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Component-based access design method for dynamic spatial database

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Abstract—In order to realize the optimal access of dynamic spatial database, a component-based optimal access method of dynamic spatial database is proposed. The statistical information distribution model for storing the characteristic data of association rules is constructed in the dynamic spatial database. The fuzzy information features are extracted by using the dynamic component fusion clustering analysis method. Combined with the distributed association feature quantity, the fusion scheduling is carried out to control the dynamic information clustering. Combined with fuzzy c-means clustering analysis method, dynamic attribute classification analysis is carried out. The dynamic component block matching model is used for update iterative optimization, and the optimal access to the dynamic spatial database is realized in the cluster center. Simulation results show that this method has strong adaptability to the optimal access of dynamic spatial database, and has high accuracy and good convergence for data information extraction in dynamic spatial database.

Keywords—Block matching model, data clustering, dynamic components, dynamic spatial database, optimize access.

I. Introduction

DYNAMIC database is a database system that stores information such as time, space and related attributes. The geographic data in the dynamic database is closely related and has a large volume. Time variables organically connect the data in the database [1]. The improvement of dynamic database function puts forward higher requirements for database model. Dynamic database model can effectively reflect spatial entities and their dynamic relationships in the real world, and provide basic concepts and methods for spatio-temporal data organization and spatio-temporal database schema design [2].

With the development of dynamic spatial database management technology, cloud database model is used to build dynamic spatial database [3]. Under the distributed network structure system, combined with the big data statistical feature analysis method, the adaptive optimal access and feature analysis of dynamic spatial database are carried out, the statistical feature quantity and association rule feature quantity of dynamic spatial database are extracted, and the fuzzy association rule detection method is used for adaptive feature extraction of dynamic spatial database [4]. In order to improve the optimal access ability of dynamic spatial database, the research on the dynamic update method of dynamic spatial database is of great significance to the optimal construction and design of dynamic spatial database.

The research on the optimal access method of dynamic spatial database has attracted extensive attention. Fuzzy information clustering method is used for adaptive control and optimization of dynamic spatial database. At present, the design of adaptive optimal access algorithm of dynamic spatial database mainly adopts statistical analysis method. Affected by the uncertain factors of big data distribution, the adaptive optimal access adaptability of dynamic spatial database is poor. Therefore, this paper proposes a component-based adaptive optimal access algorithm for dynamic spatial database. In the adaptive optimal access process of dynamic spatial database, the fuzzy correlation fusion scheduling method is used for spatial addressing and dynamic information clustering control, the adaptive fusion and adaptive optimal access of association rule feature data stored in dynamic spatial database are realized in the clustering center. The simulation results show that the improved method has superior performance in improving the adaptive optimization access ability of dynamic spatial database.

The second chapter describes the characteristics of association rules in dynamic spatial database, the analysis of data mining and storage structure, and the construction of spatio-temporal database model. The third section describes the optimization design and access rights optimization of dynamic spatial database combined with fuzzy c-means clustering analysis method. In the fourth chapter, the performance of the proposed method is proved by simulation experiments. Finally, the fifth chapter makes a comprehensive summary of the content of the article.

II. Basic Definitions

A. Feature Data Mining of Association Rules in Dynamic Spatial Database

In order to realize adaptive optimal access of dynamic spatial database based on components, a statistical information distribution model for storing association rule feature data in dynamic spatial database is established, and dynamic component fusion clustering analysis method is adopted for optimal mining of association rule feature data stored in dynamic spatial database. In a specific window function, the characteristic distribution set of association rule feature data stored in dynamic spatial database is obtained as follows:

$$\hat{x}(k/k)=\sum_{j}^{m}\hat{x}^{i}(k/k)u_{j}(k) \tag{1}$$

$$P(k/k)=\sum_{j}^{m}u_{j}(k/k)\{P^{j}(k/k) + [\hat{x}^{j}(k/k)-\hat{x}(k/k)][\hat{x}^{j}(k/k)-\hat{x}(k/k)]^{T}\} \tag{2}$$

Wherein, $\hat{x}$ is the statistical average distribution concept set of dynamic spatial database information sampling, $u_j(k)$ is the fuzzy information feature distribution set of dynamic spatial database, u_j is the association degree feature of dynamic spatial database, and P^j is the probability density function of sample selection.

