

Research Article

Multisource Target Data Fusion Tracking Method for Heterogeneous Network Based on Data Mining

Hongyan Guo ¹ and Xintao Li²

¹College of Information Engineering, Henan Open University, Zhengzhou, Henan 450046, China

²College of Innovation and Entrepreneurship, Henan Open University, Zhengzhou, Henan 450046, China

Correspondence should be addressed to Hongyan Guo; guohongyan123@stu.ahu.edu.cn

Received 15 March 2022; Revised 28 April 2022; Accepted 6 May 2022; Published 10 June 2022

Academic Editor: Jun Ye

Copyright © 2022 Hongyan Guo and Xintao Li. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This research is on heterogeneous network fusion method of multisource target data based on data mining. Firstly, it is a distributed storage structure model for building heterogeneous network multisource target data. Then, using the phase space reconstruction method, a grid distribution structure model for data fusion tracking is constructed, and realize visual scheduling and automatic monitoring of multisource target data. Finally, according to the feature extraction results, analyze the statistical characteristics of multisource target data in heterogeneous networks, combined with the fuzzy tomographic analysis method, multilevel fusion, and adaptive mining of multisource target data, extract the associated feature quantities in it, and realize the fusion tracking of data. The simulation results show that, in relatively simple heterogeneous networks, the feature mining error of the proposed method is nearly 2.11% lower than the two traditional methods. In relatively complex heterogeneous networks, the feature mining error of the proposed method is nearly 6.48% lower than the two traditional methods. It can be seen that this method has better adaptability for fusion tracking of heterogeneous network multisource target data, the anti-interference ability is strong, and the tracking accuracy in the data fusion tracking process is also improved.

1. Introduction

As the scale of heterogeneous networks continues to expand, the amount of multisource target data in heterogeneous networks is also gradually increasing; therefore, it is necessary to perform visual reconstruction and fusion tracking and identification of heterogeneous network multisource target data and ensure the stability of the network. Usually, in the process of fusion tracking and identification of multisource target data in heterogeneous networks (Figure 1), it is necessary to establish a heterogeneous network multisource target data fusion tracking model, and combined with big data mining and information reconstruction methods, the fusion detection and feature analysis of heterogeneous network multisource target data are carried out; thereby, the detection, tracking, and identification capability of multisource target data in heterogeneous networks is improved. And the related research on multisource target data fusion track-

ing method in heterogeneous network has received great attention. In general, for heterogeneous networks, the fusion tracking and identification of multisource target data are based on data fusion detection and feature analysis. This process can improve the ability to detect and identify multisource target data in heterogeneous networks, thereby improving the retrieval and access capabilities of multisource target data in heterogeneous networks [1].

The rapid development of database technology and machine learning disciplines makes data mining as a new technology on the stage of history. This is a database and other media to store data, and use machine learning algorithms to extract the knowledge that people are interested in from the data. Due to the continuous progress of machine learning in artificial intelligence, look at the rapid development of information technology: at the beginning, it was just a simple collection and creation of databases; the rapid development of data mining technology has been promoted;

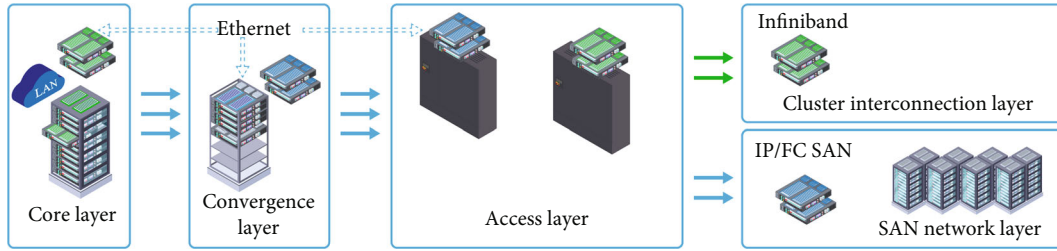


FIGURE 1: Data center heterogeneous network.

take a look at the development of information technology. The beginning is just a simple collection and sampling of data and the establishment of a database; then, start managing this data, such as the following: data storage, retrieval, and database transaction processing. Then, it developed to the analysis, understanding, and prediction of data, and then, data warehouse and data mining technology appeared. With the development of network information technology, database technology, etc., the amount of information stored in the database by humans increases over time, and adding and deleting technologies of the database are perfected; it provides conditions for the development of data mining technology; the increase in the amount of data also indicates that a technology for processing massive data is bound to emerge [2].

