$C_i = \frac{F_i}{L_i} \cdot 1\,000. \tag{6}$$

Among them, C_i represents the congestion index of the i^{th} road, F_i represents the actual traffic flow of the road, and L_i represents the length of the road. The higher the value of the congestion index, the more severe the congestion on the road. By mapping these congestion indices onto a 3D map, techniques such as color gradient can be used to present road congestion. At the same time, methods such as symbol size can also be used to reflect data characteristics such as vehicle speed.

Intelligent algorithms can also be combined with 3D interactive imaging technology to achieve more complex display effects. In 3D city models, deep learning algorithms can be used to identify the type and height of buildings and present them in the model. The 3D city model is shown in Figure 1. In this way, users can better understand the architectural structure and style of the city.

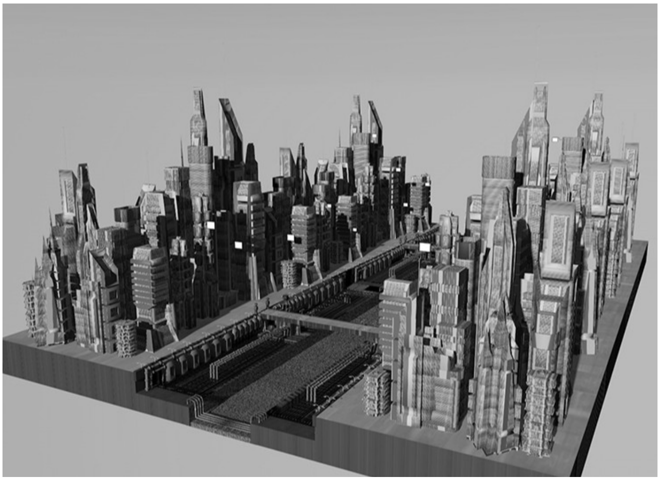


Figure 1. 3D city model

Intelligent algorithms have multiple functions, and the following are some common functions:

1. Classification: Intelligent algorithms can divide the data into different categories or labels, and predict the categories of new samples by learning the patterns and characteristics in the data.
2. Regression: The intelligent algorithm can predict the output of continuous numerical values by learning the relationship between the input variables and the output variables.
3. Clustering: Intelligent algorithms can divide samples in a dataset into different clusters or groups, without pre-defining categories.

2.2 Application of 3D Interactive Imaging Technology in Visualization of Display Space and Distribution

3D interactive imaging technology can enable users to better interact with data and improve the visualization effect of data [15, 16]. It can present spatial data in a three-dimensional space, allowing users to explore the relationships and features between data in a virtual environment. Therefore, it also plays an important role in displaying spatial and distribution visualization.

1. **Visualization effect.** The data visualization effect produced by 3D interactive image technology is usually more intuitive and vivid than that of other technologies [17, 18]. In 3D maps, users can freely rotate, zoom, and move the map perspective to better understand terrain and other information.

   3D interactive imaging technology can also display different features of data through changes in attributes such as color, size, and shape [19]. In 3D city models, the type or function of buildings is displayed through color changes, and the height or area of buildings is displayed through size changes. For example, green represents park or lawn areas, blue represents water areas, and yellow represents residential areas; High rise buildings would be more eye-catching than low rise buildings. This data visualization method can enable users to better understand and remember data, and improve the efficiency and accuracy of data analysis [20].

2. **Interactivity.** 3D interactive imaging technology can also enhance the interactivity between users and data. Users can choose different levels or perspectives of data and perform real-time editing and operations on the data. In the 3D architectural model, users can modify the height, color, texture and other attributes of the building, and view the modification results directly in the model.

   Similarly, in the process of visualizing display space and distribution, 3D interactive imaging technology is often combined with intelligent algorithms to achieve better display effects [21].

2.3 Application of the Combination of Intelligent Algorithms and 3D Interactive Imaging Technology in Display Space and Distribution Visualization

The combination of intelligent algorithms and 3D interactive imaging technology is an important research direction in the field of display space and distribution visualization. The combination of the two can better understand the characteristics and relationships of data, and achieve better display effects.