The binary semantic feature analysis model of dynamic spatial database is constructed, and the feature quantity of association rules of dynamic spatial database is obtained as follows:

$$S_{i,j}(t)=\frac{p_{i,j}(t)-sp_{i,j}(t)}{p_{i,j}(t)} \tag{3}$$

where $T_{i,j}(t)$ represents the fuzzy feature set of the dynamic spatial database and is expressed as:

$$T_{i,j}(t)=\frac{\left|p_{i,j}(t)-\Delta p(t)\right|}{p_{i,j}(t)} \tag{4}$$

Using multiple regression analysis method, dynamic mining of online dynamic spatial database is carried out, and the frequent dynamic metric distribution of dynamic spatial data is obtained as follows:

$$U_{i,j}(t)=\exp\left[-b\left[z_i(t)-z_j(t)\right]^2\right] \tag{5}$$

where: $p_{i,j}(t)$ is the cross-correlation feature quantity of heterogeneous input dynamic spatial database data; $sp_{i,j}(t)$ is the number of dynamic spatial databases with marked samples; $\Delta p(t)$ is the gain coefficient; $z_i(t)$ and $z_j(t)$ is expressed as a fuzzy function of a dynamic spatial database. Fuzzy information fusion method is adopted to optimize access to dynamic spatial database [5]. In this database, the information source collects the results, and the regulator translates, filters and synthesizes the data before returning to the client. Regulator is a kind of software module to purify information between data sources. Encapsulation is used for technology transformation, while regulator involves semantic integration of data. The biggest advantage of this structure is the field storage cost and the flexibility of integrating new data sources. Fig. 1 Shows the dynamic spatial database analysis model.

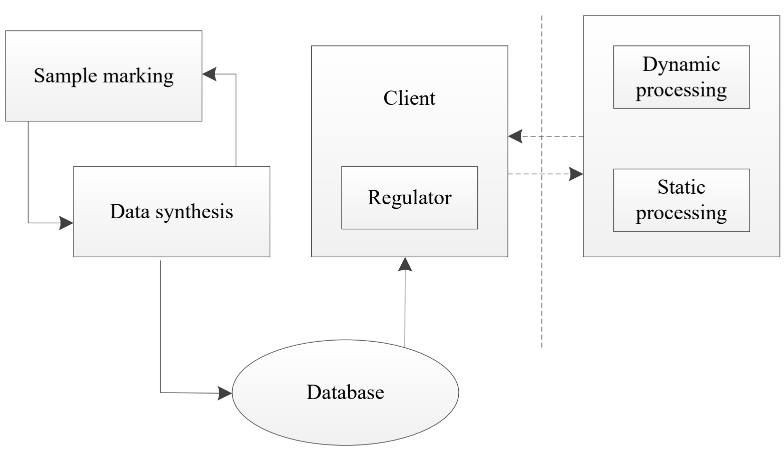

Fig. 1 Dynamic spatial database analysis model

The model can deal with a large number of dynamic and static data access contents. When the data warehouse used for static processing deals with dynamic data access with different access contents, but the query results are not stored in the data warehouse. In order to generate query results, most of the database energy is used for data link operation, and the processing effect is poor. Moreover, most of the query results of static data access are similar or the same, and almost all of them are stored in a fixed location in the storage area for easy access. Once the dynamic processing regulator is used to encapsulate the processing, each database needs to be calculated for the same data access, which also involves a large number of data queries, and the response time is long, this is inefficient in practical application. Therefore, the model is improved, the spatial attribute data and monitoring statistical data are corresponding to keywords and marked, and the one-to-one correspondence between the graph file and the attribute file is realized. The specific content is shown in Fig. 2.