2. Related Works

At present, there are experts and scholars in the field of multisource target data tracking and identification; some more mature research results are presented, such as association feature detection method, fuzzy C-means cluster analysis method, and K-means cluster analysis method. Meng et al. proposed a method to simultaneously analyze resource content information and resource network topology information, probabilistic topic models, and tag recommendation methods for unified modeling; in order to carry out the fusion of multisource heterogeneous network information, the data can be more accurate for fusion analysis [3]. Wang et al. studied the wireless body area network multisensor; due to the large amount of data collected, the data types are complicated and it is difficult to effectively integrate multidimensional data, using the algorithm based on manifold learning, the high-dimensional data points, and their corresponding low-dimensional data points; the Euclidean distance is used as the conversion condition of the probability matrix, and a multidimensional data fusion model is constructed through finite iterations [4]. In addition, Wan et al. proposed a multisource target data fusion tracking method based on data mining in heterogeneous networks, in order to improve the detection and recognition ability of heterogeneous network multisource target data [5]. In addition, in the study of Liu et al., by extracting multilayer convolution features, the target data represented by it is more comprehensive, and calculate the correlation response of the data; then, dynamically fuse all the historical data and the target position in the real-time data response, so as to realize the positioning and dynamic tracking of target data [6]. In the study of Yi et al., using the fusion redetection

mechanism to track the network target data and integrating the correlation filter into the network in the training phase, extract multisource data features through end-to-end training. In the tracking stage, the residual value is used to connect and fuse different source data, and a redetection mechanism is introduced to achieve real-time tracking [7]. Li et al. believe that data mining itself is not a new technology; after decades of research and development, people have mastered a large number of data mining algorithms and developed many data mining tools. However, these theories and tools are not necessarily applicable to large datasets [8]. Liu believes that traditional data storage methods cannot carry big data. Before the era of big data, traditional relational databases, e.g., were common tools for structured data storage. For the level of data volume, the storage efficiency of relational databases can fully meet the basic needs. And relational databases provide rich and flexible structured query statements, as well as features such as stored procedures, indexes, and database transactions [9]. Alqerm and Shihada believe some domestic scientific research institutions and universities have started research on data mining, a subject with great potential and practical application value; the domestic data mining research institutions are mainly universities, research institutes, or companies [10]. Ishaq et al. believe that the abovementioned specifications emphasize the completeness of geographic information, making the exchange format itself enormous; data reception and transmission overhead are too high for both software and hardware; this is contrary to the fast and efficient properties of dynamic target information itself; it is not conducive to the transmission of real-time information, so it is not suitable to use the spatial data format exchange standard as a reference [11].

However, when existing methods perform fusion tracking on heterogeneous network multisource target data, there are problems such as poor adaptability, high computational complexity, and poor data tracking ability. The author proposes a multisource target data fusion tracking method based on data mining in heterogeneous networks.

3. Research Methods

3.1. Data Collection. Data mining technology includes the following steps: data preparation, data mining, conclusion representation, and interpretation.

3.1.1. Data Preparation. The data preparation stage is the beginning of the whole mining process; this stage is very important; how well the data preparation stage is executed will determine the efficiency of the subsequent steps of the

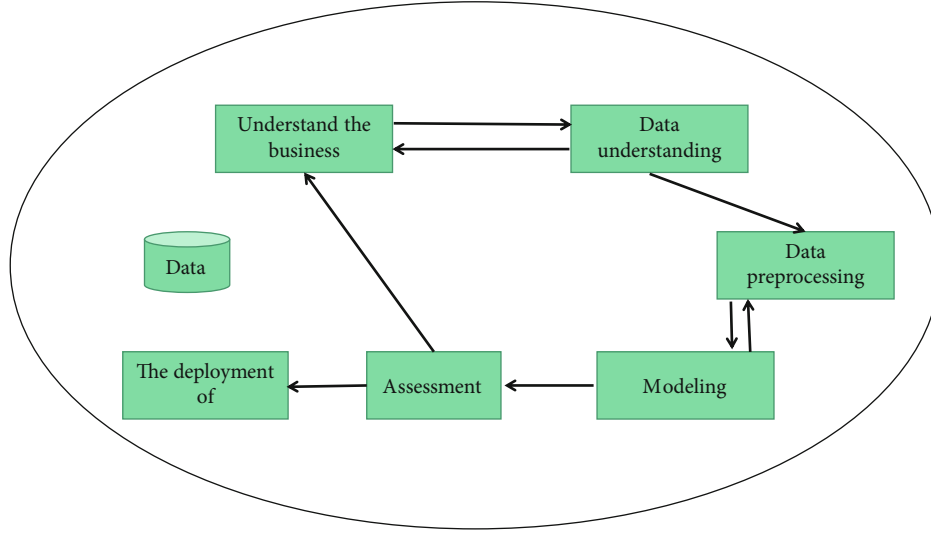


FIGURE 2: Data mining process.

entire data mining, as well as the effectiveness of the extracted information and knowledge; we can further subdivide data preparation into three stages: data integration, data selection, and data preprocessing [12].

- (1) *Data Integration*. That is, data integration from different databases agrees to be stored
- (2) *Data Preprocessing*. Preprocessing is obviously the preprocessing work before data mining, mainly carry out data form conversion and data reduction to suit the entire data mining process

3.1.2. Data Mining. Select a data mining algorithm (such as classification algorithm, association rule, regression, and clustering algorithm), mining the data prepared in the data preparation stage to obtain patterns that users are interested in.