1. **Data analysis.** Intelligent algorithms can help analyze the characteristics and relationships of data, and process and optimize the data based on this information [22]. Data analysis refers to the process of collecting, processing, analyzing, and interpreting data to obtain effective information. 3D interactive imaging technology can present these optimized data in a three-dimensional space, allowing users to better understand the distribution and relationships of the data.

   In the 3D city model, machine learning algorithms are used to predict traffic congestion in different regions, and then presented in the model. In this way, users can intuitively understand the traffic situation in different regions of the city and improve urban traffic congestion by modifying road systems or optimizing public transportation [23].

2. Feature extraction. Intelligent algorithms can also help extract features and attributes of data and combine them with 3D interactive imaging technology for display. In a 3D city model, deep learning algorithms are used to identify the type, height, and area of buildings and present them in the model [24].

An intelligent algorithm is crucial to the feature extraction process, as evidenced by the following aspects:

1. Automated feature extraction: An intelligent algorithm can make use of information and data patterns that are automatically derived from the original data of characteristics that are representative and differentiable. This can lessen the workload associated with creating artificial features and save time and energy.
2. Combined feature generation: By combining the original features, the intelligent algorithm may produce more expressive and higher-level features. This aids in identifying more complex structures and patterns within the data.
3. Removing superfluous features: Using feature selection and dimension reduction techniques, the intelligent algorithm may eliminate unnecessary and redundant characteristics. This can lower the chance of overfitting, increase computing efficiency, and simplify the complexity of the model.

In this way, users can have a better understanding of the city's architectural structure and style, and can improve the livable environment of the city by adding green spaces, optimizing public facilities, and other measures.

3. Configuration Operations. 3D interactive imaging technology can also be used to configure intelligent algorithms to optimize data display effects. In the 3D city model, intelligent algorithms are used to analyze the traffic and pedestrian flow in different regions, and public transportation routes are adjusted based on the results [25]. By combining with 3D operations, the effects of different schemes can be better demonstrated and the optimal solution can be ultimately determined. This article conducts experimental analysis on the application of intelligent algorithms and 3D interactive imaging technology in the visualization of display space and distribution. The overall research framework of this article is shown in Figure 2.

3 SPATIAL VISUALIZATION EXPERIMENTS BASED ON INTELLIGENT ALGORITHMS AND 3D INTERACTIVE IMAGING TECHNOLOGY

3.1 Experimental Design

With the continuous development of computer and network technology, intelligent algorithms and 3D interactive imaging technology are increasingly widely used in various fields. Among them, intelligent algorithms can help people process various

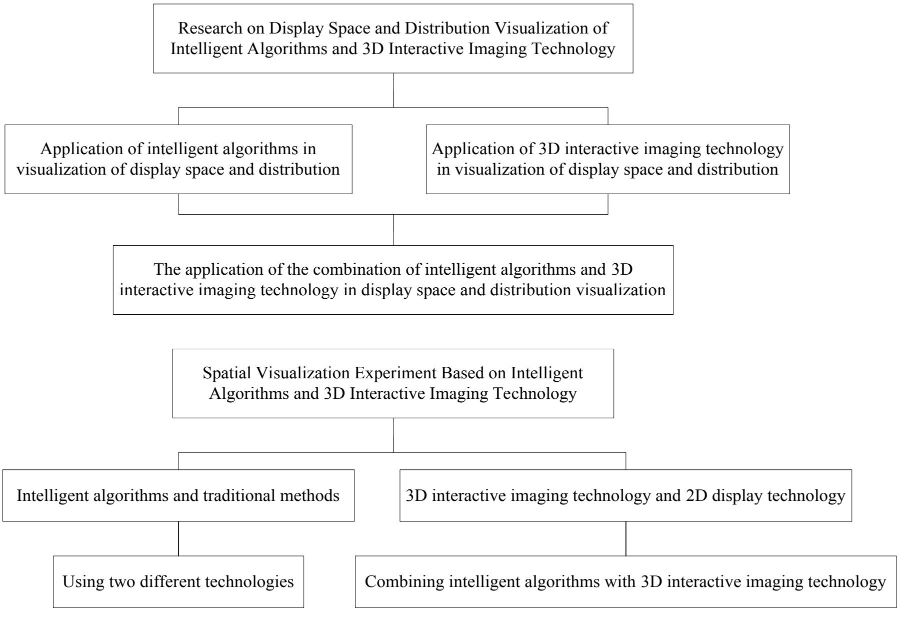


Figure 2. Overall framework

data more efficiently and provide more accurate analysis results; 3D interactive imaging technology can enable people to observe and understand complex data models and phenomena in a more intuitive way. Therefore, this article combines intelligent algorithms with 3D interactive imaging technology, which can greatly improve the visualization level of data, help people understand various data more deeply, and discover more laws and values from it.