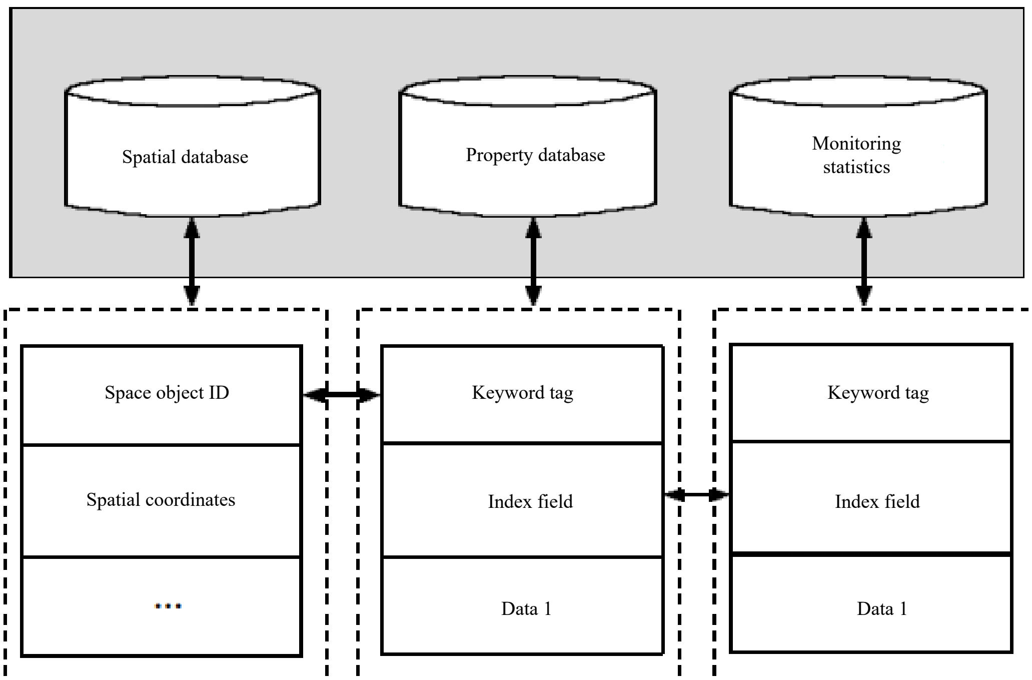

Fig. 2 Technical framework of data association

For each data table, set keywords and index fields, establish association with spatial database, complete the correspondence between graph file and attribute file, and establish links between each data table to facilitate the query and analysis of spatial data and attribute data.

B. Data Storage Structure of Dynamic Spatial Database

The dynamic component fusion clustering analysis method is adopted to extract the fuzzy information features of the dynamic spatial database of the dynamic spatial database, and the distributed association features of the dynamic spatial database are extracted, and the statistical distribution probability density features of the association rule feature data mining stored in the dynamic spatial database are obtained as follows:

$$D''_{i,j}\left(t_{n+1}\right)=\frac{D'_{i,j}\left(t_{n+1}\right)+f\left(n\right)D'_{i,j}\left(t_n\right)}{2} \tag{6}$$

Wherein the time and the time differ by one update period t_{n+1} and t_n. In the behavior set of information sampling in different dynamic spatial databases [6], the binary semantic feature distribution of association rule feature data stored in dynamic spatial databases is as follows:

$$I_{i,j}\left(t\right)=\frac{\sum D''_{i,k}\left(t\right)D''_{k,j}\left(t\right)}{\sum D''_{i,k}\left(t\right)} \tag{7}$$

The evaluation function of fuzzy information feature extraction of dynamic spatial database is expressed as follows:

$$\hat{S}_w=\sum_{i=1}^{c}p_i\frac{1}{n_i}\sum_{k=1}^{n_i}\left[\left(\vec{X}_k^{(i)}-\vec{m}_i\right)\left(\vec{X}_k^{(i)}-\vec{m}_i\right)^T\right] \tag{8}$$

A subspace training method is adopted to establish a behavior dynamic measurement model of a dynamic spatial database, and under the guidance of a training set $s_i=\{x_j:d(x_j,y_i)\le d(x_j,y_l)\}$, a frame sequence distribution of association rule feature data mining stored in the dynamic spatial database is obtained:

$$MinWH=\min\left\{w(cc),h(cc)\right\} \tag{9}$$

$$Area\_Ratio=\frac{Area(cc)}{Area(pic)} \tag{10}$$

The kernel function model of dynamic spatial database data mining is established in the distribution set of domain features, the weighted vector is adjusted to obtain N_{j*} geometric neighborhood $NE_{j*}(t)$, and the weighted adaptive feature distribution set of dynamic spatial database is obtained as follows:

$$U = \{\mu_{ik} \mid i = 1, 2, \ldots, c, k = 1, 2, \ldots, n\} \tag{11}$$

Under the guidance of association rules, the fuzzy information features of dynamic spatial database are extracted by using global statistical information, and the optimization objective function is obtained as follows:

$$J_m(U,V) = \sum_{k=1}^{n} \sum_{i=1}^{c} \mu_{ik}{}^{m} (d_{ik})^2 \tag{12}$$

In the statistical information distribution area of the local window [7], the optimized dynamic spatial database data optimized access clustering center is:

$$\mu_{ik} = 1 \Big/ \sum_{j=1}^{c} \left(d_{ik} / d_{jk} \right)^{\frac{2}{m-1}} \tag{13}$$

$$V_i = \sum_{k=1}^{m} (\mu_{ik})^m x_k \Big/ \sum_{k=1}^{n} (\mu_{ik})^m \tag{14}$$

In the formula, m is the embedding dimension of fuzzy information feature extraction of dynamic spatial database of dynamic spatial database, $(d_{ik})^2$ is the measurement distance between sample x_k and feature distribution set V_i. To sum up, fuzzy information feature extraction of dynamic spatial database of dynamic spatial database is carried out, and feature extraction and data mining are carried out according to dynamic measurement results [8]. The specific data connection design framework is shown in Fig. 3.