3.1.3. Result Description and Interpretation. Mainly the patterns and rules that will be mined, analyze the mining patterns and rules according to the specific needs of users, extract the most useful and interesting information for users, and finally submit it to users through decision-making tools. Therefore, not only the presentation and interpretation of the results (visualization tools) is the main task of this step; the final information data needs to be filtered and processed [13]. If the user is not satisfied with the conclusion, the mining process needs to be repeated. The steps and criteria of the data mining process are summarized, as shown in Figure 2 below.

3.2. Distributed Storage Structure Model and Multilevel Integration of Data

3.2.1. Distributed Storage Structure Model of Target Data. To realize the fusion tracking and optimization identification of heterogeneous network multisource target data, firstly, a distributed storage structure model of heterogeneous network

multisource target data is constructed; assuming that N_k ($k = 1, 2, \dots, l$) represents the number of multisource target data fusion tracking distribution sets in the k th heterogeneous network, a_i^k represents the heterogeneous network multisource target data, the activity of the i th node is in the k th layer in the data sampling, x_i^k is the data input at the multisource target data fusion node i of the k th layer heterogeneous network, and w_i^k represents the energy threshold at the i th node of the k th layer in the heterogeneous network, then the statistical analysis model of the sampling node of the heterogeneous network multisource target data can be obtained as $S = (\mu \sum_{i=1}^n a_i^k \times x_i^k) \times w_i^k$; among them, μ represents the connection weight of each node in the heterogeneous network. Assuming that the effective activation function of the heterogeneous network sampling data is f , analyze the amplitude of periodic oscillation of multivariate target data in heterogeneous networks, using the semantic ontology fusion method and the three-dimensional reconstruction of the multisource target data in the heterogeneous network; the fuzzy decision function of the distributed storage to obtain the target data is $F = \partial \times S/f$, where ∂ represents the ambiguity coefficient. There are several data layers at the input of the heterogeneous network, which is obtained in the normalized linear subspace; the multisource target data distribution function of heterogeneous network in the first layer is $D = \lambda \sum_{k=1}^l F \times N_k$, where λ represents the normalization coefficient [14]. Constructed from the above model, the optimal design of the distributed storage structure of the target data is realized.

3.2.2. Multilevel Fusion and Adaptive Mining of Data. In the above pair of heterogeneous networks, based on the design of the distributed storage structure model of the target data, let c_i denote the fuzzy closeness function between multisource target data sharing nodes in heterogeneous networks; extract the intracluster distribution information of multisource target data in heterogeneous networks; the intracluster distribution model of the multisource target data is

obtained as $C = D \times c_i + (S + T)\eta$; among them, η represents a natural parameter, and T represents a sufficient statistic. On the basis of, using information fusion and fuzzy tomographic analysis methods for multisource target data in heterogeneous networks, information fusion, and adaptive scheduling, extract 3D visualization feature quantities of heterogeneous network multisource target data; then, the optimized within-cluster distribution function can be rewritten as $C' = [(a \times C)/\gamma] \times g$, where a is the correlation coefficient of multilevel fusion of data, γ is the number of symmetrical voxels in the three-dimensional regular data field, and g represents the adaptive optimization function. When C' has a finite stable solution in g , it means that the optimization process is convergent; at this time, the objective function in heterogeneous network tracking and identification is gC' ; under the fixed perturbation step size, it is assumed that the fuzzy weighted value of the multisource target data fusion tracking and identification of the heterogeneous network is β ; through the optimization of the decision function, the feature optimal solution of multisource target data mining in heterogeneous network is obtained as follows:

$$J = \frac{(\beta C' - \varepsilon) \times g_c}{2}. \quad (1)$$

Among them, ε is the decision error. Based on the above analysis, build multilevel fusion and adaptive mining models of data, and by visual scheduling and automatic monitoring design of heterogeneous network multisource target data, the statistical feature extraction of heterogeneous network multisource target data is carried out.

3.3. Fusion Tracking of Multisource Target Data

3.3.1. Statistical Feature Analysis of Multisource Target Data. Based on the abovementioned distributed storage and fusion mining of multisource target data in heterogeneous networks, the author proposes a multisource target data fusion tracking method based on data mining in heterogeneous networks [15]. Using the phase space reconstruction method, a grid distribution structure model for fusion tracking of heterogeneous network multisource target data is constructed, and by visual scheduling and automatic monitoring of multisource target data in heterogeneous networks, the feature distribution dimension of the multisource target data obtained in heterogeneous networks is m ; if the type attribute of multisource data in heterogeneous networks is r , then there is a maximum independent set for all nodes:

$$P_i = \{mrN_k | i = 1, 2, \dots, k = 1, 2, \dots, l\}. \quad (2)$$

Initialize the cluster center e for heterogeneous network multisource target data classification; then, the fuzzy membership function of multisource target data fusion tracking in heterogeneous network is as follows:

$$\chi = \prod_{i=1}^n (e_i)^k (1 - \rho) P_i. \quad (3)$$

Among them, e_i represents the fusion cluster center of heterogeneous network multisource target data, and ρ represents the prior probability density of multisource target data in heterogeneous networks; on this basis, the mean phase space reconstruction of multisource target data in heterogeneous networks is obtained as follows:

$$\bar{x} = \frac{(\sum_{i=1}^n |x|)}{k}. \quad (4)$$

According to the phase space reconstruction results of multisource data of heterogeneous networks, the data state characteristics are monitored, combined with statistical analysis methods; the variance of the multitarget data fusion is obtained as follows:

$$\sigma^2 = \frac{[\sum_{i=1}^n (x - \bar{x})^2]}{k}. \quad (5)$$

Assuming that the heterogeneous network multisource target data set contains N samples, for the limited data sample set X_N , the impulse response function of the 3D visual feature reconstruction is as follows:

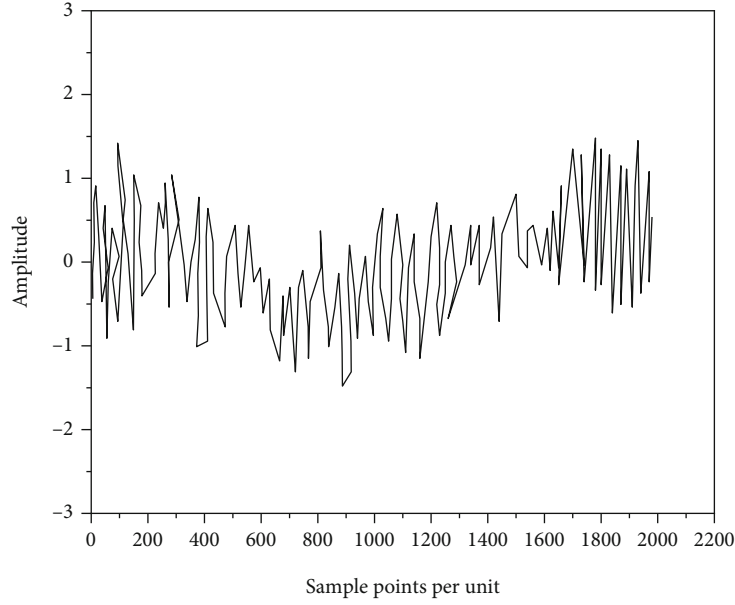
$$I = \frac{(\sum_I^N X_N \times \sigma^2)}{f_0}. \quad (6)$$

Among them, f_0 represents the initial sampling frequency. On the basis of, the metric feature extraction method is used to perform benchmark feature matching of multisource target data in heterogeneous networks, design the dominant frequency feature extraction model of multisource target data in heterogeneous network, realize the statistical feature analysis of multisource target data, and obtain the statistical feature quantity as follows:

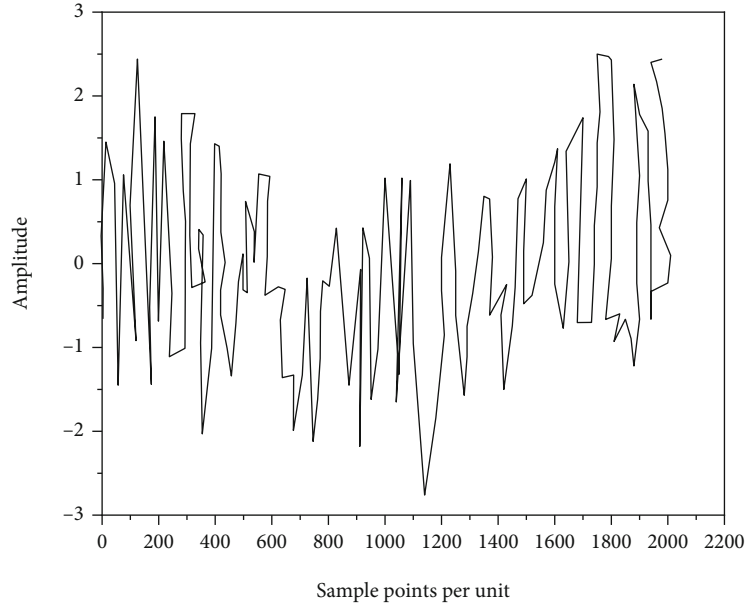
$$Q = I \times \left[\frac{(\varphi \times q - t)}{N} \right]. \quad (7)$$

Among them, q represents the feature attributes of multisource target data in heterogeneous networks, φ represents a limited data set, and t represents the time delay of data fusion tracking.

3.3.2. Data Feature Extraction and Fusion Tracking Output. For heterogeneous network multisource target data, the method used to extract adaptive feature information is information fusion, the information fusion method is used to extract adaptive feature information, the method of multilevel fusion and self-adaptive mining of multisource target data in heterogeneous network is fuzzy tomographic analysis method, and for heterogeneous network multisource target data, information fusion and fuzzy tomographic analysis methods are used to perform big data scheduling [16]; then, the rule itemset for quantitative evaluation of heterogeneous network multisource target data is as follows:



(a) Simulation result A



(b) Simulation result B

FIGURE 3: Amplitude distribution status of multisource target data in heterogeneous networks.

$$U = \frac{(\sum_{i=1}^n Q \times \delta)}{E_i}. \quad (8)$$

tracking and identification of heterogeneous network multisource target data is obtained:

$$Y = \frac{(\tau \times z)}{U}. \quad (9)$$

Among them, E_i represents the expected spectral output value of the i th node of the multisource target data output layer of the heterogeneous network, and δ represents the Kronecker function.