In order to explore the advantages and disadvantages of intelligent algorithms and 3D interactive imaging technology in display space and distribution visualization, and to compare and analyze them, four experiments were designed in this paper. The purpose of this paper is to study the differences and applicability of intelligent algorithms and 3D interactive image technology in display space and distribution visualization, and provide a reference for future data visualization research.

This article selects 50 professionals to participate in the experiment and is randomly assigned to two groups, each consisting of 25 people. Table 1 shows the information background of the participants' representatives. The individuals participating in the experiment are professionals from relevant fields, with certain theoretical and practical experience. They represent groups of different ages, genders, educational backgrounds, and work experience backgrounds, allowing for the reliability and universality of experimental results to be examined from multiple perspectives.

This article designs four experiments, namely: intelligent algorithms and traditional methods, 3D interactive imaging technology and 2D display technology, the

Participant	Age	Gender	Education	Work Experience (Years)	Professional Field
1	25	Male	Master	1	Computer science
2	32	Female	Doctor	6	Data analysis
3	28	Male	Undergraduate	3	Bioinformatics
4	35	Female	Master	8	Medical health
5	24	Male	Undergraduate	0.5	Artificial intelligence
6	27	Female	Undergraduate	4	Industrial engineering
7	31	Male	Master	3	Marketing
8	28	Female	Doctor	5	Biochemistry
9	26	Male	Undergraduate	2	Computer engineering
10	30	Female	Master	7	Finance

Table 1. Information background

combination of intelligent algorithms and 3D interactive imaging technology, and the use of two different technologies. At least three indicators were set for each experiment to evaluate the performance of various technologies in terms of display space and distribution visualization. The specific experimental design is as follows:

Experiment 1 (Intelligent algorithms and traditional methods)**.** This experiment aims to compare the performance of intelligent algorithms and traditional methods in displaying spatial and distribution visualization. Participants would be randomly assigned to two groups, the first group using intelligent algorithms to process data and visualize it, and the second group using traditional methods for visualization. Participants are required to complete the task within the specified time. The experimental indicators include time efficiency, accuracy, and ease of use.

Experiment 2 (3D interactive imaging technology and 2D display technology)**.** This experiment aims to compare the performance of 3D interactive imaging technology and 2D display technology in terms of display space and distribution visualization. Participants would be randomly assigned to two groups. The first group would use 3D interactive imaging technology to process data and visualize it, while the second group would use 2D presentation technology for visualization. Participants are required to complete the task within the specified time. The experimental indicators include interactivity, visual effects, and ease of use.

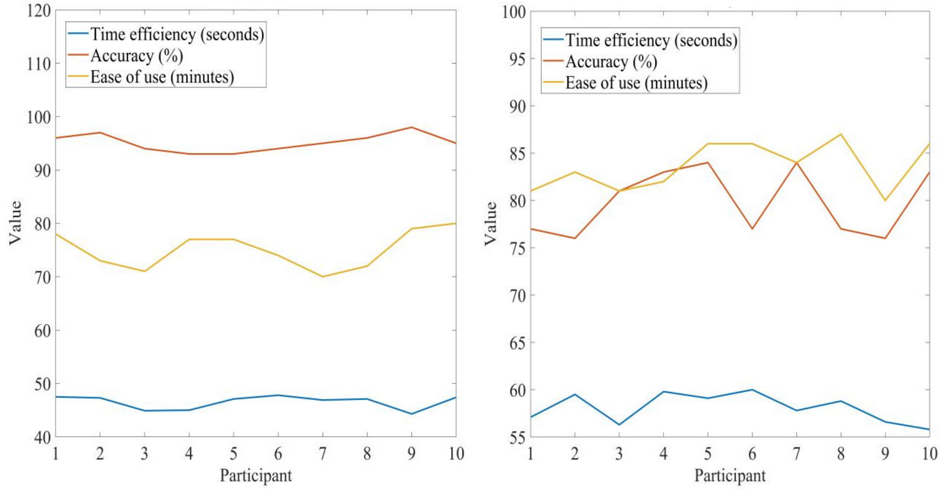
Experiment 3. (Combining intelligent algorithms with 3D interactive imaging technology.) This experiment aims to compare the performance of combining intelligent algorithms with 3D interactive imaging technology in displaying spatial and distribution visualization. Participants would use a combination of intelligent algorithms and 3D interactive imaging technology to process data and visualize it. Participants are required to complete the task within the specified time. The experimental indicators include time efficiency, interactivity, and accuracy.