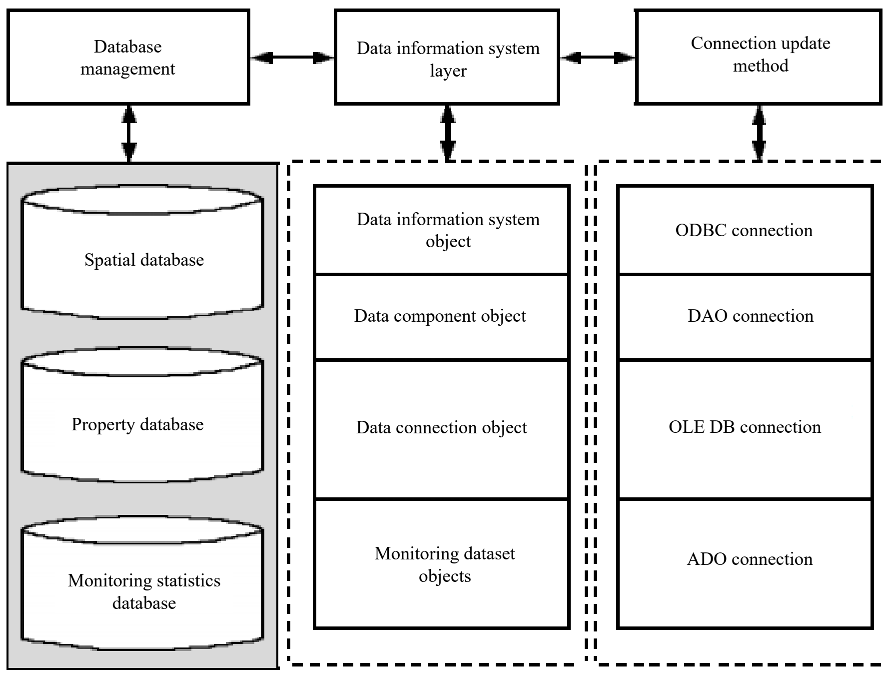

Fig. 3 Data connection design framework

As can be seen from Fig. 3, each database is connected to the data information system layer under unified management. Under the data information system layer, there are different information objects, and there are four different connection methods, including ODBC connection, DAO connection, OLE DB connection and ADO connection.

C. Spatiotemporal Database Model

At present, the standardized spatiotemporal data model is still in the exploration stage. Scholars have conducted extensive research on spatiotemporal data model from the concept, theory, structure, implementation technology and other aspects. The spatiotemporal database model can be divided into the following types:

The space-time cube (The space-time cube): The time cube model was first proposed by Hagerstrand in 1970. Later, it was further discussed by Rucker, Szego, etc. The time cube model uses two-dimensional coordinate axis to represent the real world plane space, and uses one-dimensional time axis to represent the change of plane position along time, forming a three-dimensional cube. The advantage of this model is that it can express time semantics intuitively [9]. The disadvantage is that with the increase of data, the operation of cube will become more and more complex, so that it can't be processed.

Snapshot sequence model (Sequent snapshots): Continuous snapshot is the simplest way to realize temporal dimension in GIS. At a certain time, interval or specific time, all data (including spatial data and attribute data) are stored in the database as a new layer. In the snapshot sequence model, each level is a collection of all cells of the same content at a certain time point, which shows the state of a geographic distribution at different times. The disadvantage of the model is that there is no clear temporal relationship between the layers, and a large number of time and space attributes that have not changed in any way need to be saved, resulting in a large number of data redundancy and waste of storage space.

Ground state modified model (Base state with amendments): Ground state correction model is also known as base map superposition model. The basic idea is to determine the initial state of geographical phenomena, that is, the ground state, and then record the changed areas at a certain time interval [10]. The state (snapshot) of each change can be obtained by overlaying the content of each change. Fig. 4 shows several ground state modification methods of the ground state model. It directly records and maintains the changes of single space target and topology information, and does not store all information of each state. The advantage of this model is that it can significantly reduce the burden of spatiotemporal data, greatly save the storage space of computer, and the method is simple and easy to implement. The disadvantage of this model is that it can only be used to store the dynamic database of spatial features with relatively small change frequency, and store the change amount relative to the ground state, so it needs to be overlapped when obtaining the "non initial" state data, which is more suitable for grid model, but less efficient for vector model.