Assuming that z represents the measurement feature set of heterogeneous network multisource target data, analyze the statistical vector dimension of multisource target data in heterogeneous networks, and use the correction function to correct the state; the constraint function for the fusion

Among them, τ represents the reliability factor of multisource target data sampling in heterogeneous network; it is a constant greater than 0 but less than 1. The output of the fusion of heterogeneous network multisource target data through the fuzzy C-means cluster analysis method is as follows:

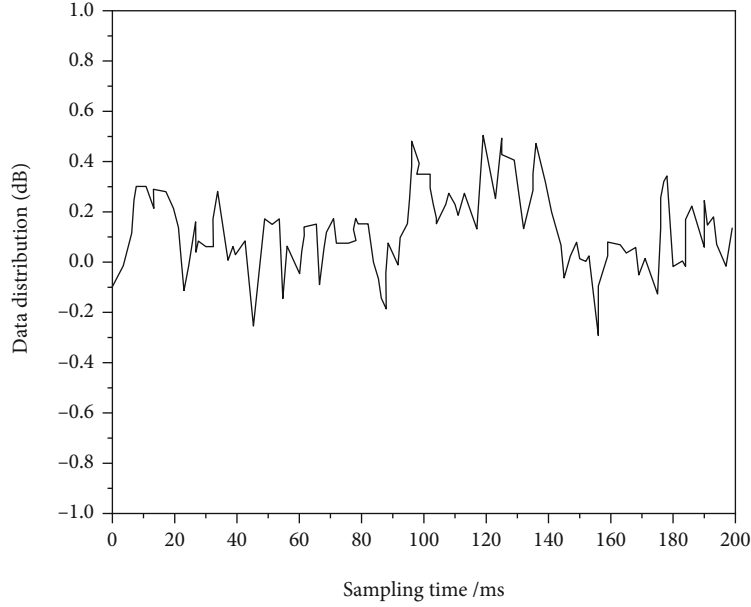


FIGURE 4: Experimental group.

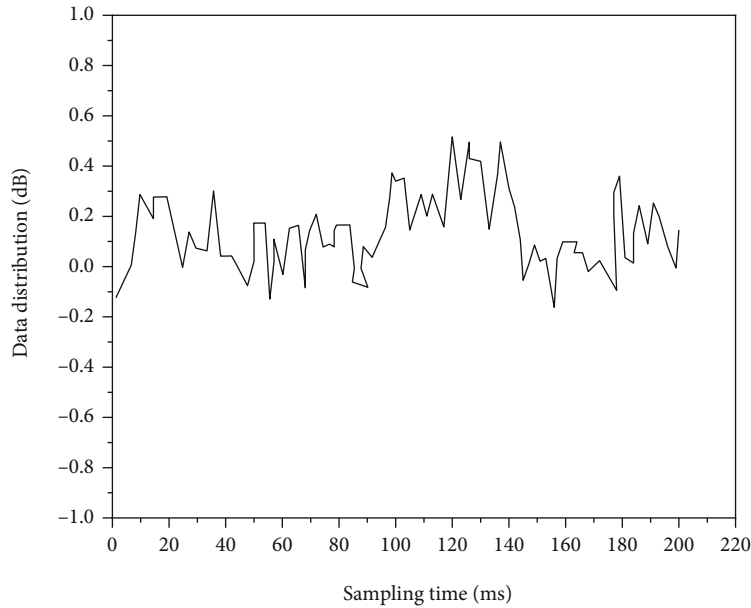


FIGURE 5: Control group 1.

$$T = \frac{(Q - U)}{\gamma \times Y}. \quad (10)$$

Among them, γ represents the fusion factor. Assuming that R represents the three-dimensional distribution attribute value of heterogeneous network multisource target data, through the above analysis, the optimal fusion tracking of multisource target data in heterogeneous networks is realized, and the output results are as follows:

$$M = \frac{(Y \times T - Q)\nu}{R}. \quad (11)$$

Among them, ν represents the distance between data nodes. Based on the above analysis, the basis of extracting associated feature quantities of multisource target data in heterogeneous networks realizes data optimization mining and fusion tracking identification.