Experiment 4 (Using two different techniques)**.** This experiment aims to compare the performance of two technologies (intelligent algorithms and 3D interactive imaging technology) in displaying spatial and distribution visualization. Participants would be randomly assigned to two groups, the first group using intelligent algorithms for visualization, and the second group using 3D interactive imaging technology for visualization. Participants are required to complete the task within the specified time. The experimental indicators include accuracy, ease of use, and visual effects.

In this experiment, this article calculates the participation of participants and scores the experimental indicators using a scoring system. The meaning of the scoring indicators for usability is as follows: 90–100 points: extremely easy to use; 80–89 points: easy to use; 70–79 points: generally easy to use; 60–69 points: difficult to use; 0–59 points: very difficult to use, users are unable to complete tasks normally, the interface is chaotic, the operation is difficult, and the response is extremely slow; For the rating indicator of interactivity: 90–100 points: highly interactive; 80–89 points: high interactivity; 70–79 points: general interactivity; 60–69 points: poor interactivity; 0–59 points: extremely poor interactivity; Scoring criteria for visual effects: 90–100 points: very excellent visual effects; 80–89 points: excellent visual effect; 70–79 points: general visual effects; 60–69 points: poor visual effect; 0–59 points: extremely poor visual effect.

3.2 Experimental Results on Visualization of Display Space and Distribution

1. **Intelligent algorithms and traditional methods.** Figure 3 shows the performance of intelligent algorithms and traditional methods in displaying spatial and distribution visualization. Figure 3 a) shows the intelligent algorithm, and Figure 3 b) shows the traditional method. Table 2 shows the average comparison of the performance of the two algorithms. In terms of intelligent algorithms, its time efficiency is 46.5 seconds, accuracy is 95 %, and usability score is 75 points. In terms of traditional methods, the time efficiency is 58.1 seconds, the accuracy is 80 %, and the usability score is 84 points. In terms of time efficiency, intelligent algorithms are 11.6 seconds faster than traditional methods, which means that when processing large amounts of data, using intelligent algorithms can greatly improve processing speed. At the same time, intelligent algorithms also perform excellently in accuracy, increasing by 15 percentage points compared to traditional methods. However, in terms of ease of use, intelligent algorithms are slightly inferior to traditional methods, and the gap is not significant.
2. **3D interactive imaging technology and 2D display technology.** Figure 4 shows the performance of 3D interactive imaging technology and 2D display technology in visualization of display space and distribution. Figure 4 a) shows 3D interactive imaging technology, and Figure 4 b) shows 2D display technology. Table 3 shows the comparison of the average performance of two technologies. In



a) Intelligent algorithm

b) Traditional method

Figure 3. Performance of intelligent algorithms and traditional methods in displaying spatial and distribution visualization

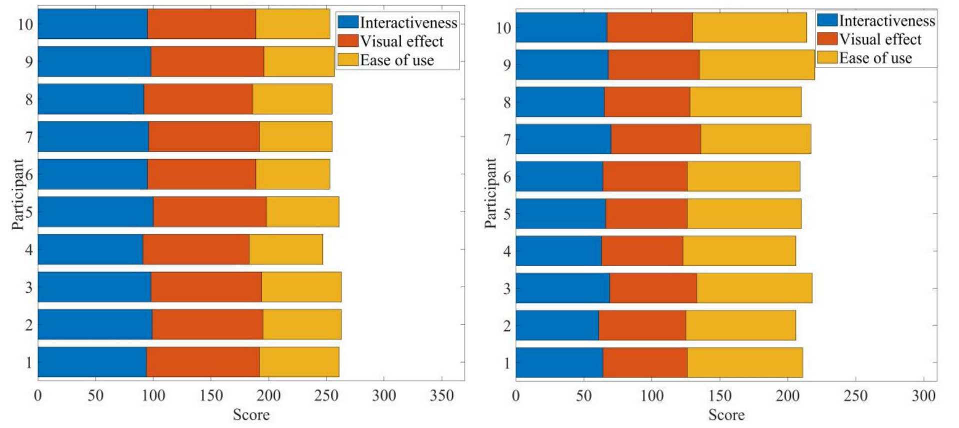
	Intelligence Algorithms	Traditional Method
Time Efficiency (Seconds)	46.5	58.1
Accuracy (%)	95	80
Ease of Use (Minutes)	75	84