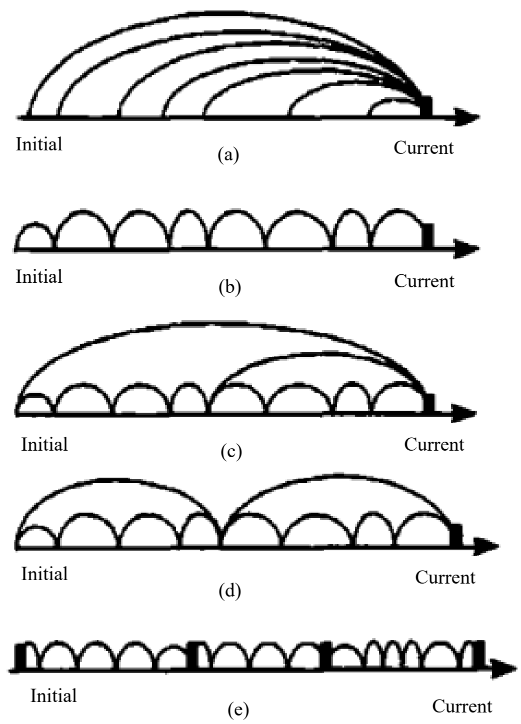

Fig. 4 Five ground state modification methods of ground state modification model

Spatiotemporal object model: Spatiotemporal object model uses object-oriented method to time stamp spatial objects. It adds a temporal dimension in the right angle direction of two-dimensional space and represents the world as a set of discrete objects composed of space-time atoms. Spatiotemporal atoms contain time and space attributes at the same time. Although not every spatiotemporal atom has changed, it can handle the changes in time and space at the same time, so it can record the collective or individual attribute changes of spatiotemporal objects in time and space dimensions [11]. The disadvantage of this model lies in the discreteness of space-time atoms, which makes it difficult to express the gradual changes of geographical elements in space after a period of time. It only represents the sudden changes in an independent, discrete and linear time structure.

These models have their own advantages and disadvantages, which are suitable for dynamic databases with different properties. However, for the large-scale dynamic database of national basic geographic information, none of the above models can well meet the characteristics of the dynamic database, such as large change range, large change frequency, uncertain change cycle and different regional range changes. In view of this, the author puts forward a new model, dynamic version difference model, which is suitable for the dynamic database of national basic geographic information.

III. Dynamic Spatial Database Optimization Access Optimization

A. *Fuzzy c-means Clustering of Dynamic Spatial Database Data*

On the basis of the statistical information distribution model of the dynamic spatial database established above, the dynamic component fusion clustering analysis method is adopted to extract the fuzzy information features of the dynamic spatial database, the adaptive optimal access of the dynamic spatial database is carried out, and the adaptive optimal access algorithm of the dynamic spatial database based on components is proposed. The dynamic component fusion clustering analysis method is adopted to analyze the reliability dynamic characteristics of the dynamic spatial database, and the distribution of the associated main characteristics of the dynamic spatial database is as follows:

$$f(k)=\begin{cases} f(k-1)-\dfrac{1}{n},1\le k<n \\ 1,k=n \end{cases} \tag{15}$$

In the reconstructed vector space structure model, the energy spectral density of the differential grouping feature quantity at S is obtained, and a feature extraction model for storing association rule feature data in a dynamic spatial database is constructed by adopting a principal component analysis method [12]. The local window distribution of dynamic spatial database mining is obtained as follows:

$$(d_{ik})^2=\|x_k-V_i\|^2 \tag{16}$$

And meet:

$$\sum_{i=1}^{c}\mu_{ik}=1,k=1,2,\mathrm{L}\ ,n \tag{17}$$

By using the differential grouping clustering method, the association rule vector set of dynamic spatial database mining is obtained as follows:

$$SL_{i'}=\begin{cases} L_i & if\ \ i=1 \\ New\mathrm{i}' & \text{otherwise} \end{cases} \tag{18}$$

Wherein, $New_{i'}=(e_{i',1},e_{i'2},\ldots,e_{i'D})$, the optimal access decision function of dynamic spatial database data under dynamic component block matching model is obtained by using wavelet analysis and joint decision-making method:

$$R_1(k)=R_2(k)\exp(-j\omega_0T_p/2),\ \ k=0,1,\ldots,(N-3)/2 \tag{19}$$

$$R_2(k)=A_k\exp(j\varphi_k),\ \ k=0,1,\ldots,(N-3)/2 \tag{20}$$

Among them, ω_0 is the distributed prediction error of dynamic spatial database, T_p is the time window, φ_k is the effective amplitude S of dynamic spatial database mining, and φ_k is the extended phase of dynamic spatial database adaptive optimization access. According to the above analysis, feature extraction and optimization mining of dynamic spatial database are carried out to improve the mining capability of dynamic spatial database [13].