4. Simulation Experiments

In order to verify the reliability of the research method, taking the data fusion method of this study as the experimental group, the traditional method 1 was used as the control group 1, and the traditional method 2 was used as the control group 2. Design simulation experiments, and verify the

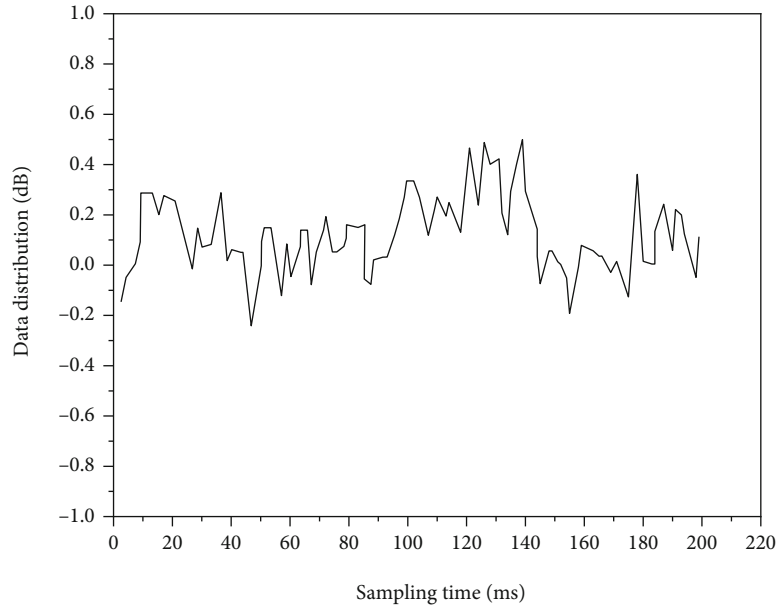


FIGURE 6: Control 2 groups.

TABLE 1: Mining error comparison of different methods/%.

Number of iterations	Test group	Control group 1	Control 2 groups
100	11.24	18.76	18.54
200	10.6	14.93	14.6
300	9.21	11.6	12.5
400	7.85	9.34	9.56
500	6.58	8.76	8.26
600	6.5	8.53	8.64
700	6.45	8.78	8.57
800	6.56	8.81	8.64
900	6.58	8.56	8.63
1000	6.45	8.86	8.52

fusion effect of different methods on multisource target data in heterogeneous networks.

4.1. Experiment Preparation. The experimental group simulated in the Matlab environment, set the number of iteration steps for heterogeneous network multisource target data fusion to 2000, and set the sampling interval to 1.0s; at the same time, ensure that the length of the sampled data to 2000. Set the dimension is 4, reconstruct spatial structure of multisource target data in heterogeneous networks, and set the embedding delay to 15 ms; the sampling frequency of multisource data is 10 kHz. According to the above basic conditions, using the simulation test software, the experimental group conducted two heterogeneous networks in different periods; build a multisource target data amplitude distribution map, as shown in Figure 3 below.

The two sets of simulation results in Figure 2 are the initial input data for the experimental group. Using two control test groups, obtain the amplitude distribution status of mul-

tisource target data in heterogeneous networks [17, 18]. Three test groups were used, respectively, mining data features in the two test environments and performing data fusion based on the mining results. In this paper, in order to make the experiment full of accuracy and authenticity, between the beginning of the test, the computer and the test software are run for trial operation, and the experiment is started after there is no problem.

4.2. Data Fusion of Simple Heterogeneous Networks. The three groups of time-domain distribution states are similar to the simulation environment A in Figure 3; as the basic test conditions of the first stage, three test groups are used; mining multisource target data features in simple heterogeneous networks, the result is shown in Figures 4–6 below.

According to the curve in the figure, when faced with a relatively simple heterogeneous network test environment; although the characteristic data obtained by the three test groups are relatively similar [19], however, the temporal characteristics of the data mined by the two control groups are slightly weaker than the experimental group. Therefore, the data mining errors of the three test groups are further calculated. Table 1 shows the experimental results.

It can be seen from the test results in Table 1 that when the number of iterations exceeds 500, mining errors for the three test groups are gradually controlled within a stable range. For ease of comparison, when computing 600 to 100 iterations, there is average mining error of the three test groups; among them, the experimental group was 6.58%, and the control group was 8.76% and 8.62%, respectively. The mining error of the experimental group is 2.18% and 2.04% smaller than that of the two control groups [20], respectively.

4.3. Data Fusion of Complex Heterogeneous Networks. In the second stage of testing, the time domain distribution state

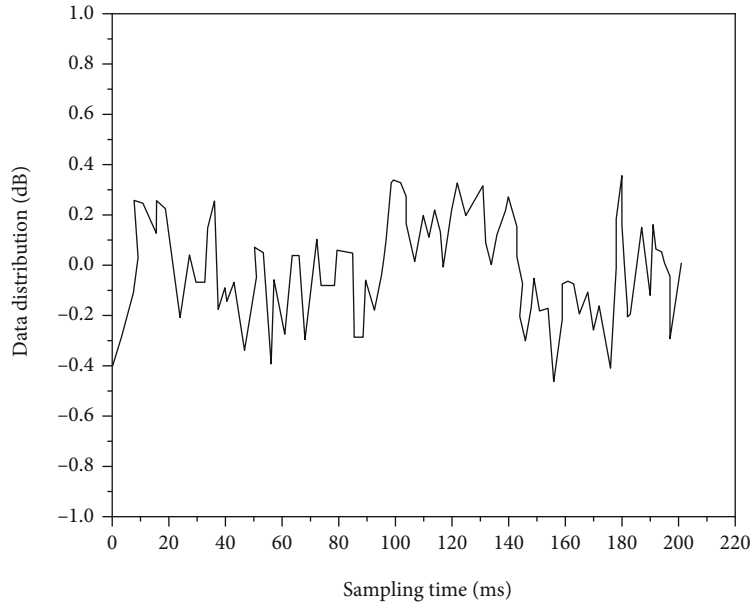


FIGURE 7: Control group 1.