Table 2. Comparison of the mean performance of two algorithms

terms of 3D interactive imaging technology, its interactivity rating is 96, visual effects rating is 96, and usability rating is 65. In terms of 2D display technology, its interactivity rating is 66, visual effects rating is 63, and usability rating is 83. It can be seen that 3D interactive imaging technology performs well. In terms of interactivity and visual effects, 3D interactive imaging technology is superior to 2D display technology, and its advantages are obvious. However, in terms of usability, 3D interactive imaging technology is slightly inferior to 2D display technology, which is also where 3D technology needs further improvement.

	3D Interactive Imaging Technology	2D Display Technology
Interactiveness	96	66
Visual Effect	96	63
Ease of Use	65	83

Table 3. Comparison of the mean performance of two technologies



a) 3D interactive imaging technology

b) 2D display technology

Figure 4. Performance of 3D interactive imaging technology and 2D display technology in visualization of display space and distribution

3. **Combining intelligent algorithms with 3D interactive imaging technology.** Figure 5 shows the performance of the combination of intelligent algorithms and 3D interactive imaging technology in displaying spatial and distribution visualization. This article combines intelligent algorithms with 3D interactive imaging technology, with a time efficiency of 50.8 seconds, interactivity of 86 minutes, and accuracy of 98 %. It indicates that combining intelligent algorithms with 3D interactive imaging technology has good time efficiency and can provide good interactivity and accuracy.
4. **Using two different technologies.** Figure 6 shows the performance of intelligent algorithms and 3D interactive imaging technology in displaying spatial and distribution visualization, respectively. Figure 6 a) shows intelligent algorithms, and Figure 6 b) shows 3D interactive imaging technology. Table 4 shows the comparison of the average performance between intelligent algorithms and 3D interactive imaging technology. In terms of intelligent algorithms, their accuracy is 92 %, their usability score is 64 points, and their visual effects score is 63 points. In terms of 3D interactive imaging technology, its accuracy is 85 %, usability score is 62 points, and visual effects score is 84 points. It can be seen that intelligent algorithms outperform 3D interactive imaging technology in terms of accuracy, and there is not much difference in usability between the two. However, in terms of visual effects, 3D interactive imaging technology scores higher and has received better evaluations.

In summary, intelligent algorithms have higher time efficiency and accuracy in displaying spatial and distribution visualization compared to traditional methods,