B. Dynamic Component Block Matching Model for Dynamic Spatial Database

Combining fuzzy C-means clustering analysis method to carry out data rough dynamic attribute classification analysis of dynamic spatial database adaptive optimal access, dynamic spatial database stores motion feature detection statistics:

$$\begin{aligned} &\min imize \quad \frac{1}{2}\|w\|^2+C\sum_{i=1}^{n}(\xi_i+\xi_i^*) \\ &subject\ to \quad y_i-(w'\Phi(x_i)+b)\le\varepsilon-\xi_i \\ &\qquad\qquad (w'\Phi(x_i)+b)-y_i\le\varepsilon-\xi_i^* \\ &\qquad\qquad \xi_i,\xi_i^*\ge 0,i=1,2,\mathrm{L}\ ,n;C>0 \end{aligned} \tag{21}$$

Seek an optimal solution to that above formula, extracting a data mine model of association rules stored in a dynamic spatial database [14-16], and obtaining a principal component characteristic distribution set of dynamic spatial database mine as follows:

$$\left.\begin{aligned} &\min_{w,b,\xi}\frac{1}{2}\|w\|^2+C\sum_{j=1}^{l}u(x_j)\xi_j \\ &s.t.\ \ y_j((w\cdot x_j)+b)+\xi_j\ge 1 \\ &\xi_j\ge 0,\ \ j=1,2,\ldots,l \end{aligned}\right\} \tag{22}$$

The linear programming method is adopted to fuse and adaptively optimize the association rule feature data stored in the dynamic spatial database, the kernel function $k(x_i,x_j)$ of adaptive mining and the adaptive linear programming model of association rule feature data mining stored in the dynamic spatial database are as follows:

$$\left.\begin{aligned} &\min_{\alpha}\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}y_iy_j\alpha_i\alpha_jK(x_i,x_j)-\sum_{j=1}^{l}\alpha_j \\ &s.t.\ \ \sum_{j=1}^{l}y_j\alpha_j=0 \\ &\qquad 0\le\alpha_j\le u(x_j)C, \qquad j=1,2,\ldots,l \end{aligned}\right\} \tag{23}$$

Combining fuzzy C-means clustering analysis method, the rough dynamic attribute classification analysis of dynamic spatial database adaptive optimal access is carried out, and the reliability distribution function of fuzzy clustering of dynamic spatial database is obtained as follows:

$$w_{ij}=\beta\times w(e_pk_q) \qquad (\beta>1) \tag{24}$$

Wherein, β is an adaptive weighting coefficient of the dynamic spatial database, $w(e_pk_q)$ indicates the reliability coefficient of association rule feature data detection stored in the dynamic spatial database, and calculates the multi-dimensional distribution set of association rule feature data stored in the dynamic spatial database, which is:

$$Y_k=[y_{k1},y_{k2},\mathrm{L}\ ,y_{kj},\mathrm{L}\ ,y_{kJ}],(k=1,2,\mathrm{L}\ ,N) \tag{25}$$

Among them, y_{kj} represents the steady-state characteristic quantity of dynamic spatial database data and N is the data length. Based on the above analysis, optimal access to dynamic spatial database is realized.

C. Dynamic Database Building based on Dynamic "Version Difference" Model

After the dynamic database model is determined, the dynamic database is built. In the dynamic database based on the dynamic "version difference" model, four logical databases are created to express different tenses, namely, the current database (current tense), the process database (ongoing tense), the historical database (past tense) and the version database (specific tense), which establish the hierarchical index [17, 18].

Current database: The current database stores the spatial location and attributes of the current tense of the operating object. According to the characteristics of dynamic "version difference" model, the current state in the most frequent operation should be taken as the ground state, so the current database is taken as the ground state of the whole data set in the system. The occurrence of the event causes the change of the object, and the latest state after the change is stored in the current database. Each tuple in the database is in the "active" state, which is the current operating object of the database.

Process library: the process library stores the change process of objects caused by events. The process library can query the data status at any time and correctly analyze the evolution process of the object. In the process of processing, it is necessary to cancel or correct the change process of the object. The process library can realize the tracking function of object evolution process. Once the condition of the event is not met, the event will fall back along the time axis until the condition is established, and stop or return to the state before the event [19].