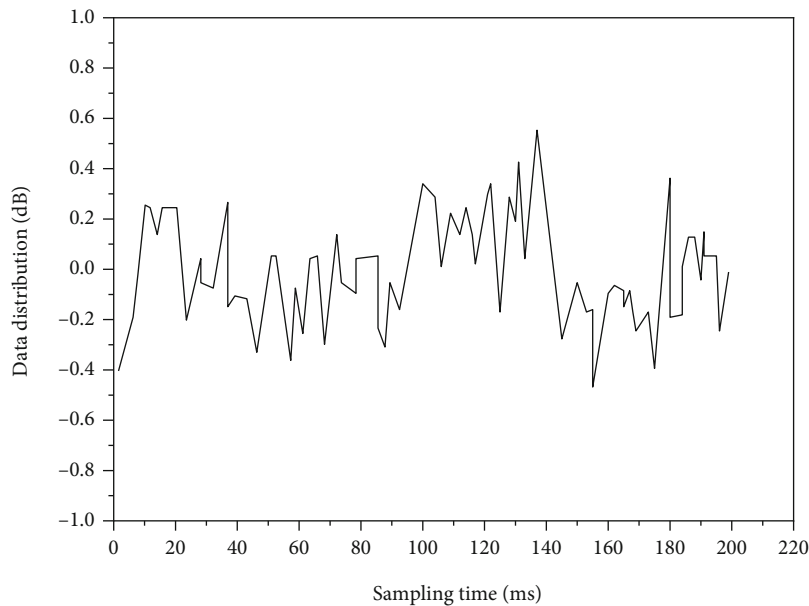


FIGURE 8: Control 2 groups.

similar to the simulation environment B in Figure 2 is used as the basic condition, using three test groups, mining complex heterogeneous networks, and the characteristics of multisource target data, and the results are shown in Figures 7 and 8 below.

According to the curve in the figure, due to the complex heterogeneous network environment, the volume of data is large, and there are many different types of data; therefore, it brings huge mining difficulty to data feature mining; therefore, the feature mining results of the two control groups do not match the data distribution characteristics of the respective simulation environment B. The data feature mining errors of different methods are fur-

ther calculated. Table 2 shows the experimental results [21].

It can be seen from the test results in Table 2 that in the process of 600-1000 iterations, the mining errors of the three test groups gradually became stable, and the average mining error of the experimental group was 7.2%, and the average mining errors of the control group were 13.81% and 13.55%, respectively. In a complex test environment, the mining error of the experimental group was 6.61% lower than that of the control group 1; it was 6.35% lower than the control group 2. Based on the above two sets of test results, it can be seen that, whether in a simple test environment or in a complex environment, the proposed data fusion

TABLE 2: Mining error comparison of different methods/%.

Number of iterations	Test group	Control group 1	Control 2 groups
100	11.78	28.36	30.96
200	11.27	24.05	24.7
300	10.23	21.16	22.2
400	9.2	17.63	20.03
500	8.36	14.6	14.56
600	8.14	13.66	13.14
700	7.26	13.57	13.5
800	7.3	13.62	13.57
900	7.25	13.7	13.5
1000	7.15	13.79	13.53

method, with the help of time series mining technology, the obtained mining results are more representative of multi-source target data and provide more realistic information for data fusion.

5. Conclusion

Based on the establishment of a heterogeneous network multisource target data fusion tracking model, combined with big data mining and information reconstruction methods, fusion detection and feature analysis of multisource target data in heterogeneous networks can be realized. The author proposes a multisource target data fusion tracking method based on data mining in heterogeneous networks. Build a distributed storage structure model of heterogeneous network multisource target data and statistical feature analysis of heterogeneous network multisource target data based on feature extraction results; for heterogeneous network multisource target data, the information fusion method is used to extract adaptive feature information, using the fuzzy tomographic analysis method, multilevel fusion, and adaptive mining of heterogeneous network multisource target data, extract the associated feature quantities of heterogeneous network multisource target data, and realize data optimization mining and fusion tracking and identification. From the experimental analysis, it can be seen that using this method for fusion tracking of heterogeneous network multisource target data has better adaptability; the information retrieval process has strong anti-interference ability and small control error and can be used to fuse and identify target data from multiple sources in the same network. However, affected by personal ability and research experience, there is no experimental demonstration of the data fusion results in this study, and only the data mining in the fusion process is simulated and tested; therefore, in future research, data fusion can also be used as an experimental test standard; the reliability of this research method is verified from more angles.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

All of the authors do not have any possible conflicts of interest.

Acknowledgments

This work was supported by the Project of Science and Technology of Henan Province (No. 212102210428).