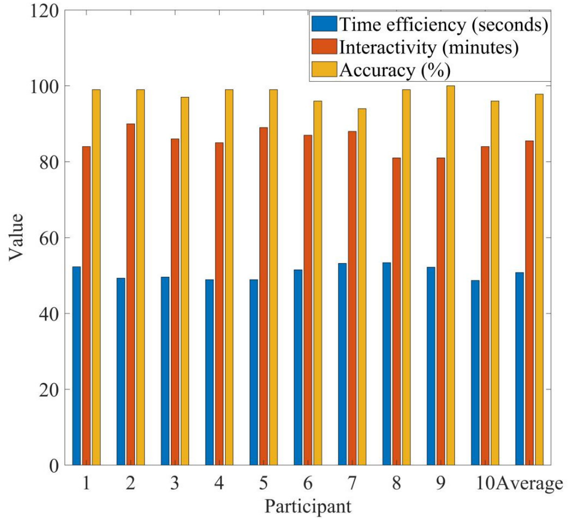
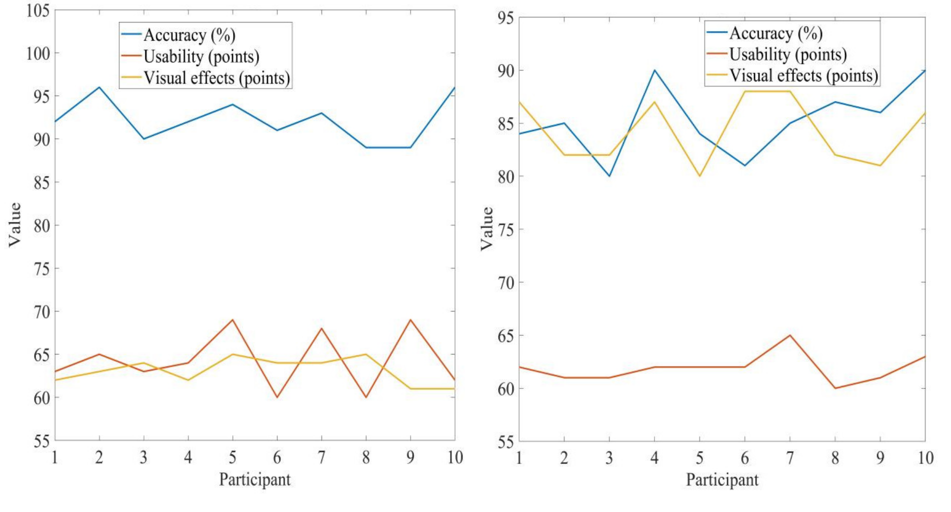


Figure 5. Performance of the combination of intelligent algorithms and 3D interactive imaging technology in displaying spatial and distribution visualization



a) Intelligent algorithm

b) 3D interactive imaging technology

Figure 6. The performance of intelligent algorithms and 3D interactive imaging technology in display space and distribution visualization, respectively

	Intelligence Algorithms	3D Interactive Imaging Technology
Accuracy (%)	92	85
Usability (points)	64	62
Visual effects (points)	63	84

Table 4. Comparison of the average performance of intelligent algorithms and 3D interactive imaging technology

but their ease of use is slightly inferior to traditional methods. Compared to 2D display technology, 3D interactive imaging technology has better interactivity and visual effects in terms of display space and distribution visualization, but its usability is slightly inferior to 2D display technology. The combination of intelligent algorithms and 3D interactive imaging technology has higher accuracy in displaying spatial and distribution visualization, but its time efficiency and interactivity are slightly inferior to using intelligent algorithms or 3D interactive imaging technology alone. When using intelligent algorithms and 3D interactive imaging technology for visualization, there is not much difference between the two in terms of display space and distribution visualization. Intelligent algorithms are slightly better in accuracy than 3D interactive imaging technology, while 3D interactive imaging technology is slightly better in visual effects than intelligent algorithms. It shows that different data visualization technologies have their own characteristics in display space and distribution visualization, and suitable technologies can be selected according to actual needs and application scenarios.

4 CONCLUSIONS

With the rapid development of digital and information technology, intelligent algorithms and 3D interactive imaging technology have become important technical means for displaying spatial and distribution visualization. Intelligent algorithms can analyze and predict data, and achieve better data visualization effect. 3D interactive imaging technology can enable users to better interact with data and improve the visualization effect of the data. This article explored the advantages and disadvantages of intelligent algorithms and 3D interactive imaging technology in displaying spatial and distribution visualization through the design of four experiments, and compared and analyzed them. Both intelligent algorithms and 3D interactive imaging technology have advantages in displaying spatial and distribution visualization. Intelligent algorithms are faster and more accurate than traditional methods, but they are not easy to get started. 3D interactive imaging technology is more attractive and interactive than 2D display, but it is not easy to use. Combining intelligent algorithms with 3D interactive imaging technology can improve accuracy, but interactivity and time efficiency are slightly inferior. Overall, different technologies should be selected based on specific needs. In future research, it should pay attention to the interpretability and efficiency of algorithms, constantly explore new algorithms and technical means, and apply them to actual scenes to provide better support for data visualization and spatial analysis. At the same time, it is also necessary to strengthen the research on human-computer interaction experience and user needs in order to better adapt to the application scenarios of data visualization and spatial analysis.

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