Historical inventory: historical inventory stores the amount of change based on the ground state. In this model, it is the difference between the current database and the current database. In order to query history quickly, all tuples are indexed hierarchically. For any given time or period of time, the state of "past" can be found from the history database, the temporal and spatial relationship of the object at that time can be restored, and the corresponding temporal and spatial operation can be carried out.

Version Library: A version is a snapshot of a dataset at a certain time on the timeline. When browsing data, users can generate data version at a certain time and store it in the version library. After the version data is generated, it can be quickly transferred into the system for viewing and operation, and can be used as the ground state before the version data time, and can be combined with the process database and the history database to realize a fast hierarchical index.

IV. Simulation Test Analysis

In order to verify the application performance of the method in realizing optimal access of dynamic spatial database, Matlab is used for simulation test analysis. It adopts windows10 system with 16 g memory, AMD ryzen 9 3900x CPU, 1 TB solid-state hard disk and geforce GTX 1660ti graphics card. The concept lattice of spatial distribution for information sampling of dynamic spatial database is 500×500, the initial length of data sampling is 1024, the initial sampling frequency of dynamic spatial database data is 0.48KHz, and the description of data feature distribution set is shown in Table I.

Table I. Distribution of test data

Dataset	Original Features of Dynamic Spatial Database		Statistical analysis value	
	Test set	Training set	Test set	Training set
Dataset1	434	14	213	55
Dataset2	456	33	345	54
Dataset3	456	45	567	45
Dataset4	545	67	543	56
Dataset5	578	54	455	78
Dataset6	545	45	577	76

According to the above sample sampling and parameter setting, dynamic spatial database adaptive optimization access is performed to obtain the original data distribution as shown in Fig. 5.

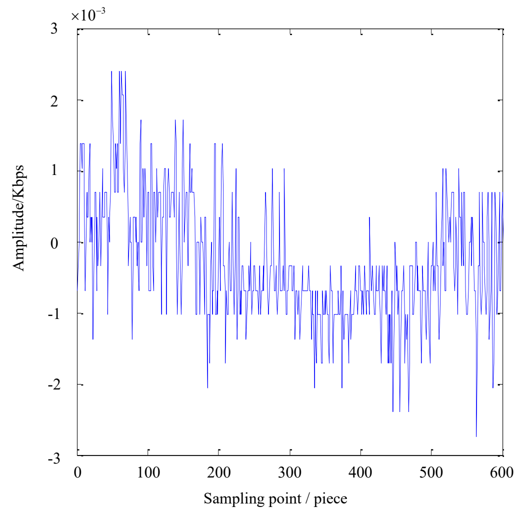

Fig. 5 Raw data of dynamic spatial database

Taking the data in Fig. 5 as input, the distributed association feature quantity of the dynamic spatial database is extracted, the statistical information distribution model of the association rule feature data stored in the dynamic spatial database is established, and the dynamic spatial database is adaptively and optimally accessed, thus obtaining the mining output as shown in Fig. 6.

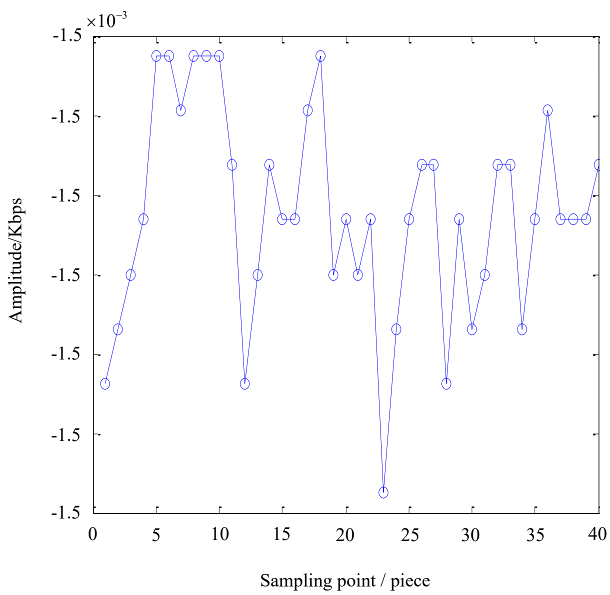

Fig. 6 Dynamic spatial database adaptive optimization access output

Comparing the adaptive optimal access output of dynamic spatial database in Fig. 6 with the original data, it can be seen that this method overlaps more with the original data, and the amplitude trajectory is similar to the original data, which can effectively realize the adaptive optimal access of dynamic spatial database. In order to better verify the performance of this method, compared with the traditional method, the convergence of the data update output of dynamic spatial database is tested. The comparison results are shown in Fig. 7.