References

- [1] G. Jiao and W. Li, "Neural network data mining clustering optimization algorithm," *IETE Journal of Research*, vol. 2, pp. 1–11, 2021.
- [2] M. Naeem, H. M. Elattar, and M. Aboul-Dahab, "An optimized load balance solution for multi-homed host in heterogeneous wireless networks," *Sensors*, vol. 19, no. 12, p. 2773, 2019.
- [3] L. Meng, C. Li, H. Zhang, and J. Dong, "Construction of community life circle database based on high-resolution remote sensing technology and multi-source data fusion," *European Journal of Remote Sensing*, vol. 3, pp. 1–16, 2020.
- [4] F. Wang, Q. I. Huan, X. Zhou, and J. Wang, "Demonstration programming and optimization method of cooperative robot based on multi-source information fusion," *Jiqiren/Robot*, vol. 40, no. 4, pp. 551–559, 2018.
- [5] J. Wan, J. Yang, S. Wang, D. Li, P. Li, and M. Xia, "Cross-network fusion and scheduling for heterogeneous networks in smart factory," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 9, pp. 6059–6068, 2020.
- [6] W. Liu, Q. Lü, Z. Cheng, G. Xing, and C. Chen, "Multi-element geochemical data mining: implications for block boundaries and deposit distributions in South China," *Ore Geology Reviews*, vol. 133, article 104063, 2021.
- [7] L. Yi, S. Ji, L. Ren, R. Su, and Y. Liang, "A nonlinear feature fusion-based rating prediction algorithm in heterogeneous network," *IEEE Transactions on Computational Social Systems*, vol. 8, no. 3, pp. 728–736, 2021.
- [8] Q. Li, Q. Xiong, S. Ji, M. Gao, Y. Yu, and C. Wu, "Multi-view heterogeneous fusion and embedding for categorical attributes on mixed data," *Soft Computing*, vol. 24, no. 14, pp. 10843–10863, 2020.
- [9] Y. Liu, "Research on heterogeneous data fusion algorithm based on IoT," *Revista de la Facultad de Ingenieria*, vol. 32, no. 4, pp. 549–556, 2017.
- [10] I. Alqerm and B. Shihada, "Sophisticated online learning scheme for green resource allocation in 5G heterogeneous cloud radio access networks," *IEEE Transactions on Mobile Computing*, vol. 17, no. 10, pp. 2423–2437, 2018.
- [11] A. Ishaq, S. Sadiq, M. Umer, S. Ullah, and M. Nappi, "Improving the prediction of heart failure patients' survival using smote and effective data mining techniques. IEEE," *Access*, vol. 9, pp. 39707–39716, 2021.
- [12] Y. Liu, D. Chen, A. Ma, Y. Zhong, and K. Xu, "Multiscale u-shaped CNN building instance extraction framework with edge constraint for high-spatial-resolution remote sensing imagery," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 59, pp. 1–15, 2020.
- [13] L. Zhang and Y.-C. Liang, "Deep reinforcement learning for multi-agent power control in heterogeneous networks," *IEEE*

- Transactions on Wireless Communication*, vol. 20, no. 4, pp. 2551–2564, 2020.
- [14] S. Baloch and M. S. Muhammad, “An intelligent data mining-based fault detection and classification strategy for microgrid. IEEE,” *Access*, vol. 9, pp. 22470–22479, 2021.
 - [15] Q. Liu, Q. Dou, L. Yu, and P. A. Heng, “MS-Net: multi-site network for improving prostate segmentation with heterogeneous MRI data,” *IEEE Transactions on Medical Imaging*, vol. 39, no. 9, pp. 2713–2724, 2020.
 - [16] W. Chen, Z. Yin, and T. He, “Enabling global cooperation for heterogeneous networks via reliable concurrent cross technology communications,” *IEEE Transactions on Mobile Computing*, vol. PP(99), pp. 1–1, 2021.
 - [17] F. Fang, G. Ye, H. Zhang, J. Cheng, and V. C. M. Leung, “Energy-efficient joint user association and power allocation in a heterogeneous network,” *IEEE Transactions on Wireless Communications*, vol. 19, no. 11, pp. 7008–7020, 2020.
 - [18] K. Yang, H. Song, K. Zhang, and J. Fan, “Deeper Siamese network with multi-level feature fusion for real-time visual tracking,” *Electronics Letters*, vol. 55, no. 13, pp. 742–745, 2019.
 - [19] S. Fu, G. Zhang, and T. Fujii, “A heuristic method-based parallel cooperative spectrum sensing in heterogeneous network,” *Journal of Supercomputing*, vol. 75, no. 6, pp. 3249–3263, 2019.
 - [20] N. Zhao, Y. C. Liang, D. Niyato, Y. Pei, and Y. Jiang, “Deep reinforcement learning for user association and resource allocation in heterogeneous cellular networks,” *IEEE Transactions on Wireless Communications*, vol. 18, no. 11, pp. 5141–5152, 2019.
 - [21] W. Yi, Y. Yuan, R. Hoseinnezhad, and L. Kong, “Resource scheduling for distributed multi-target tracking in netted collocated MIMO radar systems,” *IEEE Transactions on Signal Processing*, vol. 68, pp. 1602–1617, 2020.