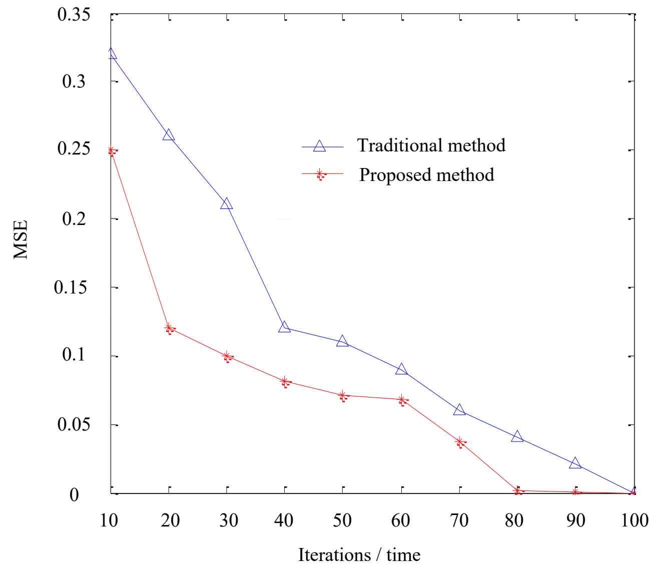

Fig. 7 Convergence comparison

It can be seen from Fig. 7 that the mean square error of the traditional method is higher than that of the proposed method at the beginning. With the increase of the number of iterations, although the mean square error decreases, it is still higher than that of the proposed method. The mean square error of the proposed method is low at the beginning. With the increase of the number of iterations, the mean square error is almost 0 at the 80th time, which shows that the proposed method has high accuracy, better convergence and good practical effect for adaptive optimal access to dynamic spatial database.

Here are a few query examples:

Users need to know the distribution of water area network in a certain area, and can send out corresponding queries. In the database, the overlay operation of r-alt map and r-water map is displayed. The query results have been stored in the data warehouse, which can quickly call out the results, save the machine time consuming superposition operation, and shorten the response time.

The user queries the difference between the actual rainfall and the predicted rainfall in a certain period of time. After the database receives the query, it needs to use the regulator to calculate, instead of using the data warehouse. Because the actual rainfall is dynamic, it is impossible for data warehouse to store the actual rainfall in advance. The predicted rainfall is static. The calculated results are returned to the user, and the query results and query pointers are stored in the buffer so that they can be easily called when the same query statement is encountered in the future, which improves the access efficiency and shortens the user response time.

The user queries the flow velocity and water level of a certain branch at a given time and a certain flow segment. Use the same principle of the first two examples to check. If the previous query results have occupied all buffers, it is necessary to adopt efficient algorithms to eliminate some query results and query pointers, and make enough storage space to store new query results and query pointers.

V. Conclusion

This paper designs a new component-based algorithm for adaptive optimal access of dynamic spatial database. In the dynamic spatial database, the statistical information distribution model for storing the characteristic data of association rules is established, the dynamic component fusion clustering analysis method is used to extract the features and distributed association features, and the fuzzy correlation fusion scheduling method is used to control the dynamic information clustering. Combined with fuzzy c-means clustering analysis method, the adaptive fusion and adaptive optimal access of association rule feature data stored in dynamic spatial database are realized. Through comparative experiments, it can be proved that the proposed method has small mean square error for adaptive optimal access to dynamic spatial database, has good convergence and high precision, can meet the needs of adaptive optimal access to dynamic spatial database, and has good practical application effect.

However, from the perspective of data sharing and concurrent access of network users, the performance is not perfect. In the next research, we will focus on analyzing the sharing service performance of dynamic spatial database and establish a separate index data module to achieve the goal of rapid indexing of massive data.

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Contribution description

In order to realize the optimal access of dynamic spatial database, Jing Wang proposed a component-based optimal access method of dynamic spatial database is proposed. Feng Xu established a statistical information distribution model for storing the characteristic data of association rules is constructed in the dynamic spatial database. The fuzzy information features are extracted by using the dynamic component fusion clustering analysis method. Combined with the distributed association feature quantity, the fusion scheduling is carried out to control the dynamic information clustering. Combined with fuzzy c-means clustering analysis method, dynamic attribute classification analysis is carried out. The dynamic component block matching model is used for update iterative optimization, and the optimal access to the dynamic spatial database is realized in the cluster center. According to the experiment, Jing Wang and Feng Xu concluded that this method has strong adaptability to the optimal access of dynamic spatial database, and has high accuracy and good convergence for data information extraction in dynamic spatial database. Jing Wang and Feng Xu jointly completed the first draft.